Volodymyr NAZARENKO
Andrii MARTYN

MONOGRAPH

Evaluating the Economic Efficiency of Digital Tools in Sustainable Environmental Management

Methodologies and Case Studies in Agriculture

Kyiv | 2026

UDC 330.131.5:004.9:502.131.1:338.43(477)

Recommended for publication by the Academic Council of the National University of Life and Environmental Sciences of Ukraine, Record № 14 on 24.06.2026

Reviewers:

Yosyp DOROSH, Doctor Hab. in Economics, Professor, Director of the Institute of Land Use of the NAAS of Ukraine, Corresponding Member of the NAAS of Ukraine.

Oleksandra KOVALYSHYN, Doctor Hab. in Economics, Professor of the Department of Land Cadaster of the Lviv National University of Environmental Management.

Oleksandr **SHEVCHENKO**, Associate Professor, Doctor of Economics, Dean of the Faculty of Land Management, National University of Life and Environmental Sciences of Ukraine.

Anton **KOSHEL**, Professor, Doctor of Economic Sciences, Department of Geoinformatics and Aerospace Research of the Earth, National University of Life and Environmental Sciences of Ukraine.

Svitlana AMELINA, Doctor of Pedagogy, Professor, Head of Foreign Philology and Translation Department, National University of Life and Environmental Sciences of Ukraine.

Volodymyr NAZARENKO, Andrii MARTYN

Evaluating the Economic Efficiency of Digital Tools in Sustainable Environmental Management: Methodologies and Case Studies in Agriculture. Monograph. 2026. - 336 p.

This monograph establishes a comprehensive theoretical and methodological framework for evaluating the economic efficiency of digital tools in sustainable environmental management, with a focus on agricultural and peri-urban systems in transition economies such as Ukraine. Moving beyond narrow financial metrics such as traditional return on investment, the study introduces an integrated evaluation architecture that captures the multi-layered value of data assets, risk mitigation, operational timing, and institutional transparency.

For teachers, postgraduate students, students, and researchers.

ISBN 978-617-8928-62-9

Contents

INTRODUCTION

The scientific work is devoted to the study of the economic efficiency of digital tools in the system of sustainable environmental management, with special attention to their application in agriculture, land management, environmental monitoring, and operational decision-making in peri-urban territories. The general scientific and practical relevance of this topic stems from the fact that modern economic development is increasingly dependent on the quality of data, the speed of decision-making, the rational use of natural resources, and the ability of institutions and enterprises to combine economic growth with environmental responsibility. In the conditions of digital transformation, agriculture and environmental management are no longer isolated sectors based only on traditional production indicators. They are becoming complex, data-driven systems in which land, water, soil, transport, energy, climate, information infrastructure, and institutional regulation interact within a single economic and ecological space.

At the present stage of development, the problem of sustainable environmental management cannot be reduced only to the protection of natural resources or to the introduction of separate technical innovations. It is necessary to determine how such innovations change the cost structure of economic activity, how they influence the use of land and other natural resources, how they reduce or increase environmental pressure, and whether they create measurable value for enterprises, communities, and the state. The modern digital toolset - geographic information systems, cadastral databases, remote sensing, satellite monitoring, unmanned aerial vehicles, Internet of Things telemetry, routing systems, cloud platforms, artificial intelligence, and analytical middleware - creates new possibilities for organizing management decisions. At the same time, the existence of such tools does not automatically justify their use. Therefore, one of the key scientific problems is not only the implementation of digital technologies but also their economic efficiency within a broader ecological, institutional, and social context.

In recent years, a significant part of scientific research has been devoted to digital agriculture, smart farming, Agriculture 4.0, environmental monitoring, and sustainable land management. Several studies emphasize that digital agriculture can contribute to the development of sustainable agricultural systems by improving the accuracy of decisions, reducing losses, optimizing the use of inputs, and increasing the resilience of production systems to climatic and market uncertainty (Basso & Antle, 2020; Finger, 2023; Klerkx et al., 2019; MacPherson et al., 2022; Walter et al., 2017). However, the available scientific literature also shows that the effects of digitalization are heterogeneous. The same technology can generate significant value in one production, institutional, or territorial context and fail to produce expected results in another. The reason for this is that the efficiency of digital tools depends not only on their technical characteristics, but also on data quality, institutional rules, cost of implementation, access to infrastructure, human capital, market conditions, and environmental constraints.

Digital tools, including geographic information systems, remote sensing, IoT telemetry, UAV monitoring, analytical platforms, and optimization algorithms, are increasingly transforming modern agriculture and environmental management. These tools create new opportunities to increase productivity, reduce resource losses, and improve environmental control, but their actual value depends on whether they generate measurable economic and ecological effects (Basso & Antle, 2020; Finger, 2023; Klerkx et al., 2019).

This creates a methodological gap that is especially important for Ukraine and other transition economies. In such conditions, digital environmental tools are often considered as promising solutions for modernization, European integration, recovery, and sustainable development. Nevertheless, there remains an insufficiently developed methodological basis for calculating their actual economic efficiency. In many cases, evaluation is limited to direct financial savings or to a general qualitative description of environmental benefits. Current research confirms the potential of digital agriculture and smart farming, but it also shows that the results of digitalization are context-dependent and cannot be assessed only through narrow financial indicators (Klerkx et al., 2019; Shang et al., 2021; Papadopoulos et al., 2024). Therefore, the methodological problem is not only how to introduce digital tools, but also how to evaluate their economic efficiency when environmental externalities, data value, risk reduction, and institutional effects are taken into account.

Such an approach is insufficient because it fails to capture the full economic impact of digital environmental management. In particular, it does not properly include the value of generated data, the value of prevented ecological damage, the economic effect of reduced risks, the cost of delayed decisions, the importance of agronomic service windows, the reduction of transaction costs, and the ability of digital systems to increase institutional transparency and auditability.

The relevance of this monograph is therefore determined by the need to develop a comprehensive methodological framework for evaluating digital tools not only as technical solutions but also as economic instruments for sustainable environmental management. Such a framework should combine direct financial indicators with environmental externalities, institutional effects, and operational resilience. In this study, economic efficiency is understood as a broader category than traditional return on investment. It includes direct cost savings, productivity gains, reduced input waste, avoided environmental damage, decreased transaction costs, improved decision timing, compliance with sustainability targets, and the ability of systems to function under uncertainty. This interpretation aligns with current research in environmental economics, which seeks to translate non-market effects, ecosystem services, carbon emissions, soil degradation, water use, and resource depletion into measurable economic parameters (Macháč et al., 2021; Moore et al., 2017; Sartori et al., 2024).

The practical importance of the problem is especially visible in agriculture. Agriculture is simultaneously a production system, a user of land and water resources, a source of food security, and a sector affected by climate change, urbanization, logistics constraints, and market volatility. Digital tools in agriculture can increase the accuracy of land-use planning, support monitoring of soil and crop conditions, optimize irrigation and fertilizer use, reduce fuel consumption, improve routing of machinery and agricultural transport, and provide data for sustainability reporting. However, these positive effects should be proven through clear indicators and models. It is not enough to state that satellite monitoring, IoT sensors, or routing algorithms are modern. It is necessary to determine whether they reduce costs, improve yields, protect resources, decrease emissions, prevent losses, and support better decisions by farms, local authorities, and policymakers.

For Ukraine, the importance of this research is additionally strengthened by the transformation of land relations, the need for effective land governance, the consequences of war for territories and infrastructure, and the strategic course toward European integration. Agricultural land, peri-urban territories, logistics networks, natural resources, and environmental restrictions are becoming components of a single decision-making system. In the case of the Kyiv agglomeration, the pressure on land resources, the concentration of economic activity, the difference between agricultural and processing-sector wages, the high cost of logistics, and the reduction of agricultural land in the urban core demonstrate that the economic use of land cannot be assessed separately from spatial development, environmental constraints, and transport accessibility. These factors create a need for digital systems capable of integrating cadastral data, remote sensing, field telemetry, transport costs, and institutional restrictions into a single analytical framework.

The monograph proceeds from the assumption that digital environmental management must be evaluated as a multi-layer system. The first layer is the measurement layer. It includes costs, savings, yields, emissions, input use, fuel consumption, land-use parameters, water indicators, risk, and time windows. The second layer is the digital layer. It includes cadastral and spatial databases, IoT telemetry, UAV and satellite monitoring, digital twins, routing systems, and analytical middleware. The third layer is the decision layer. It includes cost-benefit analysis, multi-criteria decision analysis, shadow pricing, simulation, scenario modeling, and policy evaluation. Only the combination of these three layers enables us to determine whether digital tools create real economic and environmental value.

The primary aim of the monograph is to establish a comprehensive methodological framework for assessing the economic efficiency of digital tools in environmental management and to validate it through specific empirical case studies in agriculture. The methodological framework proposed in this work aims to answer the following question: how can digital tools used in land management, environmental monitoring, and spatio-temporal optimization be evaluated from the perspectives of economic efficiency, ecological sustainability, and institutional feasibility?

To achieve this aim, the monograph sets the following research tasks:

- To clarify the theoretical foundations of economic efficiency in sustainable environmental management and to justify the need to expand the concept of efficiency beyond direct financial return.
- To analyze the digitalization of agrarian systems and to identify the main groups of digital tools used in modern environmental management, including GIS, cadastral databases, IoT, UAVs, satellite monitoring, middleware, and routing systems.
- To develop a methodological approach for evaluating digital agritech solutions through extended cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario-based simulation.
- To determine how environmental externalities such as carbon emissions, soil degradation, water stress, resource depletion, and delayed intervention can be included in economic calculations.
- To examine the economic efficiency of digital land management and cadastral systems through the analysis of spatial governance, interoperability, automated restrictions, and transaction-cost reduction.
- To evaluate the economic efficiency of IoT telemetry and environmental monitoring through the analysis of precision interventions, remote sensing indicators, input-use optimization, and yield protection.
- To assess the economic efficiency of spatio-temporal optimization and routing through the comparison of cost-optimized, time-optimized, and sustainability-adjusted scenarios.
- To formulate strategic recommendations for scaling digital environmental management through policy mechanisms, institutional incentives, data governance, and auditable sustainability metrics.

The object of the research is the system of sustainable environmental management in agriculture and peri-urban territories under conditions of digital transformation. The research focuses on the theoretical, methodological, and practical principles for determining the economic efficiency of digital tools for land management, environmental monitoring, and spatio-temporal optimization of agricultural operations.

The methodological basis of the monograph combines the approaches of environmental economics, institutional economics, land management, spatial analysis, digital agriculture, and decision science. The research uses the principles of system analysis, economic modeling, spatial modeling, comparative analysis, cost-benefit analysis, multi-criteria decision analysis, shadow pricing, scenario modeling, and simulation. Such a methodological combination is necessary because the problem under study is inherently multidisciplinary. The economic result of a digital tool cannot be separated from the ecological process it monitors, the land-use decision it supports, the institutional rule it implements, or the logistical operation it optimizes. The economic evaluation of digital environmental tools must include environmental externalities, because ecological losses are often not reflected in direct market prices but later become real costs for producers, communities, and public institutions. This is especially relevant for carbon emissions, soil erosion, water stress, biodiversity loss, and resource depletion (Macháč et al., 2021; Moore et al., 2017; Sartori et al., 2024).

The use of cost-benefit analysis in this monograph is adapted to the specific nature of digital agritech and environmental tools. Traditional cost-benefit analysis usually focuses on capital expenditures, operating expenditures, and direct financial returns. This approach is useful but insufficient. For this reason, the monograph uses an integrated methodological framework that combines extended cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario-based simulation. Such a combination is appropriate because environmental management decisions usually involve heterogeneous criteria: direct financial cost, time, environmental effect, operational risk, and institutional feasibility (Cicciù et al., 2022; Ferla et al., 2024; Li et al., 2023). Digital environmental tools generate additional forms of value that are not always visible in accounting documents. They produce data, reduce uncertainty, improve decision timing, decrease the likelihood of ecological and legal violations, support compliance with policy targets, and make management actions more transparent. Therefore, extended cost-benefit analysis in this work includes not only direct economic savings, but also the value of avoided losses, prevented environmental damage, improved service windows, and reduced institutional friction.

Multi-criteria decision analysis is used because decisions in environmental management rarely have one dominant criterion. A land parcel may be economically attractive but environmentally constrained. The route may be short but risky or emission-intensive. A precision intervention may reduce water use but require additional monitoring costs. A digital system may be expensive to implement but valuable for compliance, transparency, and long-term planning. Therefore, economic efficiency is assessed using a weighted system of criteria, including direct financial costs, time, environmental impact, operational risk, data quality, and institutional feasibility. Such an approach allows comparison of alternatives that a single indicator cannot adequately assess. Digital land management and cadastral systems are treated in this monograph as part of the institutional infrastructure of environmental management. Their economic impact extends beyond data storage; it also includes reduced transaction costs, faster verification of land-use restrictions, improved interoperability, and a lower risk of legal or ecological conflicts (Atik, 2022; Metaferia et al., 2023; van Oosterom et al., 2022).

Shadow pricing is used in this work to assign monetary value to non-market variables. Environmental management often addresses effects that lack a direct market price but have real economic consequences. These include carbon emissions, soil degradation, water losses, ecosystem damage, reduced biodiversity, and the loss of time-sensitive agronomic opportunities. The absence of a direct market price does not mean the absence of economic value. On the contrary, many environmental costs become visible only after damage has occurred. The purpose of shadow pricing in this monograph is to include such costs in the decision-making process before they become irreversible or too expensive to correct.

Simulation and scenario-based evaluation are used to test the resilience of digital tools under conditions of uncertainty. Agriculture operates under variable weather, market instability, logistical disruptions, changes in fuel prices, data gaps, sensor failures, and institutional restrictions. In Ukraine, these uncertainties are further compounded by the consequences of war, infrastructure risks, restricted access to certain land and cadastral data, and changes in transport accessibility. Therefore, the monograph does not rely only on static calculations. It uses scenarios to compare how different digital configurations perform under volatile conditions. Such an approach is especially important for the routing case study, where cost, time, emissions, and service-window feasibility must be evaluated together.

The empirical logic of the monograph is based on three interconnected case studies. The first case study examines the economic efficiency of digital land management and cadastral systems. Land management is selected as the first empirical block because it forms the spatial and institutional basis for all further decisions. Without reliable land data, zoning rules, ownership information, restrictions, environmental protection areas, and spatial interoperability, neither monitoring nor routing can produce fully reliable decisions. In this case, special attention is paid to the transition from static registries to dynamic spatial databases aligned with FAIR and OGC principles. The economic effect is expected to be realized through reduced transaction costs, faster access to reliable land-use information, the prevention of legal and ecological conflicts, and the optimization of peri-urban land allocation.

The second case study examines the economic efficiency of IoT telemetry and environmental monitoring. This block focuses on transforming raw environmental and agronomic data into actionable decisions. Satellite Earth observation, especially Sentinel-2 imagery, enables monitoring vegetation indices such as NDVI and EVI. IoT sensors can continuously provide information on soil moisture, temperature, conductivity, and other field-level indicators. UAV imagery can add high-resolution diagnostic information. However, the economic value of such monitoring becomes evident only when data are translated into concrete interventions, such as irrigation, fertilization, crop protection, risk alerts, or field inspections. Therefore, this case study evaluates how digital monitoring reduces wasted inputs, protects yield, improves timing, and mitigates localized environmental damage.

The third case study examines the economic efficiency of spatio-temporal optimization and routing. This block integrates the data and results of the first two case studies into a live logistical decision-support framework. Agricultural operations depend on time-sensitive service windows. Machinery, transport, labor, fuel, field accessibility, road conditions, and processing capacity must be coordinated. In peri-urban territories, especially around large cities, logistics is further complicated by congestion, land-use pressure, infrastructure limitations, and competing urban functions. In such conditions, routing cannot be reduced to a shortest-path approach. The route must be economically, environmentally, and temporally justified. Therefore, the routing framework evaluates cost-optimized, time-optimized, and sustainability-adjusted scenarios, including fuel costs, CO_2e emissions, reliability, and adherence to agronomic service windows.

The Kyiv agglomeration is of particular importance for the empirical logic of the monograph. It represents a territory where agricultural land, urban expansion, logistics, environmental restrictions, and economic concentration interact very closely. The available data show that agricultural land in the Kyiv urban core is extremely limited. In contrast, green zones, transport infrastructure, industrial areas, residential development, and peri-urban agricultural operations form a complex spatial system. Such a context makes Kyiv and its surrounding territories suitable for testing economic-efficiency models of digital environmental tools. The region demonstrates not only the economic value of land and logistics but also the importance of integrated digital governance for balancing agricultural production, urban-rural relations, and environmental sustainability.

The international relevance of the monograph is determined by its connection to the Sustainable Development Goals and European policy frameworks. The study is most closely connected with SDG 2, SDG 9, SDG 11, SDG 12, and SDG 17. SDG 2 is reflected in the focus on sustainable agriculture, food security, and efficient agronomic management United Nations, 2015; FAO, 2014; European Commission, 2020). Digital monitoring, precision interventions, and better routing can support agricultural productivity while reducing environmental pressure. SDG 9 is reflected in the development of innovation infrastructure, digital platforms, data integration, and resilient technological systems. SDG 11 is reflected in the connection between agriculture, peri-urban territories, smart governance, and sustainable communities. SDG 12 is reflected in reducing waste, using resources efficiently, adopting circular economy principles, and promoting responsible production. SDG 17 is reflected in the need for partnerships, data sharing, institutional coordination, international cooperation, and joint research.

These goals are not considered separately in the monograph. They are interpreted as parts of one transformation chain. Sustainable agriculture requires innovative infrastructure. Innovation infrastructure must support urban-rural linkages and sustainable communities. Sustainable communities require responsible consumption and production. Responsible production requires partnerships, shared data, and coordinated institutions. Therefore, SDG 17 has a special role as a horizontal mechanism that connects digital infrastructure, agricultural practice, policy targets, and international cooperation. In this sense, the monograph treats digital environmental management not only as a technical problem, but also as a system of cooperation between farms, universities, state institutions, local authorities, international organizations, and technology providers.

The connection with European frameworks is also important. The EU Farm to Fork Strategy, the European Green Deal, climate adaptation policy, circular economy principles, and the development of digital data spaces create a policy environment that requires agriculture to become more sustainable, transparent, and measurable. For Ukraine, this has additional significance because European integration requires the approximation of data systems, environmental indicators, land management practices, and reporting mechanisms to EU approaches. Therefore, the methodological framework proposed in this monograph may be useful not only for academic research but also for the design of practical tools for policy reporting, investment planning, sustainability audits, and agricultural modernization.

Institutional economics provides an important theoretical basis for this study. Digital tools do not operate outside institutions. Their value depends on property rights, land-use rules, access to data, the quality of public registers, regulatory stability, trust between actors, interoperability standards, the cost of capital, and enforcement mechanisms. The same technological system can produce different results depending on whether institutions support data sharing, whether land information is reliable, whether environmental restrictions are clear, whether farmers and local authorities have incentives to use digital tools, and whether sustainability indicators are auditable. Therefore, the economic efficiency of digital tools should be evaluated not only at the farm operations level, but also at the institutional arrangements level.

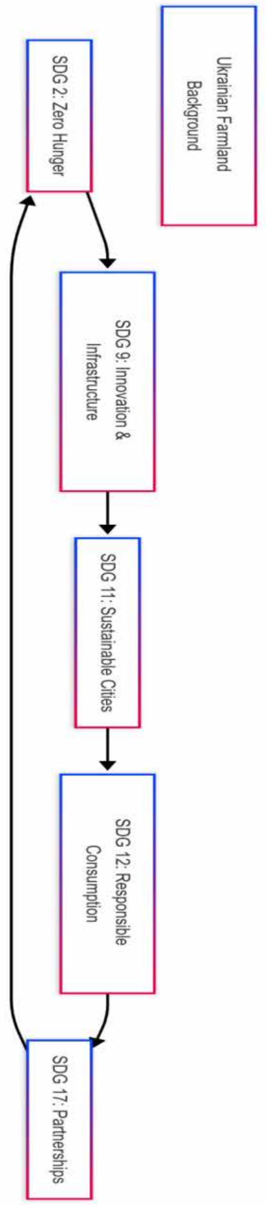


Figure 1. Digital Pathways for Sustainable Agriculture and Urban Integration in Ukraine

This is especially visible in land management. A cadastral system is not simply a database. It is an institutional infrastructure that defines how land rights, restrictions, values, and responsibilities are represented and used. When cadastral information is incomplete, outdated, inaccessible, or not interoperable, the cost of decision-making increases. Enterprises and authorities spend more time verifying data, resolving conflicts, avoiding errors, and correcting decisions. When spatial databases become interoperable, auditable, and linked with environmental constraints, they reduce uncertainty and transaction costs. Therefore, the digitalization of land administration can create economic value even before direct production activity begins.

The same institutional logic applies to environmental monitoring. IoT sensors, satellite imagery, UAVs, and analytical dashboards deliver value only when their outputs are trusted, legally interpretable, and integrated into decision-making processes. If monitoring data are not integrated with farm management, land records, environmental policy, or economic planning, they remain technical information with little managerial impact. If, however, they are integrated into a decision-support system, they can support irrigation scheduling, fertilizer optimization, crop stress detection, compliance reporting, and investment justification. Thus, the value of monitoring depends on the institutional capacity to transform data into action.

The routing case also has an institutional dimension. Transport routes, service windows, fuel costs, road restrictions, environmental penalties, and military or safety constraints are not only technical variables. They reflect economic, legal, and administrative conditions. In wartime and post-war conditions, the ability to adapt routes to changing restrictions and costs becomes a factor of resilience. A digital routing system that can adjust its weight based on cost, risk, time, and sustainability criteria can support not only enterprise-level savings but also regional food system stability. Therefore, the monograph's routing component is presented as a practical demonstration of how digital economics can support operational sustainability.

The scientific novelty of the monograph consists in the systematic combination of economic-efficiency methodology with specific digital environmental tools. Existing studies often analyze digital agriculture, land management, environmental monitoring, or routing separately. This work proposes connecting them within a single methodological framework. The logic is sequential. First, land management provides a spatial and institutional base. Second, monitoring provides environmental and operational signals. Third, routing transforms these signals into time-sensitive logistical decisions. Fourth, policy mechanisms and scaling roadmaps convert empirical results into institutional instruments. Such a structure allows evaluating digital tools as part of a single system rather than as isolated technologies.

The practical value of the monograph lies in the ability to apply its methodological framework to real decision-making. Farms and cooperatives can use the framework to evaluate whether digital monitoring or routing systems are financially justified. Local authorities can use it to assess the value of digital land management and environmental monitoring. Policymakers can use it to design eco-subsidies, tax incentives, and sustainability reporting mechanisms. Researchers can use it as a basis for empirical studies combining spatial data, economic indicators, environmental variables, and simulation. Technology providers can use it to transparently demonstrate the economic and environmental impacts of their systems.

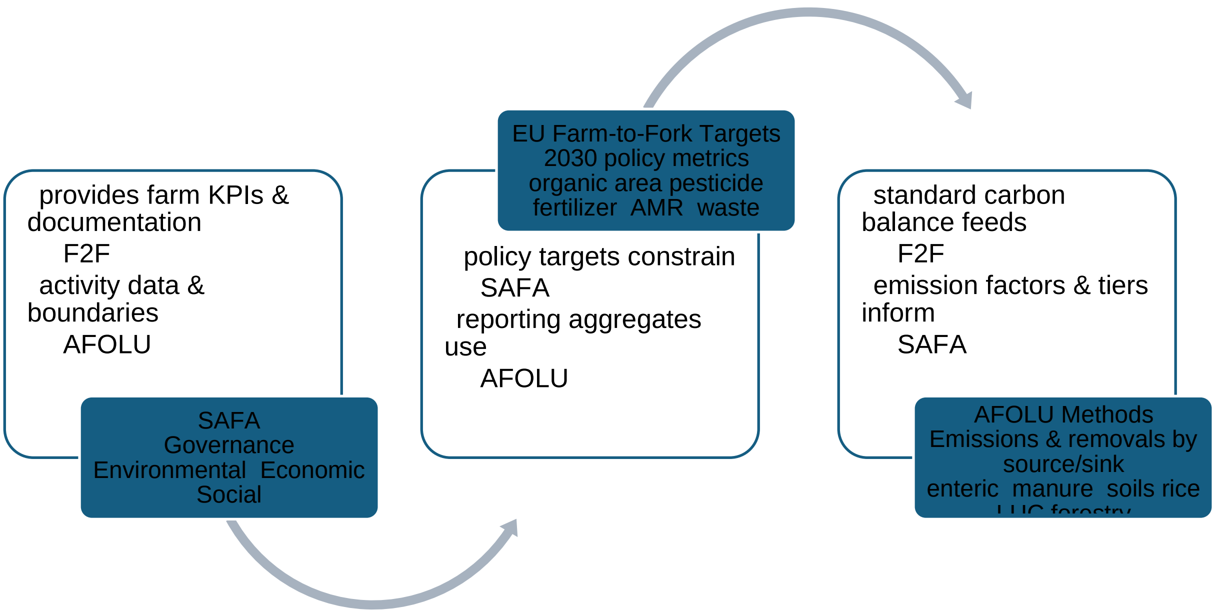


Figure 2. Example of sustainable measurements frameworks

An important feature of the proposed approach is its orientation toward measurable indicators. The monograph does not limit itself to general arguments about innovation. It requires that each digital tool be linked to indicators: reduction of transaction costs, reduction of input waste, lower fuel costs, CO_2e stability, yield protection, faster decision-making, better compliance, lower operational risk, and greater feasibility of agronomic service windows. This makes the framework suitable for audit, comparison, and replication. At the same time, the monograph recognizes that not all valuable effects can be captured by simple financial indicators. Some effects require shadow pricing, multi-criteria evaluation, or scenario-based modeling.

The research also focuses on data sources and technological infrastructure. In modern environmental management, data quality determines the quality of economic conclusions. The monograph therefore relies on the integration of public spatial data, cadastral and administrative data, satellite imagery, meteorological data, field telemetry, UAV imagery, economic records, and routing information. Such integration requires appropriate tools and standards: QGIS and PostGIS for spatial analysis and databases; GeoServer for interoperable publication of spatial layers; Copernicus Data Space, STAC, and openEO for Earth observation; ERA5 and NASA POWER for weather and agroclimatic data; OpenStreetMap, GraphHopper, OSMnx, and OR-Tools for routing and optimization; Python, R, Jupyter, and reproducible workflows for modeling. These tools are not the subject of the monograph in themselves. They are instruments for making economic and environmental evaluation verifiable.

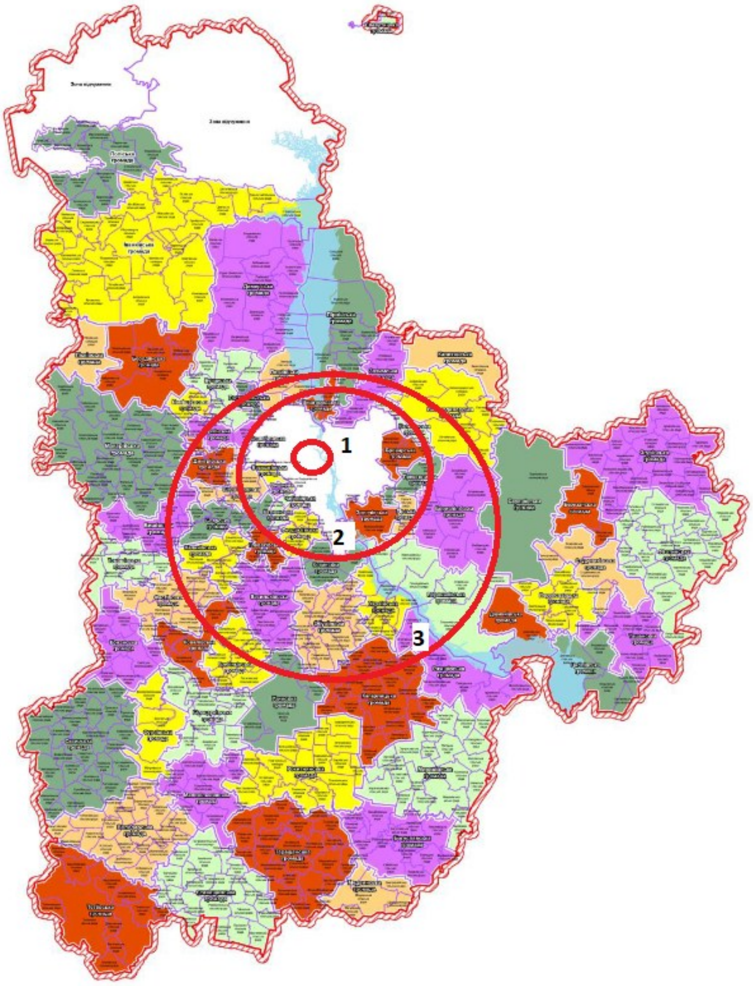


Figure 3. Kyiv agglomeration map and spatial division in the context of the study

The monograph is structured according to the logic of moving from theory to methodology and then to empirical validation. The first section examines the theoretical foundations of economic efficiency in sustainable environmental management. It defines the concept of efficiency, analyzes the digitalization of agrarian systems, discusses environmental externalities, and considers institutional and policy drivers. The second section develops the methodological framework for determining economic efficiency. It adapts cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario simulation to digital environmental tools. The third section presents the first case study on digital land management and cadastral systems. The fourth section presents the second case study on IoT telemetry and environmental monitoring. The fifth section presents the third case study on spatio-temporal routing and optimization. The sixth section formulates strategic roadmaps for scaling digital environmental management through policy, investment, interoperability, and auditable sustainability metrics.

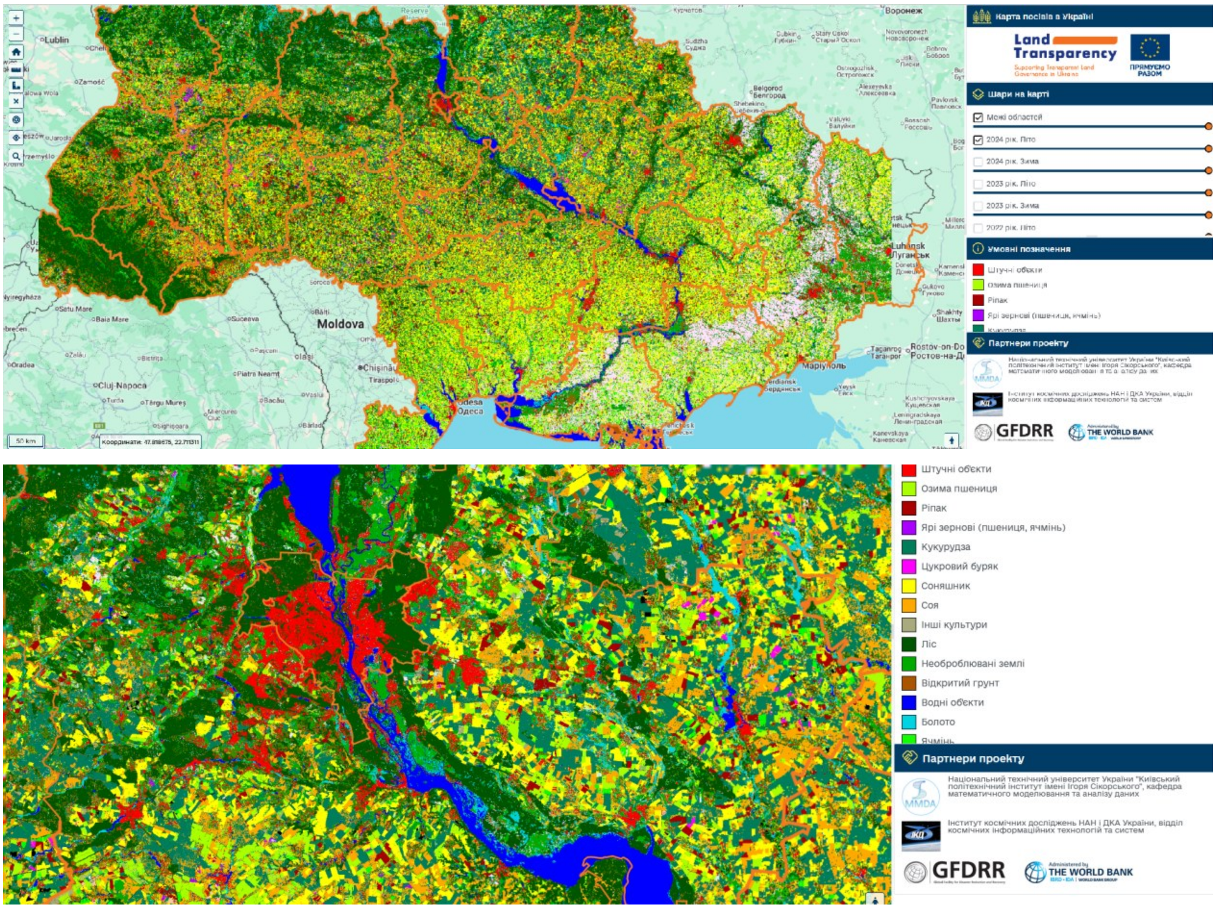


Figure 4. Ukraine (above) and Kyiv (below) crop maps

source: https://ukraine-cropmaps.com/

Thus, the monograph is based on the position that sustainable environmental management in the digital era requires a new approach to economic evaluation. Digital tools should not be assessed solely by their technical capacity or narrow financial returns. They should be evaluated by their ability to create measurable economic value while reducing environmental damage, improving institutional transparency, and increasing resilience under uncertainty. This approach is especially relevant for agriculture, where decisions are spatially distributed, time-sensitive, resource-intensive, and strongly affected by climate, land-use policy, and logistics. It is also relevant for Ukraine, where agricultural modernization, land governance, European integration, and post-war recovery require practical digital instruments and transparent methods of evaluating their effectiveness.

The central hypothesis of the monograph is that the economic efficiency of digital tools for sustainable environmental management can be more accurately assessed when financial, environmental, temporal, operational, and institutional effects are evaluated together. If digital land management, monitoring, and routing systems are assessed through such an integrated framework, it becomes possible to compare their costs and benefits more objectively, justify investments, reduce uncertainty, and support policy decisions. The following chapters are devoted to the theoretical justification, methodological development, and empirical validation of this hypothesis.

CHAPTER 1

Theoretical Foundations of Economic Efficiency in Environmental Management

1.1. Sustainable Environmental Management and the Transition from Linear Resource Use to Circular Resource Economies

This chapter establishes the theoretical foundation for evaluating the economic efficiency of digital tools in sustainable environmental management. Its purpose is not to reproduce the methodological apparatus developed in the following chapter, nor to anticipate the empirical case studies on land management, IoT-based monitoring, or spatio-temporal routing. Rather, the chapter clarifies the conceptual architecture within which such methods and cases become meaningful. Economic efficiency is treated here not as a narrow accounting ratio, but as a socio-ecological category that links resource productivity, environmental externalities, institutional coordination, and the capacity of digital systems to make ecological-economic relations observable and governable.

The central theoretical difficulty is that environmental management operates within systems in which many of the most important costs and benefits are not immediately priced. Soil organic matter, landscape connectivity, water retention, biodiversity, carbon sequestration, field accessibility, and the credibility of public registries are productive conditions of agriculture. However, they are frequently included in economic calculations only after they have been degraded. Digital technologies alter this situation by expanding the domain of measurable evidence. Remote sensing, cadastral data infrastructures, IoT telemetry, UAV diagnostics, farm management information systems, artificial intelligence, digital twins, and interoperable data spaces do not merely accelerate existing managerial routines. They change the boundary between visible and invisible costs, between private and social benefits, and between reactive environmental control and anticipatory resource governance.

The chapter, therefore, advances four connected propositions. First, the transition from linear resource use to circular resource economies should be understood as a shift from throughput maximization to metabolic coordination: the economy becomes more efficient when it can preserve the productive capacity of natural systems while reducing waste, leakage, and irreversible loss. Second, Agriculture 4.0 and smart farming should be interpreted not as a collection of isolated technologies but as a digital toolscape: a layered assemblage of sensors, spatial data, algorithms, standards, institutions, and users through which agrarian decisions become data-mediated. Third, environmental externalities must be internalized in economic reasoning not only through ex post damage valuation but through ex ante decision rules that make CO_2e, soil degradation, water stress, and resource depletion part of the logic of management. Fourth, in transition economies, including Ukraine, the economic efficiency of digital environmental management depends as much on institutional credibility, interoperability, data rights, regulatory alignment, and public trust as on the technical performance of specific tools.

This theoretical framing is particularly relevant for the European Union and Ukraine. In the EU, the European Green Deal, the Farm to Fork Strategy, the Circular Economy Action Plan, the Common Agricultural Policy for 2023-2027, the Data Act, the Nature Restoration Regulation, and the emerging soil monitoring framework have created a regulatory environment in which environmental performance is increasingly expected to be measurable, comparable, auditable, and linked to policy incentives. In Ukraine, the same agenda is refracted through the conditions of war, reconstruction, land reform, European integration, damage assessment, and uneven institutional capacity. The Ukrainian problem is therefore not simply to import European digital or environmental instruments, but to translate them into a governance context where land, ecological damage, food security, infrastructure resilience, and EU approximation are simultaneously at stake.

The theoretical contribution of the chapter is to move beyond the binary opposition between economic growth and environmental protection. The more precise distinction is between inefficient growth, which expands output by degrading its own ecological preconditions, and regenerative productivity, which increases the value generated per unit of ecological pressure. Digital environmental management becomes economically significant when it helps shift decision-making from the first trajectory to the second. It provides the measurement infrastructure through which environmental degradation can be treated not as an external background condition, but as a cost-bearing, risk-producing, and institutionally governable economic variable.

The concept of sustainable environmental management emerged from the recognition that economic activity is embedded in biophysical systems with finite regenerative capacities. Classical welfare economics identified environmental degradation as a market failure caused by external costs, but the deeper contribution of ecological economics was to show that the economy is not only a system of prices and preferences; it is also a subsystem of the biosphere, dependent on energy flows, material stocks, ecosystem services, and entropy-generating transformations (Georgescu-Roegen, 1971; Daly, 1991; Pearce & Turner, 1990). From this perspective, environmental management cannot be reduced to compensating for damages after production has occurred. It concerns the organization of production itself so that the natural capital base is not consumed faster than it can be renewed.

The linear model of resource use follows a deceptively simple sequence: extraction, production, consumption, and disposal. It is economically attractive under conditions of low resource prices, weak environmental regulation, and incomplete accounting for externalities. In agriculture, its expression is visible in input-intensive production systems that treat soil, water, nutrients, fossil energy, and landscape functions as expandable or substitutable inputs. The linear agrarian economy is not necessarily technologically backward; it may be highly mechanized and productive. Its weakness lies elsewhere: it achieves output by displacing costs onto soils, water bodies, greenhouse gas budgets, rural landscapes, and future production risks. Such displacement is not efficiency but cost postponement.

Circular resource economies are commonly associated with recycling, reuse, recovery, and waste reduction. However, a theoretically robust interpretation must go further. Circularity is not merely a waste-management doctrine. It is an economic principle of retaining material, energy, and informational value within productive systems for as long as possible, while reducing the demand for virgin inputs and the accumulation of residual pollution (Ellen MacArthur Foundation, 2013; Kirchherr et al., 2017; Korhonen et al., 2018). In agriculture, circularity includes nutrient cycling, manure and biomass valorization, water reuse where environmentally appropriate, soil organic matter restoration, precision input use, reduced post-harvest losses, local bioeconomy linkages, and the design of production systems that minimize leakage across ecological boundaries.

The transition from linearity to circularity, therefore, changes the meaning of economic efficiency. In the linear model, efficiency is often measured as output per unit of paid input or profit per hectare. In a circular model, efficiency must also include preserving productive capacity, reducing ecological leakage, and avoiding irreversible depletion. A farm that obtains high yields through soil mining, excessive nitrogen application, groundwater overuse, or fuel-intensive logistics may appear efficient in private accounts while being inefficient in social and intertemporal terms. Conversely, a system that requires higher initial coordination costs but preserves soil structure, reduces runoff, increases input-use precision, and generates reliable environmental data may be more efficient over the full ecological-economic horizon.

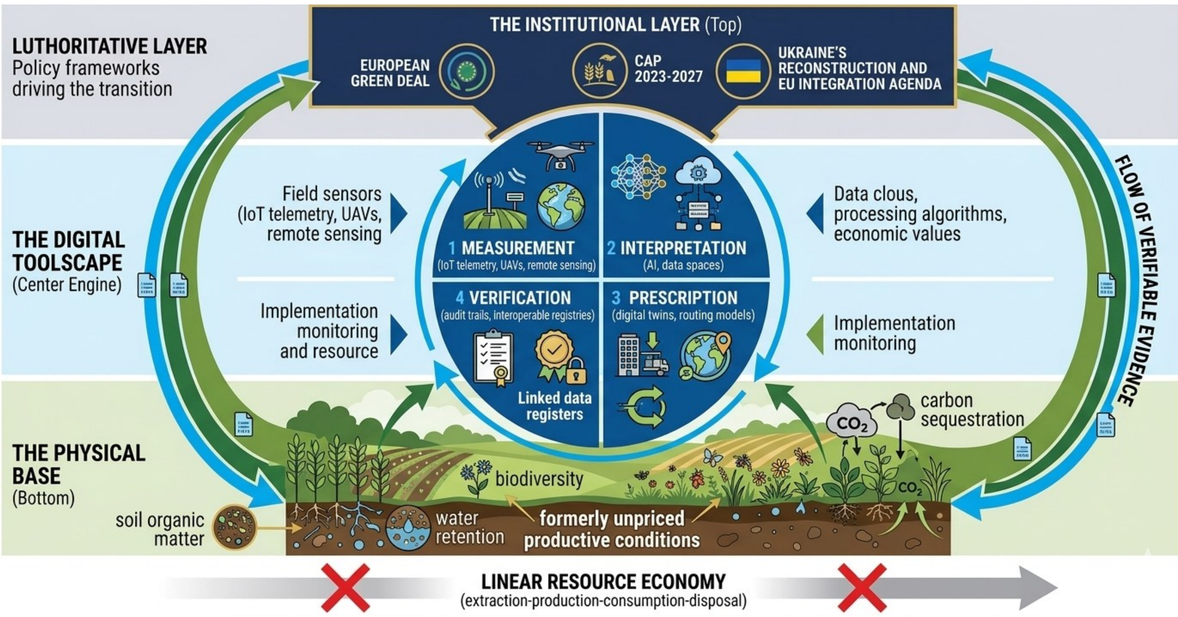


Figure 1.1 Digital Toolscape and the Circular Agrarian Economy

This point is essential for the monograph because digital tools do not automatically create circularity. A sensor network, satellite dashboard, or routing platform can reinforce linear extraction if used solely to increase throughput without ecological constraints. Digitalization becomes a component of circular resource economies only when it improves the ability to close material loops, prevent avoidable losses, coordinate interventions in time and space, verify resource savings, and document environmental performance. The economic value of digitalization is therefore conditional: it depends on whether information is used to reduce ecological entropy in the production system rather than merely accelerating production decisions.

The European Union has institutionalized this transition through a dense policy architecture. The European Green Deal set climate neutrality and resource efficiency as central objectives of European development. The Circular Economy Action Plan expanded circularity from a sectoral waste agenda into an economy-wide transformation of product design, production, consumption, and waste prevention. The Farm to Fork Strategy connected food-system sustainability with pesticide reduction, nutrient management, organic farming, antimicrobial resistance, food waste, and consumer information. The Common Agricultural Policy for 2023-2027 introduced a more performance-oriented logic in which Member States are expected to link agricultural support to environmental and climate objectives. Together, these frameworks make circularity not only a normative aspiration but an emerging condition of agricultural competitiveness and policy legitimacy in the European space.

For Ukraine, the transition to circular resource economies has a different historical and institutional profile. Ukraine is a major agrarian producer with substantial land resources, a strong export orientation, and a strategic role in regional and global food security. At the same time, its environmental management system has been shaped by post-Soviet institutional legacies, fragmented data systems, incomplete environmental accounting, uneven enforcement, and, since 2022, direct war-related destruction of land, infrastructure, ecosystems, water facilities, and monitoring capacity. The circular transition in Ukraine must therefore be interpreted not simply as resource-efficiency modernization but as part of recovery, reconstruction, EU integration, and the rebuilding of institutional trust.

The agrarian significance of circularity in Ukraine is especially visible in the relation between soil and economic value. Ukrainian agriculture is often associated with fertile chernozem soils, but fertility is not a static endowment. It is a dynamic ecological asset dependent on organic matter, structure, microbial activity, erosion control, moisture retention, and responsible land management. Treating soil as a fixed background condition is a typical error of linear economic reasoning. A circular agrarian economy treats soil as a renewable but degradable capital asset whose maintenance is part of economic efficiency. This does not mean romanticizing low-input agriculture. It means recognizing that yield, profitability, food security, and land value are inseparable from the ecological integrity of the soil system.

The literature on sustainability transitions helps clarify why the shift from linear to circular resource use is difficult. Transitions are not produced solely by technologies; they require changes in infrastructures, markets, routines, regulations, skills, and cultural expectations (Geels, 2002; Markard et al., 2012). In agriculture, these changes are complicated by biological time, climatic uncertainty, dispersed decision-making, farm heterogeneity, capital constraints, and unequal access to knowledge. Circularity is therefore not a single innovation but a reconfiguration of the agrarian regime. It demands new ways of observing resource flows, new incentives to reduce externalities, new forms of cooperation across value chains, and new mechanisms to demonstrate that environmental improvements have occurred.

The circular economy literature also warns against overly simplistic claims. Circularity can produce rebound effects if efficiency gains reduce costs, thereby stimulating higher overall consumption. Recycling can be energetically or economically inefficient if logistics and processing costs exceed the value of recovered materials. Bioeconomy pathways can create land-use conflicts if biomass demand competes with food production, biodiversity, or soil carbon needs. Precision technologies can increase inequality if they are accessible only to large farms and if data platforms concentrate market power. Therefore, the transition from linear to circular resource economies must be evaluated through a systemic lens. The question is not whether a practice is labeled circular, but whether it reduces net ecological pressure while generating durable economic and institutional value.

For sustainable environmental management, the most important theoretical consequence is that efficiency becomes relational. It is not located solely within the farm enterprise, nor solely within the public regulatory system. It emerges from the relation between production practices, ecological thresholds, market incentives, information systems, and institutional rules. A digital tool may improve private efficiency by reducing fertilizer or fuel use. It may improve social efficiency by reducing emissions or nutrient runoff. It may improve institutional efficiency by making data auditable and decisions transparent. The strongest efficiency gains occur when these three levels reinforce one another.

The transition to circularity also changes the role of time. Linear systems discount the future by converting ecological capital into present output. Circular systems preserve future options by reducing depletion, increasing resilience, and maintaining ecological functions. This is especially relevant in the context of climate change, where historical averages become less reliable, and the capacity to adapt becomes an economic asset. In Europe, more frequent droughts, heatwaves, water scarcity episodes, and soil degradation pressures make resource efficiency inseparable from climate adaptation. In Ukraine, these pressures are compounded by security risks, damaged infrastructure, contamination of territory, and disrupted logistics. A circular resource economy must therefore be both resilient and efficient.

The theoretical foundation for the monograph can be stated as follows: sustainable environmental management is economically efficient when it increases the value generated by agrarian and land-use systems without reducing the regenerative capacity of the ecological systems on which future value depends. Circularity provides the resource logic of this condition, while digitalization provides part of its measurement and coordination infrastructure. The next subsection examines the latter dimension in detail.

1.2. Digitalization of Agrarian Systems: Agriculture 4.0, Smart Farming, and the Digital Toolscape

Digitalization of agrarian systems is often described as Agriculture 4.0, smart farming, precision agriculture, digital agriculture, or cyber-physical food systems. These terms overlap but are not identical. Precision agriculture historically emphasized site-specific management of inputs and operations. Smart farming expanded the focus to sensor networks, automation, decision support, and real-time control. Agriculture 4.0 situates agriculture within the broader fourth industrial revolution, where connectivity, cloud computing, artificial intelligence, robotics, IoT, and platform-based coordination become central to production and value chains. Digital agriculture is the broader analytical category: it includes the use of digital data, infrastructures, models, and interfaces to observe, interpret, predict, prescribe, automate, and verify agrarian decisions (Klerkx et al., 2019; Walter et al., 2017; Wolfert et al., 2017).

A mature theoretical account must resist technological determinism. Digital agriculture is not a neutral sequence of devices that naturally produce sustainability. It is a socio-technical transformation in which agronomic knowledge, farm labor, property rights, environmental regulation, data governance, platform markets, and rural infrastructures are reconfigured. Studies of digital agriculture show that adoption is shaped by farm size, capital availability, skills, advisory systems, trust, perceived usefulness, interoperability, and the distribution of risks and benefits along the value chain (Caffaro & Cavallo, 2019; Finger, 2023; Pierpaoli et al., 2013; Shang et al., 2021). The same technology may be emancipatory, extractive, inefficient, or transformative depending on how it is embedded in institutions and practices.

The concept of the digital toolscape is useful because it avoids treating technologies as isolated instruments. A toolscape is the structured field of digital artifacts, data flows, standards, organizations, and decision-making routines through which environmental management is performed. In agrarian systems, this toolscape includes geospatial databases, cadastral layers, Earth observation, meteorological datasets, field sensors, machinery telemetry, UAV imagery, soil maps, farm-management platforms, artificial intelligence models, digital twins, routing engines, dashboards, mobile applications, cloud infrastructures, APIs, and interoperability standards. Its value lies not in the presence of individual tools but in the ensemble's capacity to convert heterogeneous signals into credible decisions.

This conversion involves four analytical functions. The first is measurement. Digital systems extend the range, frequency, and spatial resolution of environmental observation. Satellite imagery can detect vegetation anomalies across large territories; IoT sensors can measure soil moisture and microclimatic conditions at the field level; UAVs can provide high-resolution diagnostics; and cadastral and land-use data can locate rights, restrictions, and spatial obligations. Measurement reduces ignorance but does not eliminate uncertainty. Data may be incomplete, biased, noisy, delayed, inaccessible, or institutionally non-recognized.

The second function is interpretation. Data acquire economic value only when they are transformed into indicators, classifications, thresholds, forecasts, or alerts. A pixel value is not yet a management decision; it becomes relevant when connected to crop phenology, soil conditions, field history, weather, costs, and feasible interventions. Similarly, a cadastral polygon is insufficient for land governance unless it is linked to land-use restrictions, rights, environmental constraints, administrative procedures, and legal validity. Interpretation is therefore a hybrid operation: it combines algorithms with agronomic, economic, and institutional knowledge.

The third function is prescription. Digital systems can rank alternatives, recommend actions, optimize routes, define intervention zones, schedule irrigation, identify compliance risks, and prioritize monitoring. Prescription is where economic efficiency becomes visible, as alternative actions can be compared based on cost, time, risk, environmental impact, or expected benefit. However, a prescription also raises questions of accountability. If an algorithm recommends a fertilizer dose, route, or land-use option, responsibility remains distributed among the data provider, model designer, platform operator, farm manager, and regulatory environment. This is why data governance and explainability are not peripheral issues but components of economic efficiency: decisions that cannot be trusted, audited, or contested create institutional risk.

Figure 1.2 Digital Toolscape of Agriculture 4.0

The fourth function is verification. Digital tools can document what was done, where, when, by whom, and with what environmental consequence. Verification is increasingly important in the EU as sustainability policy shifts from declaratory commitments to measurable performance. Eco-schemes, carbon farming, soil monitoring, nutrient accounting, deforestation-free supply chains, biodiversity indicators, and sustainability reporting all require evidence. For Ukraine, verification has additional significance: reconstruction financing, EU approximation, environmental damage assessment, land governance, and international cooperation depend on credible data infrastructures. A digital tool that produces verifiable records can therefore create value even when its immediate operational savings are modest.

Digitalization also changes the object of environmental management. Traditional environmental management often treated the farm, parcel, watershed, or administrative unit as the primary object. Digital systems enable operations across nested scales: the plant, row, field, farm, landscape, municipality, region, supply chain, and policy framework. This multi-scalar capacity is central to sustainable agriculture because environmental externalities rarely respect farm boundaries. Nutrient runoff, soil erosion, water stress, greenhouse gas emissions, and biodiversity loss occur through spatial interactions. Digital toolscapes can reveal these interactions, but they can also obscure them if data are fragmented, proprietary, or limited to private productivity metrics.

The EU has become a particularly important laboratory for digital agrarian governance. The convergence of environmental ambition, market integration, data regulation, and public support mechanisms shapes its approach. The digitalization of agriculture and rural areas is explicitly connected to competitiveness, sustainability, and rural well-being. The Data Act and the Data Governance Act address access to and sharing of data. At the same time, the Common European Agricultural Data Space is designed to support secure, trusted, transparent, and interoperable data sharing. These initiatives matter because agricultural data are not simply technical inputs. They have strategic value for farmers, technology providers, insurers, processors, regulators, researchers, and consumers. Data governance determines who can capture that value and under what conditions.

In this context, the European debate increasingly shifts from the question of whether digital tools should be adopted to that of responsible digitalization. Responsible digital agriculture must avoid deepening asymmetries between large and small farms, between platform owners and data producers, and between regions with strong and weak digital infrastructure. It must also protect data sovereignty, privacy, cybersecurity, and farmer autonomy. The literature on digital agriculture emphasizes that platformisation can create new dependencies when farmers become locked into proprietary ecosystems or when data generated on farms is monetized elsewhere without fair value-sharing (Bronson & Knezevic, 2016; Carolan, 2017; Rotz et al., 2019). Thus, economic efficiency cannot be separated from distributive questions.

Ukraine's digital agrarian transformation contains both significant opportunities and structural constraints. On the opportunity side, Ukraine has a strong agricultural sector, extensive use of geospatial information in land management, developing digital public services, scientific capacity in land administration and agritech, and a strategic incentive to align with EU standards. War has also demonstrated the importance of remote sensing, digital logistics, resilient communication, and rapid spatial assessment. On the constraint side, digital infrastructure is uneven, cadastral and environmental data may be fragmented or temporarily restricted, farms differ greatly in capital and technical capacity, and institutional trust remains a decisive variable. Digitalization in Ukraine is, therefore, not only a technological upgrade but also a reconstruction of the informational foundations of governance.

The term toolscape also makes visible a key risk: the proliferation of tools without integration. Farms and public authorities may accumulate platforms, maps, dashboards, sensors, and reports that do not communicate with one another. This produces a paradox of digital inefficiency: more data can lead to poorer decisions if they are inconsistent, duplicated, non-standardized, or disconnected from authority and action. Interoperability is therefore an economic issue. Standards such as FAIR data principles, OGC services, common identifiers, metadata practices, and API-based architectures are not merely technical preferences. They reduce transaction costs, improve comparability, preserve data value, and enable cumulative learning.

The digital toolscape should also be understood as a system for managing uncertainty. Agriculture is exposed to climatic variability, pests and diseases, market volatility, logistics disruptions, labor constraints, and regulatory change. Digital systems cannot eliminate these uncertainties, but they can reduce the time between signal and response. Earlier detection of crop stress, better estimation of soil moisture, more precise land-use constraints, or more accurate route conditions can shift management from reaction to anticipation. The economic value of digitalization, therefore, lies partly in option value: it preserves the capacity to choose better actions before losses become irreversible.

Nevertheless, digitalization can create vulnerabilities of its own. Dependence on connectivity, cloud services, vendor ecosystems, cybersecurity, data quality, sensor calibration, and algorithmic assumptions introduces new forms of risk. In transition economies, these risks may be magnified by limited institutional capacity, lower availability of advisory services, weak enforcement of data rights, and difficulties in financing maintenance. A theoretically sound evaluation must therefore treat digital tools as risk-transforming, not risk-free, technologies. They reduce some uncertainties while creating others.

The theoretical synthesis of Agriculture 4.0 for this monograph can be expressed in one sentence: digitalization creates economic value in sustainable environmental management by transforming dispersed ecological and operational signals into timely, interoperable, auditable, and institutionally actionable knowledge. This proposition is deliberately stricter than the usual claim that digital technologies improve efficiency. It requires that data be connected to decisions, that decisions be connected to environmental consequences, and that consequences be connected to economic and institutional evaluation. Without this chain, digitalization remains a technological spectacle rather than a source of sustainable economic efficiency.

1.3. Environmental Externalities in Economic Evaluation: CO_2e, Soil Degradation, Water Stress, and Resource Depletion

Environmental externalities are the analytical bridge between private production decisions and social ecological consequences. Pigouvian welfare economics defined negative externalities as costs imposed on third parties that are not reflected in market prices (Pigou, 1920). Coase later shifted attention to property rights and transaction costs, showing that bargaining could internalize externalities under specific conditions (Coase, 1960). Environmental economics subsequently developed valuation, taxation, regulation, tradable permits, and cost-benefit tools to correct market failures. However, in agriculture and environmental management, externalities are often spatially diffuse, temporally delayed, scientifically uncertain, and institutionally difficult to attribute. This makes them especially resistant to simple pricing.

The first theoretical task is therefore to distinguish between the absence of price and the absence of value. A ton of soil lost to erosion, a cubic meter of water abstracted beyond recharge, a kilogram of nitrogen leached into a water body, or a ton of CO_2e emitted by fuel-intensive operations may not appear in farm accounts as a direct liability. Nevertheless, each can impose real economic costs through reduced future productivity, public remediation expenditure, climate damage, water treatment, health impacts, compliance penalties, biodiversity loss, and diminished resilience. The invisibility of these costs in market transactions is precisely why environmental externalities must be incorporated into economic evaluation.

CO_2e is the most standardized of the externalities considered in this monograph because climate policy has created relatively mature accounting conventions for greenhouse gases. Carbon dioxide equivalent allows different gases to be expressed using a common metric for warming potential. In agriculture, relevant emissions include fuel combustion, fertilizer-related nitrous oxide emissions, methane from livestock and organic matter processes, land-use change, and supply-chain energy use. Digital environmental management can reduce CO_2e by optimizing machinery operations, precision application of inputs, improved logistics, early detection of stress, improved irrigation scheduling, and avoiding unnecessary interventions. It can also improve the credibility of emissions accounting by linking activities to spatial and temporal evidence.

However, CO_2e should not be treated as a complete proxy for environmental performance. Carbon metrics are powerful because they are comparable and policy-relevant, but they can crowd out other ecological concerns if used in isolation. A practice may reduce emissions while increasing water stress, soil compaction, biodiversity pressure, or social inequality. Conversely, practices that improve soil health or landscape resilience may not show immediate CO_2e benefits but may generate long-term ecological-economic value. The theoretical challenge is to treat CO_2e as one dimension of environmental efficiency rather than the sole sustainability criterion.

Soil degradation is less easily priced but more foundational for agriculture. Soil is simultaneously a medium of production, a biodiversity reservoir, a regulator of water, a carbon stock, and a historical archive of land-use practices. Degradation includes erosion, loss of organic matter, compaction, salinization, contamination, acidification, sealing, and decline in soil biodiversity. Each form has different economic consequences and different temporal dynamics. Erosion may reduce yields and increase sedimentation; compaction may impair infiltration and root growth; organic matter decline may reduce nutrient retention and drought resilience; contamination may restrict land use and create health risks. The economic loss is therefore not only the immediate reduction in yield but the degradation of a multi-functional asset.

The European policy context is increasingly recognizing this point. The EU's soil monitoring framework, the work of the EU Soil Observatory, and the 2024 State of Soils in Europe report indicate a shift from fragmented soil protection toward more harmonized monitoring and assessment. This is significant because soil degradation has often suffered from institutional invisibility: unlike air emissions or water quality, soil condition was historically less consistently regulated and less frequently measured. The move toward harmonized soil data creates a policy environment in which digital tools for soil monitoring, remote sensing, field sampling, and spatial data integration become directly economically relevant.

In Ukraine, soil degradation must be understood in terms of both long-term agrarian pressure and war-related impacts. Intensive cultivation, erosion risks, nutrient imbalance, local contamination, and land fragmentation are not new problems. War adds land damage, pollution, mining, shelling, infrastructure destruction, altered drainage, and restricted access to monitoring and remediation. In such conditions, soil information becomes a strategic asset for recovery. It supports prioritizing demining, assessing contamination, making decisions on land returning to production, handling compensation claims, environmental restoration, and aligning with EU soil standards. The externality here is not abstract; it is linked to national economic recovery and food-system resilience.

Water stress is another critical externality because agriculture is both a major user of freshwater and a sector highly vulnerable to hydrological variability. Water stress emerges when demand approaches or exceeds available renewable supply, or when water quality deteriorates to the point that usable availability declines. In agricultural systems, water stress is connected to irrigation efficiency, crop choice, soil water retention, drainage, drought exposure, energy costs, groundwater depletion, and competing urban or industrial demand. Digital tools can improve irrigation scheduling, detect crop stress, estimate evapotranspiration, forecast drought risk, and identify inefficient water use. However, again, digitalization does not guarantee sustainability. Higher precision can increase total irrigated area or encourage more water-intensive crops, but only if embedded in water governance.

The EU water policy context demonstrates the importance of institutional framing. The Water Framework Directive, the increasing emphasis on water resilience, and recent assessments of Europe's water condition all point to the limits of fragmented management. Water quality and quantity are affected by agriculture, industry, urbanization, climate change, and ecosystem degradation. Economic evaluation must therefore move beyond the price the farmer pays for water or energy. It must include scarcity value, opportunity cost, ecological flow requirements, treatment costs, and the risk of future restrictions. For Ukraine, water stress is further shaped by war-damaged hydraulic infrastructure, regional climatic contrasts, irrigation needs in the south, and the environmental consequences of destroyed or disrupted water systems.

Resource depletion extends the externality framework beyond carbon, soil, and water. Agriculture depends on fossil energy, phosphorus, potassium, machinery, plastics, digital equipment, rare materials, and infrastructure. A circular resource economy seeks to reduce depletion by improving efficiency, substituting renewable flows where feasible, recovering nutrients, extending equipment life, and reducing waste. Digital technologies introduce an ambivalent effect. They can reduce material and energy use through precision, but they also require hardware, batteries, connectivity, data centers, replacement cycles, and electronic waste. A credible theory of digital environmental management must therefore include the environmental footprint of digitalization itself.

This is where true-cost accounting and life-cycle thinking become important. FAO's work on hidden costs of agrifood systems, life-cycle assessment literature, and environmental-economic accounting frameworks all point to the need to consider impacts across production, supply chains, consumption, and disposal. A digital tool that reduces fertilizer use but requires short-lived hardware and high energy demand may still be justified, provided its net effect is evaluated. The objective is not to reject digitalization based on its footprint. It is to avoid the illusion that immaterial data systems are environmentally costless.

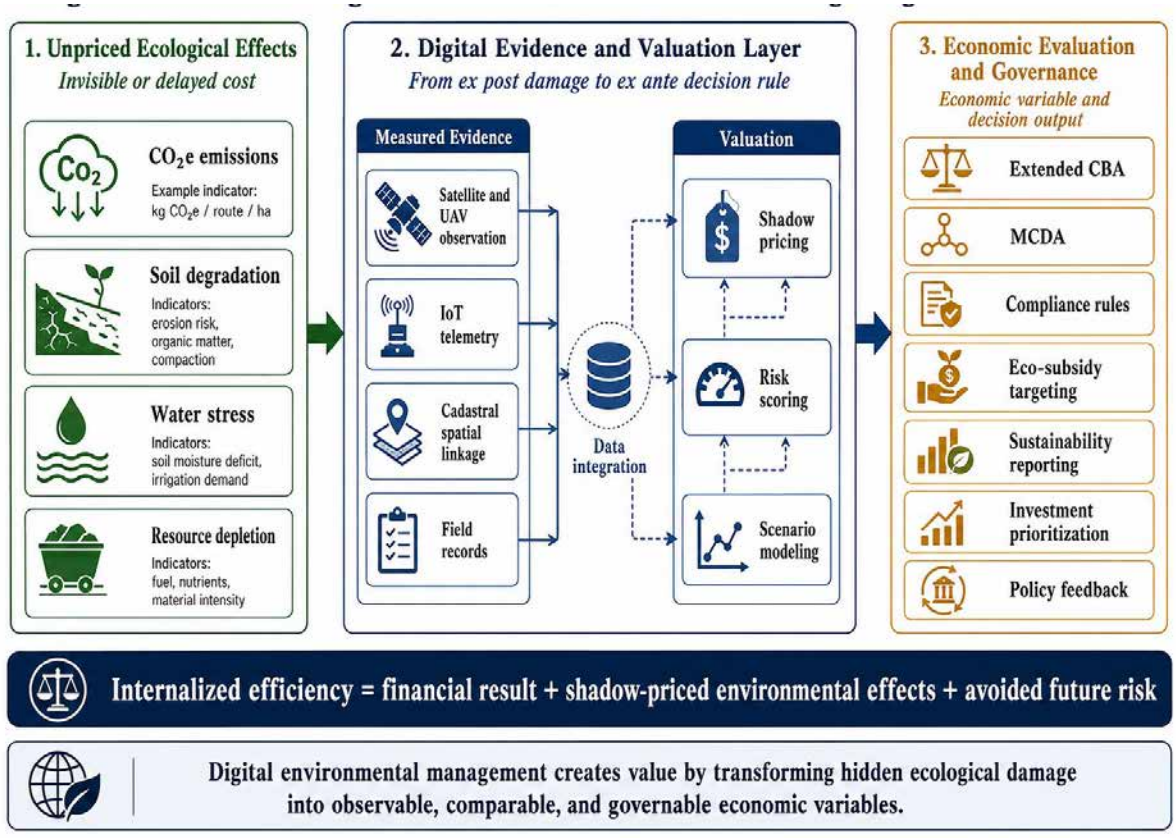


Figure 1.3 Internalizing Environmental externalities through digital evidence

From a theoretical perspective, externalities can be organized along three axes. The first is measurability: some externalities are relatively easy to measure, such as fuel-related CO_2e, while others, such as biodiversity loss or institutional distrust, are more difficult to quantify. The second is reversibility: some damages can be remediated, while soil loss, groundwater depletion, species loss, or contamination may be partially irreversible. The third is attribution: some impacts can be linked to a particular action, while diffuse runoff, landscape fragmentation, or cumulative emissions require probabilistic or systemic attribution. Digital tools improve but do not fully solve these challenges. They increase evidence, but interpretation remains theoretical, institutional, and political.

Environmental externalities also have distributional dimensions. The costs of degradation are not borne equally. Downstream communities may bear water pollution; future farmers may bear soil degradation; taxpayers may bear remediation; vulnerable rural populations may bear health impacts; small farms may lack the capital to comply with digital reporting requirements; countries in transition may face higher adaptation costs while seeking market access to the EU. Economic efficiency, if treated as a social category, cannot ignore these distributions. A management system that shifts environmental costs onto actors with less bargaining power is not efficient in a robust welfare sense; it is merely transferring losses.

The practical implication for the monograph is that externalities should enter economic evaluation before they become visible as disasters, penalties, or production losses. CO_2e, soil degradation, water stress, and resource depletion are not supplementary environmental indicators appended to financial calculations. They are constitutive variables of long-term economic efficiency. Digital environmental management is theoretically justified because it makes these variables more observable, more comparable, and potentially more governable. Its success depends on whether observation leads to changed decisions, not on observation alone.

1.4. Institutional and Policy Drivers of Digital Environmental Management in Transition Economies

Institutions define the rules by which environmental information becomes economically meaningful. Property rights determine who may use land and resources. Regulatory systems determine which environmental harms are prohibited, priced, tolerated, or ignored. Public registries determine whether land information is credible. Standards determine whether data from different sources can be compared. Courts, inspections, certification bodies, payment agencies, and markets determine whether evidence has consequences. For this reason, institutional economics is not an external supplement to digital environmental management; it is one of its theoretical foundations (North, 1990; Ostrom, 1990; Williamson, 1985).

Institutional questions are especially important in transition economies. A transition economy is not merely an economy moving from state planning to markets. It is an economy in which property regimes, administrative capacities, enforcement mechanisms, trust relations, public data infrastructures, and regulatory incentives are being reconfigured. Environmental management in such contexts often suffers from path dependency: outdated registers, fragmented authority, weak monitoring, low compliance, insufficient public funding, and a gap between formal law and practical enforcement. Digital tools can help close this gap, but only if they are embedded in institutional reforms that make data authoritative, interoperable, accessible, and actionable.

The EU provides a dense institutional framework for policy-driven environmental digitalization. The European Green Deal establishes climate neutrality and environmental sustainability as a development strategy rather than a sectoral policy. The Farm to Fork Strategy connects agriculture with food-system transformation. The Circular Economy Action Plan frames resource efficiency in terms of industrial and market competitiveness. The CAP Strategic Plans link public support to performance, environmental conditionality, and national implementation. The Data Act and Data Governance Act establish horizontal rules for access, sharing, and trust in data. The Nature Restoration Regulation and the soil monitoring framework underscore the need for measurable ecological restoration and harmonized environmental evidence. These instruments jointly increase demand for digital systems capable of measurement, reporting, verification, and policy feedback.

It is important to note that this EU architecture does not eliminate tensions. European agriculture faces contested debates over regulatory burden, farm income, global competition, biodiversity protection, pesticide reduction, climate policy, and administrative simplification. Environmental ambition can provoke resistance if costs are perceived as unfairly distributed or if farmers lack compliance support. Digital monitoring can be seen as enabling better policy design, but also as surveillance or bureaucratic intensification. Therefore, the institutional driver of digital environmental management is not simply regulation; it is the search for credible compromises between sustainability, competitiveness, social legitimacy, and administrative feasibility.

For Ukraine, EU integration turns these issues into an accession and reconstruction agenda. The opening of accession negotiations, the Ukraine Facility, the Ukraine Plan for 2024-2027, and the ongoing approximation to the EU acquis create incentives to modernize public administration, environmental governance, data systems, public finance, and sectoral regulation. In agriculture and land management, this means that digital environmental management is not an optional technological modernization. It is part of building compatibility with European policy instruments, market expectations, reporting practices, and environmental standards.

The economic significance of EU alignment for Ukraine is multidimensional. First, it affects market access. Producers integrated into European supply chains increasingly face requirements for traceability, sustainability documentation, residue control, emissions accounting, deforestation-free sourcing where relevant, and evidence of compliance. Second, it affects public investment. Reconstruction finance, green recovery initiatives, and EU-supported reforms require transparent monitoring of outputs and impacts. Third, it affects institutional credibility. Reliable digital registries and environmental datasets reduce uncertainty for investors, local authorities, farms, insurers, researchers, and international partners. Fourth, it affects policy capacity. Without integrated data, the state cannot effectively design targeted subsidies, environmental restoration programs, land-use controls, or climate adaptation measures.

A transition-economy perspective also emphasizes transaction costs. When land records are unreliable, environmental restrictions are unclear, data formats are incompatible, and procedures are opaque, actors spend resources verifying information, resolving disputes, avoiding mistakes, and navigating administrative uncertainty. These costs may be hidden but economically substantial. Digital land administration, environmental monitoring, and interoperable data systems can reduce transaction costs by making rules and evidence more transparent. However, they can also increase transaction costs if digital systems are poorly designed, duplicative, inaccessible, or not legally recognized. Institutional quality determines which outcome prevails.

Data sovereignty is another key institutional driver. Agricultural and environmental data are produced across public and private domains: farms, machinery, satellites, sensors, platforms, public registries, research institutions, and administrative bodies. The value of these data depends on access rights, control, consent, portability, security, and rules for secondary use. In the EU, the Data Act is relevant because it seeks to improve access to data generated by connected products and related services. In agriculture, this has direct implications for machinery telemetry, IoT devices, and platform ecosystems. For Ukraine, data sovereignty is additionally linked to security, wartime restrictions, public trust, and the need to balance openness with the protection of sensitive spatial information.

Interoperability is the technical expression of institutional coordination. A digital environmental system cannot be efficient if cadastral data, satellite observations, sensor records, farm logs, administrative boundaries, and environmental restrictions cannot be linked. Interoperability reduces the cost of recombining evidence across contexts. It also supports auditability, as data provenance and standards enable third parties to verify results. In transition economies, interoperability is often constrained by legacy systems, fragmented procurement processes, departmental silos, inconsistent identifiers, and limited maintenance capacity. Thus, investment in digital environmental management must include standards and governance, not only software procurement.

Policy incentives determine whether digital tools are used for sustainability or only for narrow productivity. If environmental benefits are unpriced and compliance is weak, farms may adopt digital tools primarily to increase output or reduce private costs. If eco-schemes, subsidies, carbon incentives, water tariffs, soil protection requirements, or certification schemes reward verified environmental performance, digital tools gain a stronger sustainability function. The EU's movement toward performance-based policy increases the value of auditable environmental data. Ukraine's challenge is to design incentive systems that are administratively feasible, socially legitimate, resistant to manipulation, and compatible with EU expectations.

Institutional trust is perhaps the most underestimated variable. Digital systems require users to trust that data will not be misused, that rules will be stable, that environmental indicators are scientifically credible, that public registries are accurate, that platforms will not exploit dependency, and that compliance evidence will be recognized. Where trust is low, actors may underreport, avoid participation, duplicate verification, or resist integration. Trust cannot be produced by technology alone. It requires legal clarity, transparency, accountability, participatory design, dispute-resolution mechanisms, and demonstrable benefits for users.

The Ukrainian case illustrates why digital environmental management in transition economies must be evaluated at multiple institutional scales. At the farm level, digital tools must be affordable, useful, and compatible with agronomic routines. At the community level, they must support land-use planning, environmental protection, infrastructure management, and local economic development. At the national level, they must support EU integration, recovery planning, environmental monitoring, public registries, and fiscal accountability. At the international level, they must provide credible evidence for partners, investors, donors, and markets. A tool efficient at one scale may fail at another if institutional linkages are absent.

The policy drivers of digital environmental management also include risk governance. Climate change, war-related damage, market volatility, and infrastructure disruption create conditions in which resilience becomes a central criterion of efficiency. Institutions must be able to update data, revise priorities, allocate resources, and communicate risks rapidly. Digital systems can support this capacity by providing near-real-time evidence and scenario awareness. However, resilience also requires redundancy, local capacity, cybersecurity, backup systems, and clear responsibilities. A fragile digital platform may become a single point of failure if institutional design is weak.

This subsection leads to the chapter's final theoretical synthesis. Economic efficiency in digital environmental management is not produced by technology, market prices, or regulation separately. Their alignment produces it. Technology expands observability; markets and public finance create incentives; regulation defines obligations; institutions create trust and enforceability; ecological science defines thresholds; and users translate information into action. In the EU, this alignment is advanced but contested. In Ukraine, it is emergent and strategically necessary. The core theoretical challenge is to design digital environmental management systems that are not merely modern but institutionally credible, environmentally meaningful, and economically justified.

The preceding analysis enables the formulation of a theoretical synthesis for the monograph. Economic efficiency in environmental management should be understood as the capacity of an economic system to generate durable value while minimizing ecological degradation, institutional friction, and future risk. This definition differs from narrow definitions of productivity or profitability because it treats environmental conditions as productive assets rather than mere scenery. It also differs from pure ecological evaluation because it recognizes that sustainability must be operationalized through economic decisions, incentives, institutions, and measurable trade-offs.

Digital tools enter this theory as infrastructures of observability and coordination. They do not replace economic reasoning, ecological science, or institutional design. They make it possible to connect them. A satellite image can reveal spatial heterogeneity; a sensor can detect local stress; a cadastral system can identify legal constraints; a platform can integrate datasets; an algorithm can compare alternatives; an audit trail can verify compliance. None of these functions is sufficient alone. Their value emerges when they shorten the distance between environmental signal, economic interpretation, institutional recognition, and managerial action.

The chapter also shows why the EU and Ukraine are analytically important together. The EU represents a highly institutionalized sustainability regime in which circularity, climate neutrality, data governance, agricultural support, nature restoration, and soil monitoring are becoming increasingly interconnected. Ukraine represents a transition and reconstruction context in which digital environmental management must simultaneously support productivity, recovery, EU accession, land governance, environmental damage assessment, and institutional trust. The interaction between these contexts creates a demanding but productive research field: Ukraine's digital environmental transformation must be evaluated not only by domestic efficiency gains, but also by its capacity to become interoperable with European sustainability governance.

Four theoretical generalizations follow. First, circularity changes the denominator of efficiency: the relevant unit is not only paid input but total ecological pressure. Second, digitalization changes the epistemic basis of efficiency: management can increasingly be evaluated through spatially explicit, time-sensitive, and auditable evidence. Third, externalities change the boundary of efficiency: costs displaced onto climate, soil, water, ecosystems, and future users must be brought into the evaluative frame. Fourth, institutions change the feasibility of efficiency: without credible rules, data rights, interoperability, incentives, and trust, even technically advanced tools may fail to generate sustainable value.

This theoretical foundation prepares the ground for the methodological and empirical chapters that follow. The next chapter can develop an extended cost-benefit analysis, multi-criteria assessment, shadow pricing, and scenario modeling, as this chapter has clarified why economic efficiency must be widened beyond direct financial returns. The later case studies can analyze land management, environmental monitoring, and routing because this chapter has shown that these are not isolated technical domains. They are interconnected expressions of a broader transformation: the movement from environmentally blind economic calculation toward digitally enabled, institutionally governed, and sustainability-oriented economic efficiency.

CHAPTER 2

Methodological Framework for Determining Economic Efficiency

2.1. Extended Cost-Benefit Analysis for Digital Agritech and Environmental Management

The methodological section of the monograph is designed as a practical and theoretical “how-to” guide for determining the economic efficiency of digital tools in sustainable environmental management. The general logic of this section is based on the assumption that digital tools in agriculture, land management, environmental monitoring, and routing cannot be evaluated only by the amount of money spent on their purchase, installation, or maintenance. Such a simplified approach is not sufficient because digital systems create value in several ways simultaneously: they reduce direct costs, improve the quality and speed of decision-making, generate reusable data, decrease operational risks, support compliance with environmental policy, reduce uncertainty, and make resource use more transparent.

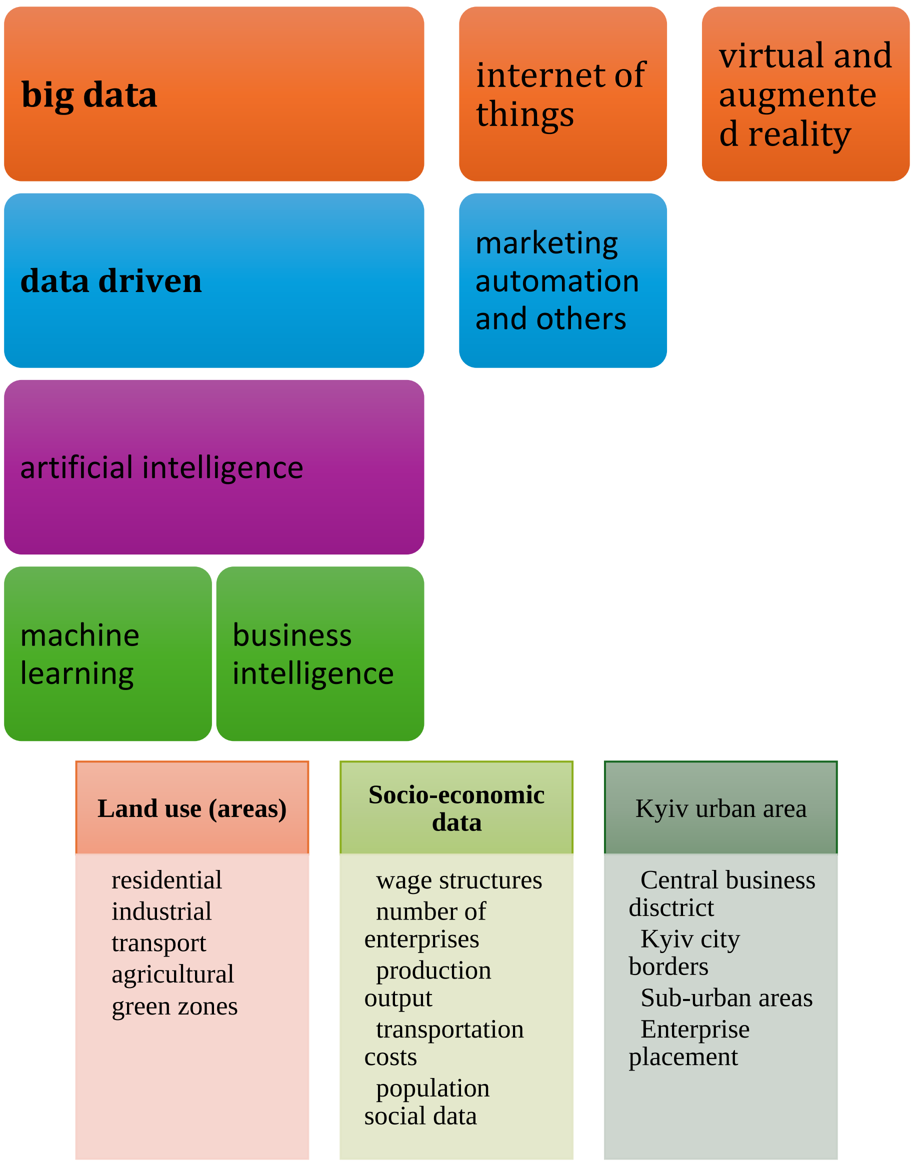


Figure 2.1 Methodological Framework foundation

In this monograph, economic efficiency is therefore understood as an integrated result of financial, environmental, temporal, operational, informational, and institutional effects. A digital tool is economically efficient not only when it reduces direct costs, but also when it prevents losses, improves the accuracy of agronomic decisions, reduces unnecessary water or fertilizer use, supports a better route, helps avoid ecological or legal conflicts, or provides reliable data for future decisions. This interpretation aligns with current developments in environmental economics and digital agriculture, where the effects of digital tools are increasingly evaluated through joint measurement of economic, ecological, and managerial outcomes (Basso & Antle, 2020; Finger, 2023; Klerkx et al., 2019; Papadopoulos et al., 2024).

The methodological framework proposed in this section comprises four interconnected elements. The first element is an adapted cost-benefit analysis for digital agritech, which expands traditional financial evaluation by including the value of data, decision support, risk reduction, and environmental effects. The second element is multi-criteria decision analysis in spatial economics, which enables the researcher to compare alternatives when evaluating cost, time, environmental impact, land-use constraints, and operational risk simultaneously. The third element is shadow pricing of environmental and temporal variables, which assigns monetary value to prevented environmental damage, saved agronomic time windows, carbon emission reductions, and other non-market effects. The fourth element is simulation and scenario-based evaluation, which assesses whether a digital solution remains economically efficient under uncertain, volatile conditions.

The methodological framework is not presented as an abstract mathematical construction detached from practice. It is built for empirical application in the three case studies of the monograph: digital land management and cadastral systems, IoT telemetry and environmental monitoring, and spatio-temporal optimization and routing. For this reason, the methodology must be capable of working with heterogeneous data: cadastral and spatial data, satellite imagery, UAV imagery, IoT telemetry, weather and climate data, economic records, fuel prices, route information, land-use restrictions, and environmental indicators. The main methodological task is to convert these different data flows into comparable economic indicators.

Cost-benefit analysis is one of the basic instruments for evaluating whether a project, policy, or technology is economically justified. In its classical form, CBA compares costs and benefits over a specified time horizon and determines whether the discounted benefits exceed the discounted costs. This logic remains useful for digital agritech. However, in the context of digital tools for environmental management, the classical version of CBA must be adapted. Digital tools generate effects that are not always immediately reflected in accounting documents. They can reduce uncertainty, improve timing, increase compliance, support auditability, prevent environmental losses, and create reusable data assets. These effects may not appear as direct income in the first year of implementation, but they strongly influence long-term economic efficiency.

This is especially important for agriculture. Agricultural production is a spatially distributed and time-sensitive process. It depends on land quality, soil moisture, crop condition, weather, market prices, machinery availability, fuel costs, labor, logistics, and regulatory constraints. A digital tool may not increase revenue directly at the moment of installation. However, it can increase the likelihood that the right action will be taken at the right time and in the right place. For example, a soil moisture sensor does not generate income on its own. Its economic value lies in helping avoid unnecessary irrigation, prevent crop stress, save water, or reduce energy costs. A satellite image does not generate profit on its own. Its value lies in detecting problems earlier than field inspection and allowing the farm to intervene before yield loss occurs. A routing system does not create value only because it produces a route. Its value lies in reducing fuel consumption, preventing missed service windows, avoiding restricted areas, and improving the reliability of agricultural operations.

Recent research on precision agriculture and digital agricultural technologies confirms that the economic and environmental effects of such tools are complex and depend on farm size, technological integration, cost structure, data availability, and the ability of users to convert information into action (Bahmutsky et al., 2024; Papadopoulos et al., 2024; Wang et al., 2023). Therefore, the task of adapted CBA is not simply to calculate whether a digital tool is “expensive” or “cheap.” The task is to determine the complete structure of costs and benefits and to show how the digital tool changes the economic behavior of the production or management system.

In this monograph, an adapted CBA for digital agritech is built on the following principle: the value of a digital tool is determined not only by its direct operational savings, but also by the decisions that become possible because of the data, models, and services it generates. This requires distinguishing between three levels of benefit: direct, indirect, and systemic.

Direct benefits are the easiest to observe. They include reduced fuel use, reduced labor hours, reduced water consumption, reduced fertilizer application, reduced agrochemical use, reduced machinery downtime, reduced transaction costs, and reduced field inspection costs. These indicators can usually be calculated from farm records, accounting data, fuel logs, machine operation reports, irrigation data, or input purchase records.

Indirect benefits are more difficult to calculate but are often more important. They include avoided yield losses, better timing of agronomic operations, reduced probability of disease spread, improved compliance with environmental restrictions, lower risk of entering prohibited or sensitive land areas, and fewer planning conflicts. These benefits are often visible only when a baseline scenario is compared with a digital scenario.

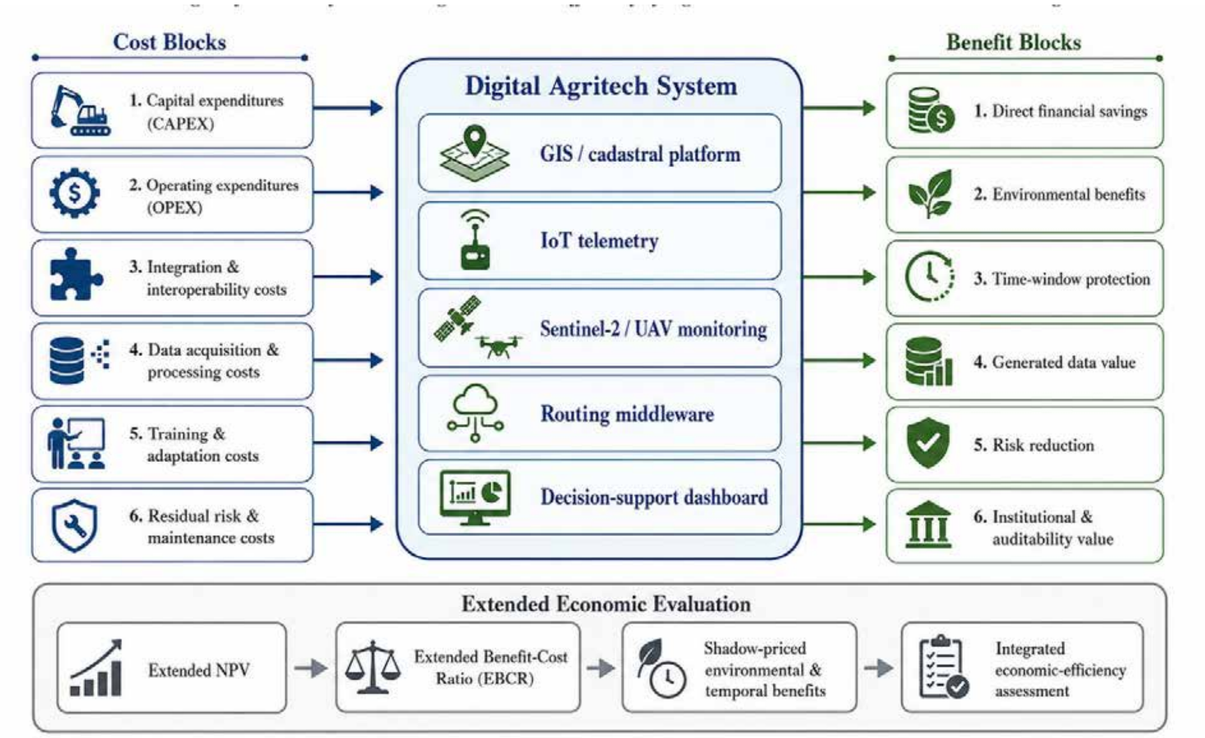


Figure 2.2 Extended cost-benefit architecture

Table 2.1 Extended CBA logic for digital agritech and environmental management tools

Evaluation block	Classical CBA interpretation	Extended interpretation for digital agritech	Example in the monograph	Main indicator type	Expected economic meaning
Capital costs	Purchase or construction cost	Hardware, software, geospatial database, platform deployment, sensors, UAV equipment, routing engine setup	IoT soil sensors, GIS database, GeoServer, routing middleware	Monetary	Initial investment burden
Operating costs	Maintenance and routine operation	Cloud services, data storage, sensor calibration, updates, connectivity, and technical support	Satellite data processing, telemetry maintenance, server support	Monetary/periodic	Long-term financial sustainability of the system
Integration costs	Usually underrepresented	API integration, data harmonization, cadastral linkage, EO/IoT/UAV fusion, metadata preparation	Integration of Sentinel-2, cadastral layers, IoT telemetry, and road network	Monetary / labor time	Cost of making heterogeneous data usable
Direct financial benefits	Direct savings or revenue increase	Reduced input use, reduced fuel consumption, reduced labor hours, and lower field-inspection costs	Less water, fertilizer, and agrochemical use; optimized machinery routes	Monetary	Immediate measurable savings
Environmental benefits	Often external to standard project accounting	Avoided CO_2e, reduced runoff, lower soil degradation, lower water stress, fewer ecological conflicts	Reduced emissions from routing; avoided over-irrigation; protected green areas	Monetary after valuation / physical indicator	Internalization of ecological effects
Time benefits	Usually treated as labor-saving	Saved agronomic time-windows, faster decision-making, lower delay losses	Earlier irrigation/spraying; faster routing response	Time + monetary equivalent	Prevention of time-sensitive agricultural losses
Data benefits	Rarely included	Reusable data assets, historical datasets, audit trails, decision-ready layers, forecasting value	NDVI/EVI archive, IoT records, parcel history, route logs	Data quality/reuse value / avoided future cost	Long-term value of generated data

Evaluation block	Classical CBA interpretation	Extended interpretation for digital agritech	Example in the monograph	Main indicator type	Expected economic meaning
Risk reduction	Usually, it is only included in sensitivity analysis	Lower probability of legal, ecological, logistical, or agronomic failure	No restricted-edge violations; fewer land-use conflicts; lower risk of missed service windows	Probability × loss	Expected avoided loss
Institutional benefits	Usually, absent	Transparency, interoperability, reporting, auditability, and lower transaction costs	FAIR/OGC-aligned data services, cadastral interoperability, sustainability reporting	Monetary proxy / qualitative score	Governance and compliance value

Source: prepared by the authors based on CBA adaptation logic for digital environmental tools and the information-system modeling approach developed in Nazarenko and Martyn (2024), Papadopoulos et al. (2024), Bahmutsky et al. (2024), and Macháč et al. (2021).

Systemic benefits include effects that accumulate over time and influence future decision-making. These include generated data repositories, improved institutional transparency, better audit trails, reusable geospatial layers, improved planning capacity, integration with sustainability reporting, and the ability to use historical data for forecasting. In digital systems, the accumulation of structured data may become one of the most important long-term benefits, especially when the data is standardized, reusable, and linked with land-use or environmental indicators.

dapted CBA framework used in this monograph m be expressed as: $NPV_D = \sum_{t=0}^{T} \frac{\left(B_t^{fin}+B_t^{env}+B_t^{time}+B_t^{data}+B_t^{risk}+B_t^{inst}\right)-\left(C_t^{capex}+C_t^{opex}+C_t^{int}+C_t^{data}+C_t^{train}+C_t^{risk}\right)}{(1+r)^t}$

(2.1)

where:

- NPV_D is the present net value of the digital tool or digital system;
- $B(t)^{fin}$ is the direct financial benefit in year or period t;
- $B(t)^{env}$ is the monetary value of environmental benefit or avoided ecological damage;
- $B(t)^{time}$ is the monetary value of saved time or protected agronomic time window;
- $B(t)^{data}$ is the value of generated, structured, reusable, and decision-ready data;
- $B(t)^{risk}$ is the value of reduced operational, environmental, or compliance risk;
- $B(t)^{inst}$ is the institutional benefit, including transparency, auditability, lower transaction costs, and improved coordination;
- $C(t)^{capex}$ is capital expenditure;
- $C(t)^{opex}$ is operating expenditure;
- $C(t)^{int}$ is integration cost;
- $C(t)^{data}$ is the cost of data acquisition, cleaning, storage, processing, and updating;
- $C(t)^{train}$ is the cost of training and organizational adaptation;
- $C(t)^{risk}$ is the residual or implementation-related risk cost;
- r is the discount rate;
- T is the evaluation period.

This formula deliberately expands the traditional financial interpretation of cost-benefit analysis. The reason is that digital environmental systems are not only investment objects. They are also instruments for producing information, reducing uncertainty, and improving decision quality. A narrow CBA that includes only purchase cost, maintenance cost, and direct savings would underestimate the real value of such systems. At the same time, an overly broad qualitative assessment would make verification difficult. The proposed structure, therefore, maintains the logic of CBA while transparently expanding the benefit and cost categories.

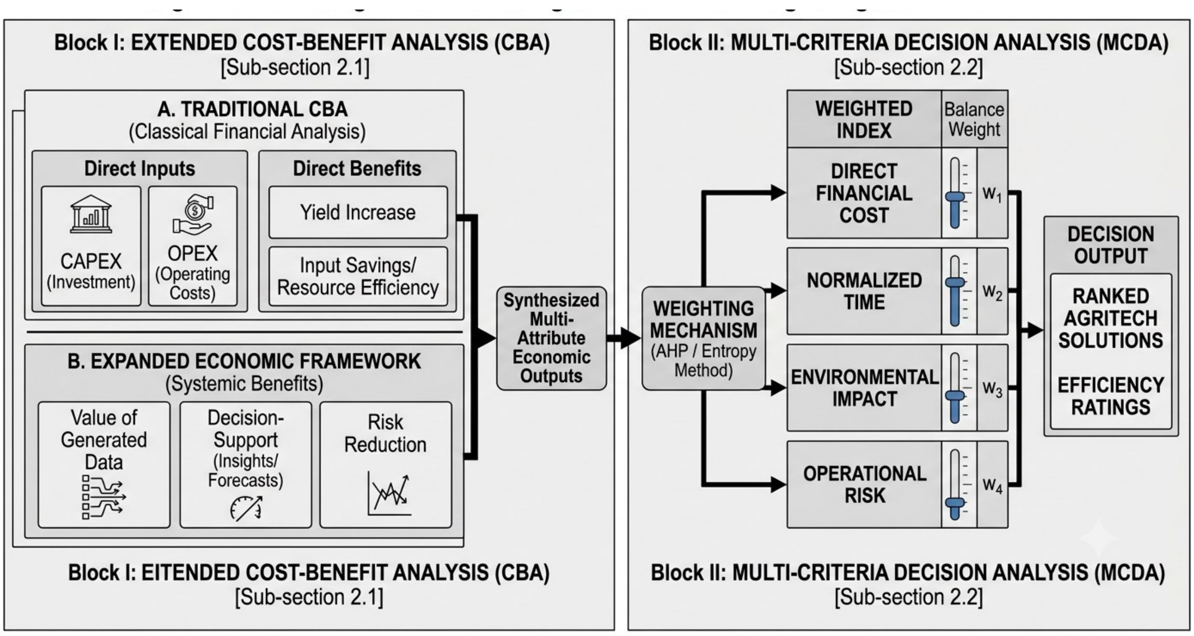


Figure 2.3 Integrated methodological workflow for digital agritech evaluation

The first group of costs includes capital expenditure. For digital agritech, this may include sensors, UAVs, edge devices, GPS equipment, weather stations, servers, software licenses, databases, field controllers, communication devices, and installation costs. In land management systems, capital expenditure may include geospatial database development, digitization of land parcels, server infrastructure, API development, and integration with existing cadastral systems. In routing systems, capital expenditure may include routing engine configuration, fleet tracking devices, interface development, and spatial data preparation.

The second group is operating expenditure. It includes maintenance, software subscriptions, cloud storage, communication costs, battery replacement, data transmission, field calibration, technical support, and routine system administration. In many projects, operating costs are underestimated. However, digital systems require continuous data updates, sensor maintenance, user support, and periodic verification. Without these expenditures, the system may formally exist but lose its decision-making value.

The third group is integration cost. This cost is especially important for digital agriculture and environmental management, as many systems rely on heterogeneous data sources. Satellite imagery, UAV orthomosaics, IoT telemetry, field logs, cadastral data, fuel prices, weather data, road networks, and administrative restrictions often exist in different formats, scales, and update cycles. Integration costs include data cleaning, format conversion, API development, georeferencing, schema harmonization, and metadata creation. These costs are not secondary. They determine whether the digital tool can support decisions or only store disconnected information.

The fourth group is the cost of data. Data are often treated as free if they are open or publicly accessible. This is a methodological mistake. Even when data are open, they require search, download, validation, processing, storage, updating, and interpretation. For example, Sentinel-2 imagery may be free for the researcher. However, the economic model must still include processing time, cloud masking, vegetation index calculation, field validation, and integration with farm boundaries. Similarly, OpenStreetMap data may be open, but routing analysis requires graph cleaning, road classification, restriction detection, and calibration of travel-time assumptions. Therefore, an adapted CBA must include not only the cost of purchasing data, but also the cost of making data usable.

The fifth group is the cost of training and organizational adaptation. This is especially important on small and medium-sized farms, in cooperatives, in municipal structures, and in transitional institutional environments. A digital tool produces economic effect only when people use it correctly. Training costs include not only formal training sessions, but also changes in work routines, adaptation of internal reporting, preparation of personnel, development of protocols, and time spent learning. Adoption studies in smart farming show that human, organizational, and external support factors significantly influence whether digital technologies are used and whether they generate value (Caffaro & Cavallo, 2019; Pierpaoli et al., 2013; Wang et al., 2023).

The sixth group is risk-related cost. Digital systems may create new risks: dependence on connectivity, cybersecurity risks, sensor malfunctions, incorrect data interpretation, vendor lock-in, incomplete cadastral data, or user failure to update information. In wartime or post-war conditions, additional risks include restricted access to fields, damaged infrastructure, no-fly zones for UAVs, temporary road closures, and incomplete administrative data. These factors must not be ignored. They are part of the real economic environment in which the system operates.

Table 2.2 Cost categories for adapted CBA of digital agritech tools

Cost category	Description	Possible data sources	Unit of measurement	Calculation approach	Notes for empirical use
CAPEX: hardware	Sensors, UAVs, servers, GPS units, routers, edge devices, field controllers	Vendor invoices, procurement records, and project budget	UAH / USD	Sum of purchase and installation costs	Should be annualized if the equipment is used over several years
CAPEX: software and platform	GIS, database setup, middleware, routing system, dashboard, custom web services	Project documentation, development contracts	UAH / USD	Development cost + license cost + deployment cost	Open-source tools reduce license cost but not integration cost
Spatial database preparation	Parcel cleaning, georeferencing, attribute harmonization, restriction layers	State cadastral data, municipal data, and project GIS layers	UAH / labor hours	Labor hours × hourly rate + software/cloud cost	Especially important for the land management case
EO data processing	Satellite image discovery, download, preprocessing, cloud masking, index calculation	Copernicus Data Space, Sentinel-2, openEO, local processing logs	UAH / image/hectare/season	Processing time + storage + labor + cloud cost	Data may be free, but processing is not free
IoT telemetry operation	Sensor maintenance, calibration, communication, and battery replacement	Sensor logs, maintenance records	UAH / sensor/month	Maintenance + connectivity + replacement cost	Must include field visits
UAV data acquisition	Mission planning, flight execution, image processing, orthomosaic generation	UAV logs, mission reports, GeoTIFF outputs	UAH / flight/hectare	Flight cost + processing cost + operator labor	May be limited by wartime or regulatory restrictions
Training and adaptation	Personnel training, workflow redesign, documentation, internal protocols	Training records, staff time logs	UAH / person/hours	Training hours × wage rate	Often underestimated in digital projects
Data storage and security	Databases, backups, access control, cybersecurity, and long-term archiving	Server/cloud invoices, IT records	UAH / GB / month	Storage + security + maintenance	Important for auditability and long-term reuse
System risk cost	Downtime, data loss, sensor errors, vendor dependency, connectivity failure	Incident logs, risk register	Expected loss	Probability × impact	Should be included in sensitivity analysis
Administrative and compliance cost	Reporting, legal verification, and coordination with public authorities	Project documents, administrative records	UAH / procedure/year	Administrative time × cost	Relevant for cadastral and environmental reporting tools

Source: prepared by the authors.

On the benefit side, the first and most direct category is financial savings. For digital agritech, this includes reduced use of water, fertilizers, agrochemicals, seed, fuel, and labor. These savings should be calculated using a baseline scenario. The baseline may be the farm's traditional practice, the average practice in the region, or a non-digital version of the operation. The digital scenario is then compared against it. For example, if an irrigation decision-support tool reduces water use from (W_0) to (W_1), the direct water-saving benefit may be calculated as:

$$B_t^{water} = (W_0 - W_1) \cdot P_w \backslash hfill(2.2)$$

where (W_0) is water used in the baseline scenario, (W_1) is waterusede in the digital scenario, and (P_w) is the cost per unit of water, including energy and delivery costs. A similar logic applies to fertilizer, agrochemicals, fuel, labor, and machinery time.

The second benefit category is yielding protection. In digital agriculture, the effect of technology is often not expressed as a dramatic increase in yield but as the prevention of yield loss. This is especially true for monitoring systems that identify stress, disease, water deficit, or delays in field operations. The economic value of yield protection can be expressed as:

$$B_t^{yield} = \left(Y_{loss,0} - Y_{loss,1}\right) \cdot A \cdot P_y \backslash hfill(2.3)$$

where (Y{loss,0}) is expected yield loss without the digital tool, (Y{loss,1}) is expected yield loss with the digital tool, (A) is the affected area, and (P_y) is the market price of production. This category is especially important for IoT telemetry and satellite monitoring because its value lies in helping reduce the scale or duration of a negative agronomic event.

The third benefit category is environmental benefits. Environmental benefits may include lower emissions, reduced water withdrawal, lower nutrient runoff, reduced agrochemical leakage, improved soil protection, lower compaction risk, and avoided ecological damage. Some of these benefits can be measured directly; others require shadow pricing, which is developed in subsection 2.3. However, in CBA, they must already be identified as benefit categories. Environmental externalities in agriculture require monetary valuation because many ecological costs are not included in market prices but still create real economic consequences for society, public institutions, and future production (Macháč et al., 2021; Moore et al., 2017; Sartori et al., 2024).

The fourth benefit category is the time benefit. Agricultural decisions are often time-sensitive. A delayed intervention may be economically equivalent to a direct loss. For example, if spraying is delayed beyond the optimal agronomic window, the farm may face higher disease pressure, lower yield, or increased chemical use later. If irrigation is delayed during a stress period, the damage may become irreversible. Therefore, saved time must be treated as an economic variable, not only as an operational convenience. The time benefit may be expressed as the reduction in expected loss due to better timing:

$$B_t^{time} = L_{delay,0} - L_{delay,1} \backslash hfill(2.4)$$

where (L{delay,0}) is the expected loss from delayed decision-making in the baseline scenario, and (L{delay,1}) is the expected loss after implementation of the digital tool.

The fifth benefit category is data value. This is one of the most important adaptations of CBA for digital agritech. Traditional CBA usually treats data as an input or cost. In digital environmental management, data is also an output. Structured data accumulated through satellite analysis, field sensors, UAV surveys, digital logs, and routing records can be reused for planning, audit, certification, forecasting, sustainability reporting, and future model improvement. Therefore, the value of data can be divided into three components: $B_t^{data} = V_t^{decision} + V_t^{reuse} + V_t^{audit} \backslash hfill(2.5)$ where (V^{decision}{t}) is the value of improved decisions based on data, (V^{reuse}{t}) is the value of reusing data in future planning or modeling, and (V^{audit}_{t}) is the value of data for compliance, verification, reporting, or access to programs and markets.

This is particularly important for digital land management and environmental monitoring. A single satellite image or sensor reading has limited value if used once. However, a structured historical dataset has a much stronger economic impact because it enables comparison, trend detection, anomaly detection, and evidence-based decision-making. It can support the calculation of sustainability indicators, AFOLU-related emissions reporting, Farm-to-Fork-aligned metrics, and enterprise-level sustainability dashboards. In this sense, data becomes a productive asset of the farm, cooperative, local authority, or research system.

The sixth benefit category is risk reduction. Risk reduction is often not visible in direct revenue, but it can be economically substantial. Digital land management can reduce the probability of legal conflict over land-use restrictions. IoT monitoring can reduce the likelihood of crop damage by enabling a faster response. Routing tools can reduce the probability of machinery entering restricted areas or missing service windows. The benefit of risk reduction may be expressed as:

$$B_t^{risk} = (P_0 \cdot L_0) - (P_1 \cdot L_1) \backslash hfill(2.6)$$

, where (P_0) is the probability of a negative event without the digital tool, (L_0) is the loss if the event occurs without the tool, (P_1) is the probability of the negative event with the tool, and (L_1) is the loss if the event occurs after implementation.

The seventh benefit category is institutional benefit. In environmental and land-use management, institutional efficiency has real economic value. It includes reduced time for data verification, fewer conflicts among actors, greater transparency in decision-making, lower reporting costs, improved policy compliance, and clearer accountability for decisions. In digital cadastral and land management systems, institutional benefits may include faster access to parcel information, improved detection of restrictions, and fewer errors in land-use planning. In environmental monitoring systems, they may be reflected in transparent records of interventions and auditable sustainability indicators.

Table 2.3 Benefit categories for adapted CBA of digital agritech tools

Benefit category	Description	Example	Data required
Input-use reduction	Reduction in water, fertilizer, agrochemicals, fuel, seed, or labor	Reduced irrigation due to soil-moisture telemetry	Baseline input use; digital scenario input use; input price
Fuel-cost savings	Lower fuel use due to optimized machinery routes	Shorter or more efficient tractor/truck routes	Route distance, vehicle consumption, fuel price
Yield protection	Avoided yield losses due to earlier detection or intervention	Timely spraying after NDVI anomaly	Expected yield loss without tool; yield loss with tool; crop price
Time-window protection	Avoided losses from missed agronomic windows	Irrigation before drought stress becomes irreversible	Delay losses; operation windows; crop sensitivity
Environmental damage prevention	Monetary value of reduced emissions, soil loss, runoff, or ecological degradation	Reduced CO_2e from route optimization	Physical reduction; shadow price
Reduced transaction costs	Lower administrative and verification costs	Faster land-use verification through cadastral GIS	Time spent before/after; wage rate; number of procedures
Reduced risk exposure	Lower probability of legal, ecological, or logistical failure	Avoided entry into restricted land zones	Event probability; loss severity
Data reuse value	Value of structured data for future planning, forecasting, and reporting	Multi-season NDVI archive, IoT logs, routing history	Cost to recreate data; reuse frequency; decision impact
Audit and compliance value	Value of verifiable records for state reporting, certification, or subsidies	GeoJSON/CSV route advisories with provenance	Reporting cost, certification requirements, and subsidy access

Source: prepared by the authors based on adapted CBA logic and digital agriculture evaluation literature.

In the practical application of CBA, the first step is to define the evaluation object. This may be a single digital tool, such as an IoT soil moisture network; a platform, such as an integrated land management system; or a service, such as a routing decision-support module. The object must be clearly defined because unclear boundaries lead to incorrect calculations. For example, if a farm evaluates an IoT irrigation tool, it must decide whether the CBA includes only sensors or also communication devices, software, training, data storage, and agronomist interpretation. The more complex the digital tool, the more important it is to define the system boundary.

The second step is to define the baseline. The baseline is the non-digital or less digital alternative against which the system is compared. It may include manual field inspection, paper-based land-use records, non-optimized machinery movement, fixed irrigation schedules, or traditional input application. The baseline must be realistic. It should not be artificially weak because this would overestimate the value of the digital tool. It should also not be idealized, as this would underestimate the impact of digital transformation.

The third step is to define the time horizon. For digital agritech, a one-year horizon is often insufficient, as many benefits unfold over several seasons. Hardware and software costs may be high in the first year, while data value, decision quality, and institutional effects accumulate over time. A practical evaluation horizon may be 3 to 5 years for farm-level tools and 5 to 10 years for institutional or land management systems. In the case of digital cadastral infrastructure or public environmental monitoring platforms, the horizon may be longer.

The fourth step is to identify all cost categories. These include capital costs, operating costs, integration costs, data processing costs, training costs, replacement costs, and residual risks. It should be noted that hidden costs are often the main reason why digital tools do not deliver expected results. Such hidden costs include poor data quality, lack of interoperability, duplicated data entry, technical support, and the time required to adapt internal processes.

The fifth step is to identify benefits. Benefits must relate to measurable indicators. If a benefit cannot be measured directly, it must be approximated through a justified proxy. For example, the value of reduced input waste can be calculated through input cost; the value of reduced emissions can be calculated through emission factors and carbon price; the value of avoided delay can be calculated through yield loss or additional cost; and the value of reduced transaction cost can be calculated through saved working time or fewer administrative procedures.

The sixth step is to discount future values. Since costs and benefits appear at different times, they must be compared in present value terms. The discount rate should reflect the study's context. For private farm investment, the discount rate may be closer to the cost of capital or expected alternative return. For public environmental infrastructure, a lower social discount rate may be justified. Since the discount rate strongly affects long-term environmental benefits, sensitivity analysis should be used.

The seventh step is to calculate CBA indicators. The main indicators include net present value, benefit-cost ratio, payback period, internal rate of return, and extended benefit-cost ratio. For this monograph, the most important indicator is the extended benefit-cost ratio:

$$EBCR = \frac{PV(B^{fin} + B^{env} + B^{time} + B^{data} + B^{risk} + B^{inst})}{PV(C^{capex} + C^{opex} + C^{int} + C^{data} + C^{train} + C^{risk})} \backslash hfill(2.7)$$

where (PV) means present value. If (EBCR > 1), the digital tool is economically justified under the extended evaluation logic. However, interpretation must be cautious. A high benefit-cost ratio based only on uncertain environmental benefits may require additional verification. A low short-term ratio may still be acceptable if the tool creates strategic data infrastructure or supports regulatory compliance.

The eighth step is sensitivity analysis. Since digital agritech operates in an uncertain environment, the CBA should not present a single result. It should test how the result changes when key parameters change: fuel price, input price, yield price, sensor failure rate, data availability, discount rate, carbon price, labor cost, and adoption rate. This is especially important in Ukraine, where agricultural production faces additional volatility from war-related logistics, infrastructure risks, and changing market conditions.

The ninth step is interpretation for decision-making. The result should not only state whether the digital tool is efficient; it should also explain why. It should explain under which conditions it is efficient, for whom it is efficient, and which component creates the largest share of value. For example, a satellite monitoring system may be efficient for large farms because of scale, but less efficient for small farms unless used through a cooperative model. A routing system may be efficient under high fuel prices but less important when transport costs are low. An IoT system may be efficient in irrigated agriculture but less effective where water is not a limiting factor.

Table 2.4 Data requirements for CBA of the three empirical case studies

Case study	Main digital tool	Required cost data	Required benefit data	Environmental data	Institutional / governance data	Main CBA output
Case Study I: Digital land management and cadastral systems	GIS, PostGIS, GeoServer, cadastral database, restriction layers	System development, database preparation, data cleaning, integration, training	Reduced transaction cost, avoided land-use conflicts, faster verification, fewer legal/ecological violations	Protected zones, land cover, soil/green cover, and ecological restrictions	Land-use rules, cadastral status, restrictions, ownership/rights, FAIR/OGC compliance	Extended benefit-cost ratio of the digital land-management system
Case Study II: IoT telemetry and environmental monitoring	IoT sensors, Sentinel-2, UAV imagery, monitoring dashboard	Sensors, connectivity, calibration, EO processing, UAV missions, data storage	Input reduction, yield protection, earlier intervention, and reduced field inspection	NDVI/EVI, soil moisture, water stress, agrochemical pressure, emissions proxy	Data reliability, access rights, monitoring protocol, and auditability	Net economic value of precision monitoring
Case Study III: Spatio-temporal routing and optimization	OSMnx, GraphHopper, OR-Tools, routing middleware	Routing engine setup, road graph preparation, fleet data integration, system maintenance	Fuel savings, time savings, service-window feasibility, and lower operational risk	CO_2e per route, environmental restrictions, risk zones	Road restrictions, safety notices, cadastral masks, service rules	Scenario-based direct and extended routing efficiency

Source: prepared by the authors.

In the context of the case studies in this monograph, the adapted CBA has three applications. In digital land management, it is used to evaluate reductions in transaction costs, avoided conflicts, faster verification of restrictions, and better land allocation. In IoT telemetry and environmental monitoring, it is used to evaluate avoided input waste, yield protection, and reduced environmental damage. In spatio-temporal routing, it is used to evaluate fuel-driven cost savings, travel time, emissions, risk, and service-window feasibility.

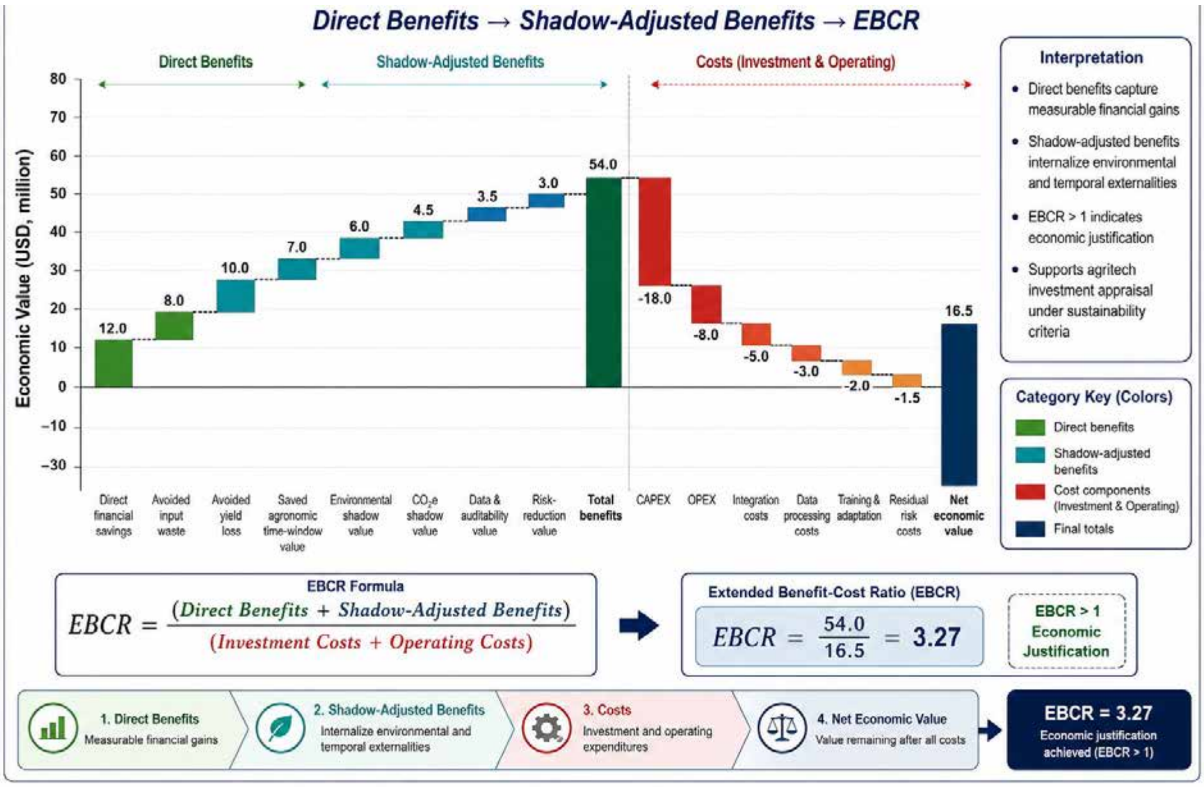


Figure 2.4 Extended economic-efficiency chart for evaluating digital agritech tools

Thus, the adapted CBA becomes a bridge between digital technology and economic reasoning. It allows the author not only to describe the digital tool but to answer the main practical question: what exactly changes economically after the tool is introduced? This is why CBA in this monograph must move beyond direct costs. The most important value of digital agritech is often not the tool itself, but the better decisions it enables.

Table 2.5 CBA implementation algorithm for digital agritech evaluation

Step	Action	Practical explanation	Output
1	Define the boundary of the digital tool or system.	Clarify whether the evaluation covers only hardware, software, data processing, or the whole service architecture.	Evaluation object
2	Define baseline scenario	Establish the non-digital or less-digital alternative	Baseline model
3	Define a digital scenario	Describe how the digital tool changes decision-making and resource use	Digital model
4	Select evaluation horizon	Choose 3–5 years for farm tools; 5–10 years or more for infrastructure and land systems.	Time horizon
5	Identify all cost categories.	Include visible and hidden costs: CAPEX, OPEX, integration, training, data, and risk.	Cost register
6	Identify benefit categories	Include direct savings, environmental benefits, time benefits, data value, risk reduction, and institutional effects.	Benefit register
7	Select monetary valuation methods.	Use market prices, avoided cost, replacement cost, shadow pricing, or willingness-to-pay were justified.	Valuation rules
8	Calculating annual net effects	Estimate yearly costs and benefits	Annual cash-flow table
9	Discount future values	Apply the discount rate and compute the present values	Present-value table
10	Calculate CBA indicators	NPV, EBCR, payback period, IRR, avoided cost, risk-adjusted effect	Economic-efficiency result

Step	Action	Practical explanation	Output
11	Conduct sensitivity analysis	Test fuel price, yield price, input price, discount rate, carbon price, adoption rate	Robustness profile
12	Interpret decision relevance	Explain under what conditions the tool is efficient and for whom	Practical recommendation

Source: prepared by the authors.

2.2. Multi-Criteria Spatial-Economic Assessment: Normalization, Weighting, and Integrated Efficiency Indices

Multi-Criteria Decision Analysis is used in this monograph as the primary methodological tool for situations in which a single indicator cannot adequately capture economic efficiency. This is a typical situation in spatial economics, land management, agricultural monitoring, and routing. A land parcel may be cheap but environmentally risky. The route may be short but unsafe. A technological option may reduce emissions but increase direct costs. A monitoring system may require investment, but it improves decision timing and reduces input waste. Therefore, the researcher must compare alternatives across several criteria simultaneously.

In spatial economics, MCDA is particularly important because each decision is tied to location. Land-use decisions, environmental restrictions, crop monitoring, infrastructure accessibility, and routing all have a spatial dimension. The value of the same digital tool or management decision may differ depending on distance, terrain, soil condition, land category, water availability, road access, risk zones, and proximity to markets or processing facilities. For this reason, MCDA in this monograph is not used only as an abstract scoring method. It is used as a spatial-economic method that combines geospatial data, economic indicators, environmental constraints, and operational priorities.

The literature on MCDA confirms that multi-criteria methods are appropriate for sustainability assessment because such assessments usually require comparing heterogeneous indicators and balancing economic, environmental, and social objectives (Cicciù et al., 2022; Cinelli et al., 2014; Ferla et al., 2024; Siksnelyte et al., 2018). Spatial MCDA is especially relevant for agricultural land-use evaluation because land suitability and sustainability cannot be determined only by productivity or market value. They must include soil, slope, accessibility, environmental restrictions, water availability, and socio-economic context (Boggia et al., 2018; Ustaoglu et al., 2021). This logic aligns with the empirical direction of the monograph, which integrates land management, environmental monitoring, and routing into a single decision-support system.

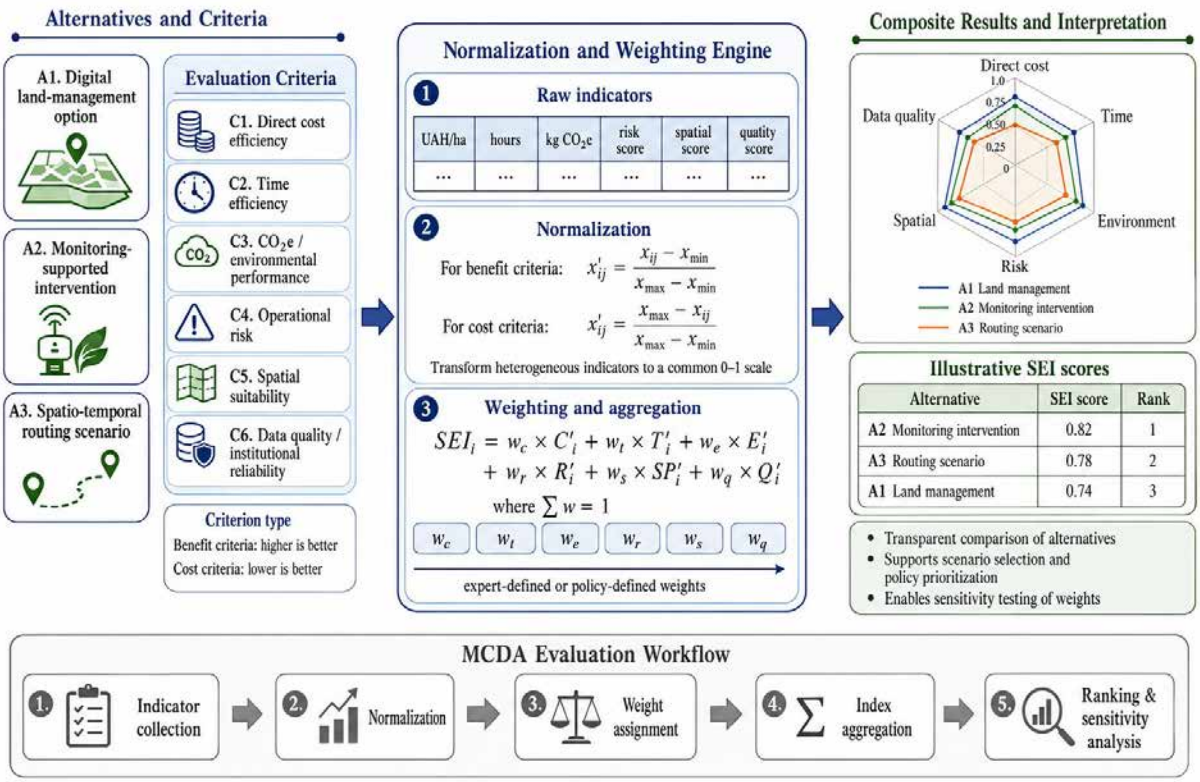


Figure 2.5 MCDA-based spatial-economic index

The main methodological idea in MCDA is to convert multiple criteria into a single comparable decision index. This does not mean that complex decisions are reduced mechanically to one number. Rather, the index is used to make the decision-making process transparent. It shows which criteria are included, how they are normalized and weighted, and how the final decision score is calculated. This is important because many decisions in land and environmental management are made implicitly. MCDA makes these implicit priorities visible.

In this monograph, the general MCDA score for an alternative (i) may be written as:

$$S_i = \sum_{j=1}^{m} w_j \cdot x'_{ij} \backslash hfill(2.8)$$

where:

- S_i is the integrated score of alternative i;
- w_j is the weight of criterion j;
- x'_{ij} is the normalized value of alternative i according to criterion j;
- m is the number of criteria;

The alternatives may be land parcels, intervention zones, technology options, route segments, weekly operational plans, monitoring configurations, or policy scenarios. The criteria may include direct cost, time, emissions, operational risk, data quality, land suitability, environmental sensitivity, accessibility, compliance risk, and institutional feasibility. Sum of Criterion Weights can be expressed as follows:

$$\sum_{j=1}^{m} w_j = 1 \backslash hfill(2.9)$$

The first stage of MCDA is defining the alternatives. In land management, alternatives may include different land-use options for a parcel: agriculture, conservation, infrastructure, processing facility, warehouse, or mixed use. In environmental monitoring, alternatives may include different intervention zones ranked by urgency. In routing, alternatives may include different routes, route segments, fleet schedules, or weekly operational plans. In technology evaluation, alternatives may include satellite-only, IoT-based, UAV-assisted, or a combined system.

The second stage is defining the criteria. Criteria must be directly connected with the research problem. In this monograph, criteria are grouped into six categories: economic, temporal, environmental, spatial, risk-related, and institutional.

Economic criteria include direct costs, capital costs, operating costs, maintenance costs, cost per hectare, cost per kilometer, labor costs, fuel costs, and expected financial benefits. These criteria are necessary because the monograph focuses on economic efficiency.

Figure 2.6 Risk and analytics system flow

Temporal criteria include travel time, delay, speed of data update, time to decision, time to intervention, and compliance with agronomic service windows. These criteria are necessary because agriculture is time-sensitive, and many losses occur because the right action is taken too late.

Environmental criteria include CO_2e emissions, water use, soil degradation risk, fertilizer runoff risk, agrochemical pressure, biodiversity sensitivity, and potential ecological damage. These criteria are necessary because economic efficiency in this monograph is evaluated within the broader framework of sustainable environmental management.

Spatial criteria include land category, parcel location, distance to roads, distance to processing facilities, proximity to restricted zones, terrain slope, road accessibility, and land fragmentation. These criteria are necessary because land and logistics decisions are spatially determined.

Risk-related criteria include operational risk, safety risk, data uncertainty, weather risk, route disruption, machinery failure, and legal-compliance risk. These criteria are necessary because digital systems must function under uncertainty.

Institutional criteria include data availability, cadastral reliability, interoperability, regulatory clarity, auditability, and alignment with policy targets. These criteria are necessary because digital tools operate within institutional systems, not only within farms.

The third stage is data preparation. Since MCDA combines different indicators, data must be prepared in a comparable form. This includes spatial data harmonization, cleaning, coordinate system alignment, temporal aggregation, handling missing data, and classifying criteria as benefit or cost. For example, lower cost is better, so cost is a cost criterion. Higher data quality is better, so data quality is a benefit criterion. Lower emissions are better, so emissions are a cost criterion. Higher service-window feasibility is better, so feasibility is a benefit criterion.

The fourth stage is normalization. Indicators have different units: UAH, hours, kilograms of CO_2e, meters, hectares, percentages, risk points, and index values. They cannot be added directly. Normalization converts them into a comparable scale, usually from 0 to 1. For a benefit criterion, where a larger value is better, normalization can be calculated as, Normalization for Benefit Criteria:

$$x'_{ij} = \frac{x_{ij} - (x_j)}{(x_j) - (x_j)} \backslash hfill (2.10)$$

For a cost criterion, where a smaller value is better, normalization can be calculated as:

$$x'_{ij} = \frac{(x_j) - x_{ij}}{(x_j) - (x_j)} \backslash hfill (2.11)$$

This means that all criteria are transformed so that higher normalized values indicate better performance. This is important for interpretation. If the researcher does not normalize correctly, the final MCDA score may be distorted by indicators with large numerical ranges or different units.

The fifth stage is weighing. Weights reflect the relative importance of criteria. In this monograph, weights may be determined in several ways: expert judgment, stakeholder consultation, policy priorities, empirical sensitivity analysis, or scenario design. For example, in a baseline scenario, cost and time may be equally important. In a stress scenario with high fuel prices, the direct cost may carry greater weight. In a sustainability-adjusted scenario, CO_2e and environmental impact may receive higher weights. This approach is consistent with the routing logic used in the empirical case study of the Kyiv agglomeration, where time, direct cost, CO_2e, and operational risk are treated as tunable weighted criteria.

A basic weighted index for spatial-economic evaluation may be written as:

$$SEI_i = w_c \cdot C'_i + w_t \cdot T'_i + w_e \cdot E'_i + w_r \cdot R'_i + w_s \cdot SP'_i + w_q \cdot Q'_i \backslash hfill (2.12)$$

where:

- SEI_i is the spatial-economic index for alternative (i);
- C'_i is the normalized direct cost;
- T'_i is the normalized time efficiency;
- E'_i is normalized environmental performance;
- R'_i is the normalized operational risk;
- SP'_i is normalized spatial suitability;
- Q'_i is normalized data quality or institutional reliability;
- w_c, w_t, w_e, w_r, w_s, w_q are corresponding weights.

This index can be adapted for each empirical case. In land management, spatial suitability and institutional reliability may receive higher weights. In environmental monitoring, environmental performance and data quality may dominate. In routing, time, direct cost, emissions, and risk may dominate.

It should be noted that MCDA is not used to hide political or managerial choices. On the contrary, it makes them explicit. If the researcher gives a high weight to cost, the model will produce a cost-oriented solution. If the researcher gives a high weight to emissions, the model will produce a sustainability-oriented solution. If the researcher gives a high weight to risk, the model will avoid uncertain or restricted alternatives. Therefore, the transparency of weights is one of the central requirements of MCDA.

In the spatial context, MCDA must also distinguish between hard constraints and soft criteria. Hard constraints are conditions that cannot be violated. For example, protected environmental zones, military restrictions, prohibited land-use areas, legally restricted parcels, or unsafe road segments may be treated as hard masks. An alternative that violates a hard mask must be removed from the feasible set regardless of its economic score. Soft criteria are conditions that influence the score but do not automatically eliminate the alternative. For example, a road with poor surface quality may receive a risk penalty, but it may still be used if no better option exists. A parcel with moderate environmental sensitivity may be less preferred but not completely excluded.

This distinction is important to the monograph's methodology. In many economic models, all criteria are treated as trade-offs. However, in land management and environmental governance, some constraints are non-negotiable. A route cannot cross a prohibited area simply because it is cheaper. A land parcel cannot be assigned to an activity that contradicts legal restrictions simply because it has high commercial value. Therefore, the spatial MCDA model used in this monograph includes both hard masks and soft penalties.

The adjusted MCDA score may be expressed as:

$$S_i^* = H_i \cdot \left(\sum_{j=1}^{m} w_j \cdot x'_{ij} - P_i \right) \backslash hfill(2.13)$$

where:

- S^*_i is the adjusted score;
- H_i is the hard-mask feasibility variable, where ($H_i = 1$) if the alternative is allowed and $H_i = 0$ if the alternative is prohibited;
- w_j is the weight of criterion j;
- x'_{ij} is the normalized value of alternative i according to criterion j;
- m is the total number of evaluation criteria;
- P_i is the soft penalty value.

If ($H_i = 0$), the alternative is excluded from the solution. If ($H_i = 1$), the alternative remains in the analysis but may be penalized for risk, lower reliability, lower data quality, or higher environmental sensitivity.

Table 2.6 General MCDA structure for spatial-economic evaluation

MCDA element	Meaning in spatial economics	Example in land management	Example in monitoring	Example in routing	Methodological role
Alternatives	Objects or scenarios being compared	Land parcels, land-use options	Field zones, intervention options	Routes, route segments, fleet plans	Defines what is being ranked
Criteria	Dimensions of evaluation	Land value, restrictions, access, and ecological sensitivity	NDVI anomaly, soil moisture, intervention cost	Time, direct cost, CO_2e, risk	Defines what matters in the decision
Data layers	Spatial and economic evidence	Cadastre, zoning, soil, road access	EO, IoT, UAV, weather	OSM, fuel prices, restrictions, vehicle data	Provides measurable values
Normalization	Conversion to a comparable scale	Parcel score 0–1	Field-zone urgency score 0–1	Route score 0–1	Makes indicators comparable
Weights	Importance of each criterion	Higher weight for legal restrictions or land suitability	Higher weight for crop stress or input cost	Tuned weights for time/cost/CO_2e/risk	Reflects decision priorities
Hard constraints	Non-negotiable restrictions	Protected zones, legal prohibitions	No access, failed data quality threshold	Closed roads, restricted areas	Removes infeasible options
Soft penalties	Negative but not prohibitive factors	Poor road access, fragmentation	Cloud cover, lower sensor reliability	Congestion, road quality, safety risk	Reduces score but does not exclude

MCDA element	Meaning in spatial economics	Example in land management	Example in monitoring	Example in routing	Methodological role
Final score	Integrated weighted result	Parcel suitability index	Intervention priority index	Generalized route cost or utility	Supports ranking and selection
Sensitivity analysis	Weight and parameter testing	Different policy priorities	Different urgency assumptions	Different fuel or risk conditions	Tests robustness

Source: prepared by the authors.

For land management, hard masks may include protected natural areas, water protection zones, legally restricted territories, contaminated land, mine-risk zones, military restrictions, or parcels with unresolved legal status. Soft penalties may include poor road access, high fragmentation, lower soil suitability, long distance to processing facilities, or high environmental sensitivity.

For IoT and environmental monitoring, hard constraints may include a lack of legal access to a field, insufficient data quality, or sensor failure beyond acceptable limits. Soft penalties may include lower update frequency, higher uncertainty, partial cloud cover in satellite imagery, or lower spatial resolution.

For routing, hard masks may include prohibited roads, closed bridges, restricted land parcels, military exclusion zones, or protected ecological zones. Soft penalties may include congestion, road quality, safety risk, weather-related delays, or higher fuel consumption.

The sixth stage is calculation and ranking. After normalization, weighting, and constraint processing, the alternatives are ranked by their integrated scores. However, ranking should not be interpreted mechanically. The researcher must examine whether the ranking is stable, whether it depends on a single criterion, and whether the ranking is sensitive to changes in the weights. In applied research, the first-ranked alternative is not always automatically selected. Sometimes the second or third alternative may be preferable because it is more robust, easier to implement, or institutionally acceptable.

The seventh stage is sensitivity analysis. Since weights influence results, the model must test whether conclusions change when weights are modified. For example, if a land parcel is ranked first only when environmental weight is very low, it may not be a stable choice for sustainable land management. If a route is efficient only at low fuel prices, it may be risky during periods of market volatility. If a monitoring system is efficient only when data quality is assumed to be high, the model must test what happens when sensor data are incomplete. Sensitivity analysis prevents the model from becoming a formal justification for a predetermined decision.

The eighth stage is interpretation and policy translation. The final MCDA results must be interpreted to support practical decisions. For farms, this may mean selecting technology or prioritizing interventions. For local authorities, it may mean identifying land-use conflicts or selecting areas for monitoring. For policymakers, it may mean designing incentives based on auditable sustainability metrics. For researchers, it may mean comparing scenarios and showing how economic, ecological, and operational priorities interact.

In the context of this monograph, MCDA has four main applications. The first application is land suitability and land-use prioritization. In this case, the alternatives are parcels or land-use zones. The criteria may include land value, soil quality, current land category, environmental restrictions, road access, distance to markets, availability of infrastructure, and ecological sensitivity. The purpose is to identify which areas are most suitable for agricultural use, conservation, infrastructure, or mixed development. Spatial MCDA is particularly relevant here because it can combine cadastral and environmental data into a single decision-support layer.

The second application is the prioritization of precision interventions. In this case, the alternatives are field zones or management units. The criteria may include NDVI anomaly, soil moisture deficit, expected yield loss, distance to machinery, intervention cost, water availability, and environmental sensitivity. The purpose is to determine which intervention should be performed first when resources are limited. This is important because digital monitoring often generates more alerts than a farm can address immediately. MCDA helps prioritize them.

The third application is technology selection. In this case, the alternatives are different digital tools or platform configurations. For example, a farm may compare satellite-only, IoT-only, UAV-assisted, or integrated monitoring. Criteria may include implementation cost, operating cost, spatial resolution, temporal resolution, data reliability, user complexity, interoperability, and expected economic benefit. This application is important for investment decisions.

The fourth application is routing and operational planning. In this case, alternatives are route segments, routes, daily schedules, or weekly plans. Criteria may include travel time, direct cost, CO_2e emissions, operational risk, road accessibility, service-window feasibility, and compliance with spatial restrictions. This application is central for the fifth section of the monograph, where spatio-temporal routing is treated as a decision-support problem rather than a simple transport problem.

In the routing application, the MCDA score may be calculated for each route segment (e):

$$U(e) = w_t \cdot f_t(e) + w_c \cdot f_c(e) + w_{co2} \cdot f_{co2}(e) + w_r \cdot f_r(e) \backslash hfill(2.14)$$

where:

- U(e) is the utility score of the edge or route segment e;
- f_t(e) is normalized time performance;
- f_c(e) is normalized cost performance;
- f_{co2}(e) is normalized emission performance;
- f_r(e) is normalized risk performance;
- w_t, w_c, w_{co2}, w_r are the corresponding weights for each criterion.

In a cost-minimization version, the model can be transformed into a generalized route cost:

$$GC(e) = w_t \cdot T(e) + w_c \cdot C(e) + w_{co2} \cdot E(e) + w_r \cdot R(e) \backslash hfill(2.15)$$

where T(e) is travelling time, C(e) is direct cost, E(e) is emissions, and R(e) is risk. The route with the lowest generalized cost is then selected, subject to hard spatial constraints and service-window requirements.

This routing logic is especially useful for peri-urban agriculture. In the Kyiv agglomeration, agricultural operations face land-use pressure, variable logistics costs, road accessibility issues, and safety-related restrictions. Under such conditions, the economically best route is not necessarily the shortest route. It may be the route that best balances cost, time, emissions, and risk while preserving service-window feasibility. This is why MCDA is an appropriate methodological bridge between spatial data and economic decision-making.

An important methodological issue is how to treat data quality. Digital systems may produce highly detailed data, but not all data is equally reliable. Satellite imagery may be affected by clouds. UAV data may be unavailable because of restrictions. IoT sensors may fail or transmit incorrect values. Cadastral data may be incomplete or outdated. Therefore, data quality should be included either as a separate criterion or as a penalty. This is especially important in Ukraine, where wartime conditions may restrict access to some types of spatial and cadastral information.

Table 2.7 Recommended MCDA criteria for the monograph's empirical cases

Criteria group	Criterion	Unit/scale	Benefit or cost criterion	Relevant case study	Possible data source
Economic	Direct cost	UAH, USD, UAH/km, UAH/ha	Cost	All cases	Accounting data, fuel prices, investment budgets
Economic	Expected financial benefit	UAH / period	Benefit	All cases	CBA outputs, yield/input data
Economic	Cost per hectare	UAH/ha	Cost	Monitoring, land management	Farm accounting, GIS area
Economic	Cost per route	UAH/route	Cost	Routing	Fleet logs, route engine
Temporal	Travel time	minutes/hours	Cost	Routing	OSM, GraphHopper, GPS logs
Temporal	Time to decision	hours/days	Cost	Monitoring, land management	Workflow logs
Temporal	Service-window feasibility	% jobs on time	Benefit	Routing, monitoring	Agronomic calendar, task logs
Environmental	CO_2e emissions	kg CO_2e / route/ha	Cost	Routing, monitoring	Fuel use, emission factors
Environmental	Soil degradation risk	index 0–1	Cost	Land management, monitoring	Soil maps, erosion models
Environmental	Water stress	index 0–1	Cost	Monitoring	IoT, Sentinel, ERA5/NASA POWER
Environmental	Green-cover sensitivity	index 0–1	Cost	Land management	Land cover, EO, cadastral layers

Criteria group	Criterion	Unit/scale	Benefit or cost criterion	Relevant case study	Possible data source
Spatial	Distance to infrastructure	km	Cost	Land management, routing	GIS / OSM
Spatial	Road accessibility	index 0–1	Benefit	Land management, routing	OSM, local road data
Spatial	Parcel fragmentation	index 0–1	Cost	Land management	Parcel geometry
Spatial	Restriction proximity	m / index	Cost	Land management, routing	Protected zones, safety restrictions
Risk	Operational risk	index 0–1	Cost	Routing, monitoring	Safety notices, field records
Risk	Data uncertainty	index 0–1	Cost	All cases	Metadata, cloud cover, sensor reliability
Institutional	Data reliability	index 0–1	Benefit	All cases	Source authority, update frequency
Institutional	Interoperability	index 0–1	Benefit	All cases	OGC/FAIR compliance
Institutional	Legal feasibility	binary / index	Benefit or hard constraint	Land management, routing	Cadastre, legal documents, restrictions
Institutional	Auditability	index 0–1	Benefit	All cases	Metadata, provenance, exported reports

Source: prepared by the authors.

The data-quality criterion may include completeness, updating frequency, spatial resolution, temporal resolution, source reliability, and legal usability. A high-resolution dataset that cannot be legally used in decision-making may have lower institutional value than a lower resolution but authoritative dataset. Similarly, a real-time sensor stream with frequent errors may be less useful than a stable satellite-based indicator. Therefore, MCDA should not treat all digital data as equal.

The institutional feasibility criterion is also important. Some alternatives may be technically attractive but difficult to implement because of legal, administrative, or organizational barriers. For example, a routing system may require access to road restriction data that is not publicly available. A land management tool may require interoperability with public registers. A monitoring system may require coordination between farms, local authorities, and environmental agencies. If such conditions are not met, the expected economic efficiency may not be realized.

For this reason, the MCDA framework of the monograph includes institutional feasibility as an optional but recommended criterion:

$$S_i = w_c C'_i + w_t T'_i + w_e E'_i + w_r R'_i + w_q Q'_i + w_{inst} I'_i \backslash hfill(2.16)$$

where (I'$_i$) represents normalized institutional feasibility. This criterion may include legal clarity, data access, stakeholder acceptance, interoperability, and administrative readiness.

In applied form, MCDA should follow a clear procedure:

1. Define the decision problem.
2. Define alternatives.
3. Define criteria.
4. Separate hard constraints from soft criteria.
5. Collect and prepare data.
6. Normalize criteria.
7. Assign weights.
8. Calculate scores.
9. Rank alternatives.
10. Conduct sensitivity analysis.
11. Interpret results.
12. Prepare decision recommendations.

This procedure is simple enough for practical application but sufficiently formal for scientific analysis. It allows the researcher to explain how a decision was made and why one alternative is preferred over another.

It should be emphasized that MCDA does not replace economic analysis. It complements it. CBA answers whether the total benefits of a digital tool exceed the total costs. MCDA answers which alternative is preferable when several criteria must be considered simultaneously. In this monograph, CBA and MCDA are therefore used together. CBA provides a financial and economic foundation. MCDA provides the spatial and decision-structuring mechanism. Together, they allow digital tools to be evaluated not only as investments but as elements of complex land-use and environmental management systems.

For example, when evaluating a digital monitoring system, a CBA may show whether it creates a positive net benefit over five years. MCDA may then help choose which fields should receive sensors first, which crop zones require priority intervention, and which data sources should be integrated. Similarly, when evaluating a routing system, CBA may calculate total savings from reduced fuel and protected service windows. At the same time, MCDA determines which route or schedule is best under cost, time, emissions, and risk criteria.

The methodological value of MCDA is particularly strong in conditions of uncertainty and competing priorities. Agriculture in peri-urban zones is exposed to pressure from urban expansion, land-use changes, climate variability, market instability, and infrastructure constraints. In such conditions, decision-makers rarely choose between “good” and “bad” options. More often, they choose between alternatives that each has advantages and disadvantages. MCDA provides a transparent way to represent these trade-offs.

In this monograph, the most important result of MCDA is not only the final ranking but also its explanation. The method shows what criteria dominate the decision, how sensitive the result is, and where the main conflict between economic and environmental objectives appears. This is especially important for sustainable environmental management because many conflicts are hidden in aggregated financial indicators. A project may be financially attractive but environmentally damaging. Another project may be environmentally beneficial, but too expensive. A third project may be balanced and therefore more suitable for sustainable policy.

Thus, MCDA in spatial economics serves as the second core methodological component of the monograph. It transforms heterogeneous spatial, economic, environmental, and operational data into a structured decision model. It enables the comparison of land parcels, digital tools, monitoring priorities, and routing alternatives. It also creates the methodological basis for later subsections on shadow pricing and scenario simulation. In combination with an adapted CBA, MCDA enables evaluation of digital tools not only by their cost but also by their role in achieving economically efficient, environmentally responsible, and institutionally feasible decisions.

Table 2.8 MCDA application by empirical case study

Case study	Alternatives	Main criteria	Hard constraints	Soft penalties	Output index
Digital land management	Land parcels, land-use options, planning zones	Land value, legal feasibility, environmental sensitivity, road access, parcel size, transaction cost, data reliability	Protected zones, legally incompatible use, and unavailable ownership status	Poor access, fragmentation, low data quality, and environmental sensitivity	Land-use suitability index
IoT telemetry and environmental monitoring	Field zones, monitoring configurations, intervention priorities	Crop stress, soil moisture, expected yield loss, intervention cost, water availability, data reliability	No access, critical data failure, legal prohibition	Cloud cover, sensor uncertainty, and lower spatial resolution	Intervention priority index
Spatio-temporal routing	Route segments, route alternatives, fleet schedules	Travel time, direct cost, CO_2e, operational risk, service-window feasibility	Closed roads, restricted zones, prohibited parcels	Congestion, road quality, weather delay, safety risk	Generalized route cost/route utility index

Source: prepared by the authors.

2.3. Shadow Pricing of Environmental, Temporal, and Risk-Reduction Effects

The previous subsections developed two methodological foundations for the economic evaluation of digital environmental tools. Subsection 2.1 adapted cost-benefit analysis to the specific nature of digital agritech by expanding the calculation beyond direct costs and direct financial savings. Subsection 2.2 introduced multi-criteria decision analysis as a means of comparing alternatives when economic, spatial, environmental, temporal, risk-related, and institutional indicators must be considered together. The present subsection develops the third methodological component of the monograph: shadow pricing of environmental and temporal variables.

Shadow pricing is necessary because many of the most important effects of digital environmental management lack direct market prices. Soil degradation, carbon emissions, water stress, loss of green cover, biodiversity loss, delayed agronomic operations, and reduced resilience of production systems are rarely fully reflected in standard accounting. However, their consequences are economically real. They influence production costs, land value, public expenditure, environmental recovery costs, crop losses, health-related costs, compliance risks, and long-term territorial development. Therefore, if these effects are excluded from the economic model, the evaluation of digital tools becomes incomplete.

In this monograph, shadow pricing is used as a bridge between environmental indicators and monetary evaluation. Its role is to translate prevented ecological damage, reduced emissions, saved water, avoided soil loss, and protected time-sensitive agricultural operations into economic values that can be included in extended CBA, MCDA, and scenario modeling. This approach is consistent with the broader literature on externalities in agriculture and environmental economics, which holds that non-market effects must be included in decision-making if sustainability is to be evaluated realistically (Macháč et al., 2021; Moore et al., 2017; Sartori et al., 2024). It also aligns with the practical logic of digital agriculture research, where digital tools are evaluated not only for productivity or cost reduction but also for environmental and operational benefits (Bahmutsky et al., 2024; Papadopoulos et al., 2024).

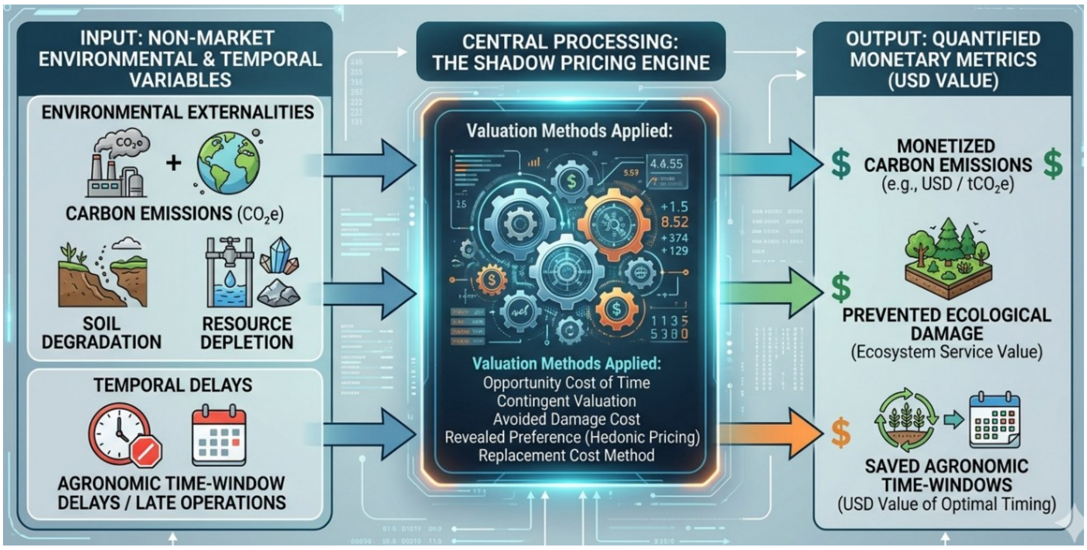


Figure 2.7 Visualization of the shadow pricing mechanism for environmental and temporal externalities

The central methodological premise of this subsection is that digital tools create economic value by enabling damage prevention, loss reduction, better timing, or the avoidance of future costs. This means that a monitoring system, a routing system, or a digital land-management system can be economically justified even when part of its benefit is not expressed as direct revenue. For example, a satellite-based crop-monitoring system may reduce the likelihood of delayed intervention. An IoT soil moisture system may help prevent excessive water use. A routing platform may reduce fuel consumption and CO_2e emissions. A cadastral GIS may prevent an agricultural operation from entering a protected or restricted zone. Each of these effects has a monetary dimension, even if it is not directly reflected in market prices now of decision.

The purpose of shadow pricing in this monograph is therefore not to replace market valuation. Its purpose is to supplement market prices when they are absent, incomplete, distorted, or delayed. In digital environmental management, this is especially important because some benefits become visible only when a negative event does not occur: a loss is avoided, a fine is prevented, a field operation is completed on time, a degraded soil area does not expand, or a restricted ecological zone is not violated. Shadow pricing allows such foregone effects to be incorporated into the economic-efficiency model.

Table 2.9 Role of shadow pricing in the methodological framework of the monograph

Methodological element	Main question answered	Role of shadow pricing	Example in the monograph	Output
Extended CBA	Do benefits exceed costs?	Converts environmental and temporal benefits into monetary values	Reduced CO_2e from optimized routing; avoided soil degradation from precision intervention	Expanded NPV and EBCR
MCDA	Which alternative is preferable under several criteria?	Converts non-market criteria into comparable economic or semi-economic scores	Land parcels ranked by environmental sensitivity and restoration cost	Weighted spatial-economic score
Environmental monitoring	What is the economic value of detected and prevented ecological risk?	Assigns value to avoid ecological damage	Early detection of water stress or crop stress	Avoided damage value
Spatio-temporal routing	What is the economic value of lower emissions and saved service windows?	Monetizes CO_2ereduction and avoids delay	Route avoids longer fuel-intensive paths and preserves agronomic timing	Route-level shadow benefit
Land management	What is the economic value of avoiding restricted or ecologically sensitive land-use conflicts?	Values avoided legal/ecological conflict and restoration cost	Hard masks prevent the use of protected zones	Avoided conflict / avoided fine / avoided restoration cost
Policy and scaling	How can digital metrics support public incentives and sustainability reporting?	Converts sustainability indicators into auditable economic metrics	Eco-subsidies, tax incentives, and compliance reporting	Policy-ready sustainability value

Source: *prepared by the authors.*

In classical economic theory, market prices are used to allocate resources and compare alternatives. However, environmental management often addresses goods and losses that are not fully reflected in market prices. The productive value of fertile soil, the regulating value of green cover, the social cost of carbon emissions, the value of clean water, the cost of ecosystem degradation, and the cost of missed agronomic timing may not appear in a market transaction, but they influence the long-term economic result. This is why environmental economics uses shadow prices: estimates of the economic value of non-market goods.

For this monograph, a shadow price is defined as an estimated monetary value assigned to an environmental, temporal, risk-related, or institutional variable that lacks a direct or complete market price but has measurable economic consequences for agricultural production, land management, territorial governance, or ecological sustainability.

The general logic of shadow pricing may be expressed as:

$$SV_i = \Delta Q_i \times SP_i \backslash hfill(2.17)$$

where:

- SV_i is the shadow value of variable i;
- ΔQ_i is the physical change in variable i;
- SP_i is the shadow price per unit of variable i.

For example, if a routing system reduces CO_2e emissions by a measurable amount, the shadow value of this reduction is calculated by multiplying the avoided emissions by the selected social or policy-relevant carbon price. If an IoT monitoring system prevents crop loss by protecting the optimal irrigation window, the shadow value is calculated as the avoided loss from delayed action. If a digital land-management system prevents use of an ecologically sensitive area, the shadow value can be calculated as the avoided restoration costs, avoided penalties, or avoided ecosystem-service losses.

The shadow-pricing method is particularly relevant for digital tools, which often operate before damage occurs. A sensor identifies a deficit before it becomes a loss. A satellite index detects a stress pattern before it becomes visible at the whole-field scale. A routing system avoids a restricted or high-risk route before a violation occurs. A cadastral system identifies land-use constraints before an investment decision is made. Therefore, the value of the tool lies in prevention, and prevention requires a valuation method.

This monograph uses three main groups of shadow pricing:

1. Environmental shadow pricing - assigning monetary value to avoided CO_2e emissions, soil degradation, water stress, runoff, green-cover loss, biodiversity pressure, and ecosystem damage.
2. Temporal shadow pricing - assigning monetary value to saved agronomic time-windows, reduced delay, faster detection, faster intervention, and improved logistics timing.
3. Risk-adjusted shadow pricing - assigning monetary value to reduced probability of ecological, legal, operational, or compliance-related losses.

The combined shadow value of a digital environmental tool may be expressed as:

$$SV_{total,t} = SV_{env,t} + SV_{time,t} + SV_{risk,t} + SV_{inst,t} \backslash hfill(2.18)$$

where:

- $SV_{total,t}$ is the total shadow value in period t;
- $SV_{env,t}$ is the environmental shadow value;
- $SV_{time,t}$ is the temporal shadow value;
- $SV_{risk,t}$ is the risk-reduction shadow value;
- $SV_{inst,t}$ is the institutional or compliance-related shadow value.

The discounted total shadow value over the evaluation period is:

$$PV(SV_{total}) = \sum_{t=0}^{T} \frac{SV_{total,t}}{(1+r)^t} \backslash hfill(2.19)$$

where:

- $PV(SV_{total})$ is the present value of all shadow-priced benefits;
- r is the discount rate;
- T is the evaluation horizon.

This present value can then be included in the extended cost-benefit model developed in subsection 2.1.

Table 2.10 Main environmental and temporal variables requiring shadow pricing

Variable	Why is the market price incomplete	Recommended shadow-pricing method	Possible digital data source	Monograph application
CO_2eemissions	Fuel price does not include the full climate damage	Social cost of carbon; carbon market price; policy carbon price	Fuel logs, route data, emission factors, machinery data	Routing and fleet optimization
Soil degradation	Soil loss is often not immediately priced	Restoration cost, productivity-loss cost, erosion-damage cost	Soil maps, EO, field surveys, land-use data	Land management and monitoring
Water stress	Water cost may not reflect scarcity or ecological cost	Scarcity price; avoided irrigation cost; replacement cost	IoT soil moisture, weather data, and irrigation logs	Precision irrigation and monitoring
Nutrient runoff	Fertilizer price does not include water-quality damage	Avoided treatment cost; damage cost; regulatory cost	Fertilizer records, runoff proxies, slope/soil data	Precision fertilization
Agrochemical pressure	Chemical cost does not include ecosystem and health externalities	Avoided damage cost; compliance cost	Spraying logs, EO anomaly zones, and field records	Precision crop protection
Green-cover loss	Land conversion does not fully price ecosystem services	Restoration cost; ecosystem-service value; avoided heat/flood cost	Land cover, satellite imagery, and cadastral data	Land-use planning
Biodiversity pressure	Biodiversity loss often has no direct market price	Habitat restoration cost, replacement cost, and avoided damage	Protected zones, land cover, and ecological sensitivity layers	Spatial constraints and land allocation

Variable	Why is the market price incomplete	Recommended shadow-pricing method	Possible digital data source	Monograph application
Delayed irrigation	Delay cost appears later as yield loss	Yield-loss function; avoided loss	IoT sensors, weather data, irrigation logs	Agronomic time-window valuation
Delayed spraying	Delay cost appears as disease/pest damage	Yield-loss function; additional treatment cost	NDVI/EVI, scouting logs, spraying logs	Intervention prioritization
Route delay	Time loss is not fully captured by fuel cost	Service-window penalty; labor/machinery opportunity cost	Routing engine, GPS, task logs	Spatio-temporal routing
Legal/ecological violation	Risk may not appear until a violation occurs	Expected avoided fine; restoration cost; conflict cost	Cadastral layers, hard masks, restriction zones	Digital land management and routing

Source: prepared by the authors.

Carbon emissions are among the clearest examples of environmental externalities. Fuel consumption has a direct market price, but this price does not fully reflect the social and environmental costs of greenhouse gas emissions. In agricultural logistics, emissions are generated by tractors, trucks, irrigation pumps, machinery operations, transport routes, and sometimes by energy use in monitoring systems or processing facilities. Digital tools can influence emissions by reducing unnecessary travel, improving route planning, minimizing repeated field visits, optimizing machinery use, and supporting more precise interventions.

For the routing case study, the central variable is CO_2e emissions per route, per fleet operation, or per weekly operational plan. The basic carbon shadow value can be calculated as:

$$B_{CO_2,t} = \left(CO_2e_{0,t} - CO_2e_{1,t}\right) \times SCP_t \backslash hfill(2.20)$$

, where:

- $B_{CO2,t}$ is the shadow value of carbon emission reduction in period t;
- $CO_{2e0,t}$ is the total emissions generated under the baseline scenario;
- $CO_{2e1,t}$ is the total emissions generated under the digital or optimized scenario;
- SCP_t is the selected shadow carbon price in period t.

The value of SCP_t may be selected from several possible sources: social cost of carbon estimates, national or regional carbon-pricing instruments, EU-related policy assumptions, or internally adopted sustainability prices. Moore et al. (2017) emphasize that climate impacts on agriculture may imply a higher social cost of carbon when agricultural damage is included. This is especially important for agricultural systems because climate damage is not external to the sector; it returns to agriculture through lower productivity, drought risk, soil degradation, water stress, and increased volatility.

For transport and field operations, CO_2e emissions may be calculated through fuel consumption:

$$CO_2e_t = \sum_{v=1}^{V} \left(Fuel_{v,t} \times EF_v\right) \backslash hfill(2.21)$$

where:

- $CO2_{et}$ - total emissions in period t;
- $Fuel_{v,t}$ - fuel consumed by vehicle or machinery class v;
- EF_v - emission factor for fuel or machinery class v;
- V - number of vehicle or machinery classes.

For route-level analysis:

$$CO_2e_{route} = \sum_{e=1}^{m} \left(Dist_e \times FC_{v,e} \times EF_v\right) \backslash hfill(2.22)$$

where:

- $CO2_{eroute}$ - total emissions for route;

- $Dist_e$ - distance of route edge e;
- $FC_{v,e}$ - fuel consumption per distance unit for vehicle v on edge e;
- EF_v - emission factor;
- m - number of route edges.

In a simplified applied model, where detailed fuel consumption by road class is unavailable, emissions can be approximate as:

$$CO_2e_{route} = Distance_{route} \times EF_{km,v} \backslash hfill(2.23)$$

where:

- $EF_{km,v}$ - average CO_2e emission factor per kilometer for vehicle class v.

The choice of formula depends on data availability. A high-detail routing model should use vehicle class, load, terrain, road quality, and speed. A simpler model may use average emissions per kilometer. In both cases, the shadow value is the difference between baseline and digital scenarios multiplied by the carbon shadow price.

The important methodological point is that carbon shadow pricing should not be isolated from direct cost analysis. Fuel savings and carbon savings are related but not identical. A route can be cheaper because it is shorter, but it may not always be lower in emissions if road quality, speed, congestion, or vehicle load increase fuel intensity. Conversely, a slightly longer route may produce fewer emissions if it avoids stop-and-go movement, poor road conditions, or high-risk detours. For this reason, carbon shadow pricing should be linked to the MCDA structure developed in subsection 2.2, in which CO_2e is one of the weighted criteria.

Table 2.11 Carbon emission shadow pricing in routing and agricultural operations

Evaluation object	Baseline variable	Digital scenario variable	Shadow price	Equation	Output
Route plan	Baseline CO_2e per route	Optimized CO_2e per route	Social cost of carbon or policy carbon price	B_CO2 = (CO2e_0 - CO2e_1) × SCP	UAH / route
Weekly fleet plan	Baseline weekly emissions	Optimized weekly emissions	Carbon price per tCO_2e	B_CO2_week = (CO2e_0,week - CO2e_1,week) × SCP	UAH / week
Machinery operation	Baseline fuel use	Fuel use after optimization	Carbon price and fuel emission factor	CO2e = Fuel × EF	kg or tCO_2e
Irrigation pumping	Energy use before the tool	Energy use after telemetry-based irrigation	Energy emission factor and carbon price	B_CO2 = (Energy_0 - Energy_1) × EF_energy× SCP	UAH / season
Field inspection	Manual inspection travel	Digital monitoring with fewer trips	Vehicle emission factor and carbon price	B_CO2 = (km_0 - km_1) × EF_km × SCP	UAH / monitoring cycle

Source: *prepared by the author.*

Soil is one of the most important productive assets in agriculture. However, soil degradation is often not fully reflected in market transactions. A farm may use land today in ways that decrease soil fertility, increase erosion, reduce water retention, or lower future productivity, while the economic consequences become visible only later. In land management and peri-urban agricultural systems, soil degradation is also connected with land conversion, road construction, compaction, industrial pressure, construction activity, and fragmented land use.

For this monograph, soil degradation is treated as both an environmental and economic variable. Digital tools can reduce soil-related losses by improving land-use planning, detecting vegetation stress, preventing unnecessary field traffic, optimizing machinery movement, identifying erosion-prone areas, and integrating soil and terrain indicators into decision-support systems. Shadow pricing enables the calculation of the monetary value of avoided soil degradation.

The basic formula for the avoided soil degradation value is:

$$B_{soil,t} = \left(SD_{0,t} - SD_{1,t}\right) \times A \times SP_{soil,t} \backslash hfill(2.24)$$

where:

- $B_{soil,t}$ - shadow value of avoided soil degradation in period t;
- $SD_{0,t}$ - soil degradation indicator in the baseline scenario;
- $SD_{1,t}$ - soil degradation indicator in the digital scenario;
- A - affected area;
- $SP_{soil,t}$ - shadow price per unit of soil degradation.

The soil degradation indicator may be expressed in several ways: tons of soil loss per hectare, productivity-loss index, erosion-risk score, compaction-risk score, or restoration need per hectare. The most suitable indicator depends on the available data and the empirical case. For land management, a spatial erosion-risk or degradation-risk index may be appropriate. For monitoring, a vegetation-stress or soil-moisture-deficit indicator may serve as an early proxy. For routing, repeated machinery traffic and field access patterns may be used to estimate compaction risk.

The restoration-cost approach can be written as:

$$SP_{soil} = C_{restore} + C_{yield\_loss} + C_{ecosystem} \backslash hfill(2.25)$$

where:

- SP_{soil} - shadow price per unit of soil degradation;
- $C_{restore}$ - cost of soil restoration;
- C_{yield_loss} - expected productivity loss;
- $C_{ecosystem}$ - value of related ecosystem-service loss.

The total avoided soil damage over the evaluation horizon is:

$$PV(B_{soil}) = \sum_{t=0}^{T} \frac{B_{soil,t}}{(1+r)^t} \backslash hfill(2.26)$$

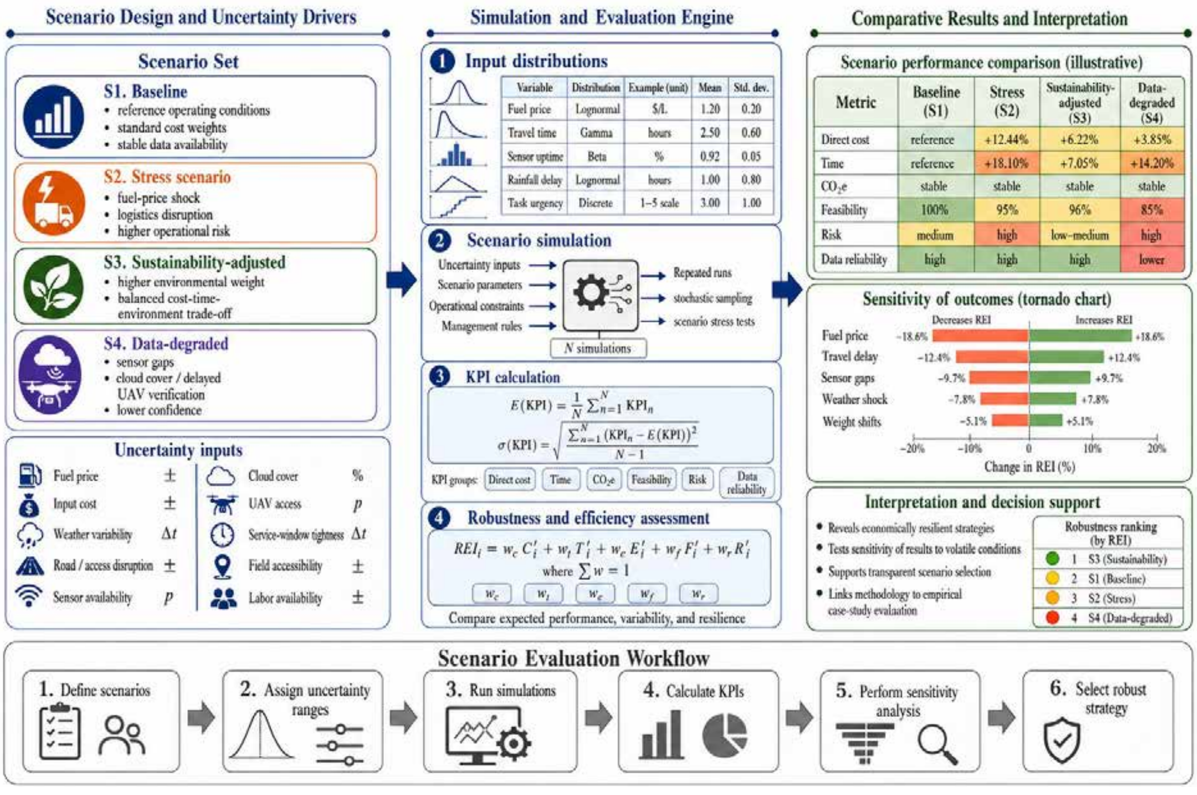


Figure 2.8 Scenario-based economic-efficiency evaluation under uncertainty

Sartori et al. (2024) show that soil erosion affects food security and agricultural production, while Macháč et al. (2021) emphasize the need to account for externalities in agricultural decision-making. In the logic of this monograph, soil degradation should therefore not be treated as a qualitative background issue. It must be included as a measurable economic factor, especially when digital tools are used to avoid or mitigate degradation.

Table 2.12 Shadow pricing methods for soil and land-use damage

Damage type	Physical indicator	Recommended shadow-pricing method	Required data	Digital tool contribution	Output
Soil erosion	t/ha/year or erosion-risk index	Restoration cost + productivity-loss cost	Soil maps, slope, land cover, and field records	Identifies risk zones and prevents unsuitable operations	UAH/ha/year
Soil compaction	Compaction-risk index or affected area	Yield-loss cost + remediation cost	Machinery routes, soil moisture, and field traffic	Optimizes movement and reduces repeated passes	UAH/field operation
Loss of soil fertility	Nutrient decline/productivity index	Replacement cost of nutrients + yield loss	Soil tests, fertilizer records, yield maps	Supports targeted fertilizer and soil management	UAH/ha/season
Land-use conflict	Incompatible use of the land parcel	Avoided fine + avoided restoration + transaction cost	Cadastre, zoning, restrictions	Prevents illegal or unsuitable land use	UAH/case
Green-cover degradation	Ha of green cover affected	Restoration cost + ecosystem-service value	EO land cover, municipal data	Detects loss and supports spatial planning	UAH/ha
Contamination risk	Pollution-risk index or contaminated area	Remediation cost + productivity loss	Field data, industrial proximity, soil tests	Avoids or flags risky areas	UAH/site

Source: *prepared by the authors.*

Water stress is a key environmental and production variable in agricultural systems. Its economic value is not limited to the direct price of water. In many cases, the direct tariff does not reflect scarcity, energy used for pumping, future depletion, ecological pressure, or crop losses caused by untimely irrigation. Digital tools such as IoT soil moisture sensors, weather stations, satellite-based vegetation indices, and decision-support systems can reduce water-related losses by improving irrigation timing and amount.

The shadow value of water savings may be calculated as:

$$B_{water,t} = (W_{0,t} - W_{1,t}) \times (P_{water,t} + P_{energy,t} + SP_{scarcity,t})$$

where:

- $B_{water,t}$ - shadow value of water savings in period t;
- $W_{0,t}$ - water use in the baseline scenario;
- $W_{1,t}$ - water use in the digital scenario;
- $P_{water,t}$ - direct price of water;
- $P_{energy,t}$ - energy cost associated with water delivery or pumping;
- $SP_{scarcity,t}$ - scarcity-related shadow price.

If the main effect is not water savings but prevention of crop stress, the valuation should use avoided yield loss:

$$B_{water\_stress,t} = (YL_{0,t} - YL_{1,t}) \times A \times P_{crop,t}$$

where:

- $YL_{0,t}$ - yield loss due to water stress in the baseline scenario;
- $YL_{1,t}$ - yield loss due to water stress under digital monitoring;
- A - affected area;
- $P_{crop,t}$ - crop price.

In a more complete model, both effects should be included, but double counting must be avoided. If the same intervention results in both water savings and yield protection, the researcher must clearly define whether the benefit is cost savings, avoided loss, or both. For example, reduced over-irrigation can produce water and energy savings without yield reduction. Early irrigation during stress can protect yield but may not reduce total water use. These are different benefit mechanisms.

Digital monitoring systems are especially valuable when they help distinguish between these situations. Soil moisture telemetry can indicate when irrigation is needed. Satellite vegetation indices can show where stress has already appeared. Weather data can indicate future water demand. Together, these data sources enable evaluation not only of how much water was saved, but also of whether it was used at the right time.

Table 2.13 Shadow pricing of water, irrigation, and resource-use variables

Variable	Baseline problem	Digital tool effect	Shadow pricing method	Equation	Output
Water overuse	Fixed irrigation schedule	Soil-moisture-triggered irrigation	Avoid water + energy + scarcity cost	B_water = (W_0 - W_1) × (P_water + P_energy + SP_scarcity)	UAH/season
Water stress	Irrigation too late	Early warning and timely irrigation	Avoided yield loss	B_stress = (YL_0 - YL_1) × A × P_crop	UAH/field
Pumping energy	Unoptimized pumping	Lower pumping volume / better timing	Energy cost + carbon cost	B_energy= (E_0 - E_1) × P_energy	UAH/season
Runoff risk	Excessive irrigation/fertilizer movement	Targeted intervention	Avoided treatment or damage cost	B_runoff = (R_0 - R_1) × SP_runoff	UAH/ha
Drought-response delay	Late reaction to weather stress	Faster detection and field prioritization	Time-window loss avoided	B_delay = L_delay,0 - L_delay,1	UAH/event

Source: *prepared by the author.*

One of the most important, yet often underestimated, benefits of digital agritech is the protection of agronomic time windows. Agricultural production is not only spatially distributed but also temporally constrained. Irrigation, fertilization, spraying, harvesting, soil treatment, and machinery movement must be carried out within certain windows. If the operation is delayed, the cost may appear as yield loss, higher input use, additional machinery cost, lower product quality, or missed market opportunity.

In standard financial accounting, time is often measured as labor cost or machinery time. However, in agriculture, time also has biological and ecological meaning. A one-day delay during a critical crop stage may have a much larger economic effect than a one-day delay during a low-risk period. Therefore, the shadow price of time must be connected to the agronomic context.

The basic value of saved agronomic time may be expressed as:

$$B_{time,t} = \sum_{i=1}^{n} \left[\left(D_{0,i,t} - D_{1,i,t} \right) \times LR_{i,t} \times A_i \right] \backslash hfill(2.29)$$

, where:

- $B_{time,t}$ - shadow value of saved agronomic time in period t;
- $D_{0,i,t}$ - delay duration for operation or field i in the baseline scenario;
- $D_{1,i,t}$ - delay duration for operation or field i in the digital scenario;
- $LR_{i,t}$ - loss rate per hectare per unit of delay;
- A_i - area affected;
- n - number of operations or field units.

If delay losses are nonlinear, a penalty function should be used:

$$L_{delay,i} = A_i \times Y_i \times P_{crop} \times \theta_i \times (0, D_i - W_i) \ \backslash hfill(2.30)$$

, where:

- $L_{delay,i}$ - loss caused by delay for operation i;
- A_i - affected area;
- Y_i - expected yield per hectare;
- P_{crop} - crop price;
- θ_i - sensitivity coefficient for the crop and operation;
- D_i - actual delay;
- W_i - acceptable delay threshold or service-window tolerance.

The value of the digital tool is then:

$$B_{window,i} = L_{delay,0,i} - L_{delay,1,i} \backslash hfill(2.31)$$

This formulation is particularly useful for monitoring and routing case studies. In monitoring, satellite, UAV, and IoT systems detect stress or operational need earlier. In routing, the optimization system helps ensure that field tasks are completed within required time windows. The routing article's scenario structure already treats service-window feasibility as a core performance indicator; this subsection provides the monetary logic for converting that feasibility into economic value.

Saved agronomic time windows should not be treated as a general time-saving variable. They must be tied to specific operations. For example:

- saved time before irrigation has value if it prevents water stress;
- saved time before spraying has value if it prevents disease or pest expansion;
- saved time before harvesting has value if it protects crop quality or prevents weather-related losses;
- Saving time in route planning has value if it allows all scheduled operations to remain feasible.

Table 2.14 Agronomic time-window variables and shadow pricing logic

Operation	Time-window risk	Digital tool contribution	Main loss if delayed	Shadow pricing method	Output
Irrigation	Soil moisture drops below the crop threshold	IoT + weather + EO alert	Yield stress, lower biomass, reduced quality	Avoided yield loss / avoided stress loss	UAH/ha/event
Spraying	Pest or disease spreads beyond the control window	NDVI/EVI anomaly + UAV/field verification	Higher crop damage, more chemical use	Avoided yield loss + avoided extra treatment	UAH/field
Fertilization	Nutrient application misses the optimal stage	Monitoring + intervention prioritization	Lower nutrient efficiency, yield reduction	Avoided nutrient loss + yield protection	UAH/ha
Harvesting	Weather or maturity window missed	Weather forecast + route scheduling	Quality loss, harvest loss, storage loss	Quality-price differential + avoided loss	UAH/ton
Machinery routing	Field tasks are not served on time	Weighted routing and scheduling	Missed the agronomic service window	Delay penalty function	UAH/route/week
Land-use verification	Decision delayed by fragmented data	Digital cadastre and GIS services	Transaction cost and planning delay	Administrative time + opportunity cost	UAH/procedure

Source: *prepared by the authors.*

Preventing ecological damage is one of the main categories of shadow value in sustainable environmental management. Digital systems can prevent ecological damage by identifying sensitive zones, restricting unsuitable operations, detecting early stress, monitoring land-cover change, and supporting better spatial planning. The economic value of this prevention may be estimated through avoided restoration cost, avoided damage cost, avoided regulatory penalties, avoided productivity loss, or avoided public expenditure.

The general formula for preventing ecological damage is:

$$B_{eco,t} = \sum_{m=1}^{M} \left[\left(D_{0,m,t} - D_{1,m,t} \right) \times SP_{damage,m,t} \right] \backslash hfill(2.32)$$

, where:

- $B_{eco,t}$ - shadow value of prevented ecological damage in period t;
- $D_{0,m,t}$ - expected damage of type m in the baseline scenario;
- $D_{1,m,t}$ - expected damage of type m in the digital scenario;
- $SP_{damage,m,t}$ - shadow price per unit of damage type m;
- M - number of damage categories.

If restoration cost is used:

$$B_{restore,t} = \left(A_{0,t} - A_{1,t} \right) \times C_{restore,t} \backslash hfill(2.33)$$

, where:

- $A_{0,t}$ - affected area under baseline scenario;
- $A_{1,t}$ - affected area under digital scenario;
- $C_{restore,t}$ - restoration cost per hectare or per unit.

If avoiding regulatory or compliance costs is relevant:

$$B_{compliance,t} = P_{violation,0,t} \times F_{0,t} - P_{violation,1,t} \times F_{1,t} \backslash hfill(2.34)$$

, where:

- $P_{violation,0,t}$ and $P_{violation,1,t}$ - probability of violation before and after digital tool implementation;
- $F_{0,t}$ and $F_{1,t}$ - expected fine, restoration, or compliance cost.

This logic is especially important for digital land-management systems. A cadastral or geospatial system that integrates environmental protection zones, water-protection zones, military restrictions, land categories, and ecological sensitivity layers create value by preventing decisions that would later generate legal, ecological, and restoration costs. It is also relevant for routing, where hard masks can prevent agricultural machinery from entering prohibited zones. In such cases, the economic value is not only the avoided penalty but also the avoided environmental and institutional cost.

Nazarenko's earlier ecological-economic modeling work already treats environmental expenditures, green-cover restoration, natural resource value, CO_2 emissions, and land-use effects as economic variables within a broader information-system framework. In this monograph, this logic is transferred from urban ecological-economic modeling to agricultural and peri-urban environmental management.

Table 2.15 Methods for preventing ecological damage

Valuation method	Best used when	Required data	Example	Strength	Limitation
Avoided cost method	Digital tool prevents a known cost	Baseline cost, digital scenario cost	Avoided fuel, avoided inspection, avoided field damage	Simple and transparent	May miss long-term effects
Restoration cost method	Damage would require physical recovery	Area affected, restoration cost per unit	Soil restoration, green-cover restoration	Practical for land and ecology	Restoration cost may not equal full ecological value
Replacement cost method	Natural function can be replaced artificially	Replacement technology or service cost	Water filtration, artificial drainage, and soil improvement	Useful for ecosystem services	Replacement may be imperfect
Damage cost method	Damage has measurable economic consequences	Damage level, cost per unit	Yield loss, health cost, and infrastructure damage	Captures actual consequences	Requires strong assumptions

Valuation method	Best used when	Required data	Example	Strength	Limitation
Social cost method	Damage affects society beyond the direct user	Social cost per unit	Carbon emissions	Suitable for CO_2e	Carbon price selection varies
Regulatory cost method	Violation or non-compliance generates cost	Fine, penalty, compliance cost	Restricted zone violation	Easy to explain institutionally	Only captures legal cost, not full ecological damage
Opportunity cost method	Damage prevents alternative use	Alternative land-use value	Loss of agricultural productivity	Useful in land-use planning	Depends on assumptions about alternatives
Expected loss method	Damage is uncertain but probable	Probability and loss estimate	Risk of contamination or route violation	Supports risk modeling	Requires probability estimates

Source: *prepared by the authors.*

Environmental and temporal effects are uncertain. A digital tool may reduce the probability of a negative event rather than eliminate it. For example, monitoring may reduce the probability of delayed irrigation; routing may reduce the probability of missing a service window; land-use masks may reduce the probability of entering a restricted area; data-quality checks may reduce the probability of incorrect decisions. In such cases, the shadow value should be calculated as the expected avoided loss.

The general formula is:

$$B_{risk,t} = \left(P_{0,t} \times L_{0,t}\right) - \left(P_{1,t} \times L_{1,t}\right)\backslash hfill(2.35)$$

, where:

- Brisk,t - shadow value of risk reduction in period t;
- P0,t - probability of a negative event in the baseline scenario;
- L0,t - loss if the event occurs in the baseline scenario;
- P1,t - probability of a negative event after digital tool implementation;
- L1,t - loss if the event occurs after digital tool implementation.

For multiple risk categories:

$$B_{risk,total,t} = \sum_{k=1}^{K} \left[\left(P_{0,k,t} \times L_{0,k,t}\right) - \left(P_{1,k,t} \times L_{1,k,t}\right)\right]\backslash hfill(2.36)$$

, where:

- K - number of risk categories.

The risk-adjusted shadow value can also be modified by data reliability:

$$B_{risk,adj,t} = B_{risk,t} \times Q_{data,t}\backslash hfill(2.37)$$

where:

- Qdata,t - data reliability coefficient from 0 to 1.

This is important because digital tools depend on data quality. If data are incomplete, outdated, clouded, legally uncertain, or generated by unreliable sensors, the shadow value should be adjusted downward. This prevents overestimation of digital benefits.

Shadow pricing should no longer be a separate calculation. It must be integrated into the broader methodological framework of the monograph. In extended CBA, shadow-priced variables enter the benefit side of the model. In MCDA, they can either become monetary criteria or be transformed into normalized scores. In simulation, shadow prices are used to compare scenarios under different conditions.

The extended CBA equation from subsection 2.1 can be expanded as follows:

$$NPV_D = \sum_{t=0}^{T} \frac{\left(B_{fin,t} + SV_{env,t} + SV_{time,t} + SV_{risk,t} + SV_{inst,t}\right) - C_{total,t}}{(1+r)^t}\backslash hfill(2.38)$$

, where:

- $B_{fin,t}$ - direct financial benefit;
- $SV_{env,t}$ - environmental shadow value;
- $SV_{time,t}$ - temporal shadow value;
- $SV_{risk,t}$ - risk-reduction shadow value;
- $SV_{inst,t}$ - institutional shadow value;
- $C_{total,t}$ - total cost of the digital tool.

The shadow-adjusted extended benefit-cost ratio is:

$$EBCR_{shadow} = \frac{PV\left(B_{fin} + SV_{env} + SV_{time} + SV_{risk} + SV_{inst}\right)}{PV\left(C_{total}\right)} \backslash hfill(2.39)$$

If $EBCR_{shadow} > 1$, the digital tool is economically justified under the expanded valuation model. However, the researcher must always present both direct and shadow-adjusted results. This avoids hiding weak financial performance behind uncertain environmental assumptions. A good empirical presentation should show:

1. Direct financial CBA results.
2. Shadow-adjusted CBA result.
3. Sensitivity of the result to selected shadow prices.
4. Explanation of which shadow-price component creates the largest effect.

For MCDA, shadow-priced variables can be included as criteria:

$$S_i = w_{fin} \times Fin'i \; + \; wenv \times SV'_{env}i \; + \; wtime \times SV'_{time}i \; + \; wrisk \times SV'_{risk}i \; + \; winst \times Inst'_i \#(2.40)$$

, where all variables are normalized to a comparable scale.

In routing, the generalized cost function can be expanded as:

$$GC(e) = w_t \times T(e) + w_c \times C(e) + w_{co2} \times [CO_2e(e) \times SCP] + w_r \times R(e) \backslash hfill(2.41)$$

where:

- $GC(e)$ - generalized cost of route edge e;
- $T(e)$ - time cost;
- $C(e)$ - direct cost;
- $CO2e(e) \times SCP$ - shadow carbon cost;
- $R(e)$ - operational risk cost.

This equation allows comparing routes not only by distance or direct fuel cost, but also by carbon- and risk-adjusted impact.

Table 2.16 Integration of shadow pricing into the monograph's three empirical case studies

Case study	Shadow-priced variable	Main equation	Required data	Expected output
Digital land management	Avoided land-use conflict	B_conflict = (P_0L_0) - (P_1L_1)	Cadastral data, restrictions, conflict/fine costs	Avoided institutional and ecological costs
Digital land management	Avoided restoration cost	B_restore = (A_0 - A_1) × C_restore	Restricted areas, affected area, restoration cost	UAH avoided restoration
IoT / monitoring	Avoided water stress	B_stress = (YL_0 - YL_1) × A × P_crop	Soil moisture, crop price, and yield-loss estimates	UAH protected yield
IoT / monitoring	Reduced input waste	B_input = (Q_0 - Q_1) × P_q	Input records, monitoring logs	UAH saved inputs
IoT / monitoring	Avoided runoff / environmental pressure	B_runoff = (R_0 - R_1) × SP_runoff	Fertilizer, slope, soil, water data	UAH avoided ecological pressure
Routing	Reduced CO_2e	B_CO2 = (CO2e_0 - CO2e_1) × SCP	Fuel, route, emission factor	UAH carbon benefit
Routing	Saved service window	B_time = Σ[(D_0 - D_1) × LR × A]	Route time, task logs, and agronomic window	UAH avoided the delay loss

Case study	Shadow-priced variable	Main equation	Required data	Expected output
Routing	Reduced operational risk	B_risk = (P_0L_0) - (P_1L_1)	Risk zones, route violations, and delay costs	Expected avoided loss

Source: *prepared by the authors.*

Shadow pricing depends on data quality. The same equation may produce weak or misleading results if the underlying data are incomplete. Therefore, each shadow-priced variable must be connected to a clear data source, measurement unit, and reliability level. The monograph should distinguish between authoritative public data, open data, project-generated data, and expert-estimated values.

Environmental and temporal shadow prices can be calculated using several groups of data:

1. Spatial and cadastral data - parcel boundaries, land-use categories, restrictions, protected zones, ownership or access conditions.
2. Earth observation data - land cover, NDVI/EVI, crop stress, vegetation condition, green-cover change.
3. IoT and field telemetry - soil moisture, microclimate, soil temperature, sensor alerts, irrigation triggers.
4. Operational data - fuel logs, machinery hours, routes, task completion time, service windows, field-operation records.
5. Economic data - input prices, fuel prices, crop prices, labor cost, restoration cost, fines, transaction costs.
6. Environmental valuation data - carbon prices, restoration costs, emission factors, water scarcity proxies, ecosystem-service estimates.
7. Institutional data - legal restrictions, policy requirements, reporting rules, subsidy conditions, sustainability metrics.

A shadow-pricing model should always identify which data are measured, which are estimated, and which are assumed. This distinction is essential for scientific transparency.

Table 2.17 Data requirements for shadow pricing of environmental and temporal variables

Shadow-priced variable	Primary data	Secondary data	Measurement unit	Data source type	Reliability concern
CO_2ereduction	Fuel consumption, route distance, vehicle class	Emission factors, load, road type	kg or tCO_2e	Fleet logs, routing system, emission-factor database	Fuel use may be estimated rather than measured
Soil degradation	Soil risk, slope, land cover, field traffic	Restoration cost, yield-loss estimate	ha, t/ha, index	Soil maps, EO, field records	Soil data may be coarse or outdated
Water savings	Irrigation volume, soil moisture	Energy cost, water price, scarcity proxy	m^3, UAH/m^3	IoT, irrigation logs, weather data	Sensor calibration and missing data
Yield protection	Expected yield, observed yield, crop price	Stress duration, intervention timing	t/ha, UAH/t	Farm records, monitoring logs	Counterfactual yield may be uncertain
Time-window protection	Operation schedule, actual completion time	Crop sensitivity, delay-loss function	hours/days, UAH/ha/day	Task logs, routing system, and agronomic model	Loss function depends on crop stage
Avoided land-use violation	Restriction map, route or parcel decision	Fine, restoration cost, conflict cost	UAH/case	Cadastre, legal data, GIS	Legal data may be incomplete
Green-cover protection	Land-cover change, green-zone area	Restoration cost, ecosystem value	ha, UAH/ha	EO, cadastral layers, municipal records	Ecosystem value is difficult to localize
Data reliability adjustment	Metadata, update frequency, source authority	Sensor uptime, cloud cover, QA flags	0–1 coefficient	System logs, metadata	Requires transparent scoring

Source: *prepared by the authors.*

Shadow prices are estimates. They are methodologically necessary, but they can be uncertain. Carbon price, restoration cost, water scarcity value, yield-loss rate, delay-loss coefficient, and probability of violation may vary depending on location, season, policy assumptions, and data quality. Therefore, the monograph must not present shadow-price results as fixed and unquestionable. Each shadow-pricing model should include sensitivity analysis.

The basic sensitivity logic is:

- Result_low = Model(SP_low)
- Result_base = Model(SP_base)
- Result_high = Model(SP_high)

For carbon pricing:

- B_CO2_low = ΔCO2e × SCP_low
- B_CO2_base = ΔCO2e × SCP_base
- B_CO2_high = ΔCO2e × SCP_high

For time-window valuation:

- B_time_low = ΔD × LR_low × A
- B_time_base = ΔD × LR_base × A
- B_time_high = ΔD × LR_high × A

For ecological restoration:

- B_restore_low = ΔA × C_restore_low
- B_restore_base = ΔA × C_restore_base
- B_restore_high = ΔA × C_restore_high

Sensitivity analysis is especially important for policy interpretation. A digital tool may be financially weak under direct accounting but efficient when environmental benefits are included. However, if this conclusion depends entirely on a very high shadow price, the result must be presented carefully. The best practice is to report a range of valuation scenarios: low, baseline, and high.

Table 2.18 Algorithm for applying shadow pricing in digital environmental management

Step	Action	Practical explanation	Output
1	Define a shadow-priced variable	Select CO_2e, soil degradation, water stress, delay, violation risk, or other non-market effect	Variable register
2	Define baseline scenario	Establish what happens without the digital tool	Baseline value
3	Define a digital scenario	Establish what changes after the digital tool is applied	Digital scenario value
4	Measure physical difference	Calculating avoided emissions, saved water, avoided delay, protected area, or reduced probability	ΔQ
5	Select valuation method	Choose avoided cost, restoration cost, social cost, expected loss, or scarcity price	Valuation rule
6	Select the shadow price	Use literature, policy values, local costs, expert estimation, or empirical data	SP
7	Calculate the shadow value	Multiply physical change by the shadow price or the expected loss difference	SV
8	Adjust for data reliability	Apply the reliability coefficient if needed	Adjusted shadow value
9	Discount over time	Convert future values to present value	PV(SV)
10	Integrate into CBA / MCDA	Add value to the extended CBA or normalize as an MCDA criterion	Decision model input
11	Run sensitivity analysis	Test low, baseline, and high assumptions	Robustness range

Step	Action	Practical explanation	Output
12	Interpret carefully	Explain what is measured, estimated, and assumed	Transparent conclusion

Source: *prepared by the author.*

2.4 Simulation, Scenario Analysis, and Robustness Testing under Uncertainty

The introduction of shadow pricing changes the logic of economic-efficiency evaluation. It shows that a digital tool may create value in at least three ways. First, it may reduce direct costs, which are captured by ordinary financial analysis. Second, it may prevent environmental or temporal losses, which require shadow pricing. Third, it may improve institutional transparency and reduce risk, which requires a risk-adjusted valuation approach.

For this monograph, shadow pricing is not an optional methodological addition. It is necessary because the main empirical objects - land management systems, monitoring systems, and routing systems - all operate in areas where non-market effects are substantial. Digital land management prevents unsuitable spatial decisions. Environmental monitoring prevents delayed or excessive interventions. Routing optimization prevents wasted fuel, avoidable emissions, and missed agronomic windows. If these effects are not valued, the economic contribution of digital tools will be underestimated.

At the same time, shadow pricing must be used with discipline. It must not become a means of artificially inflating benefits. Each shadow price must be explained, each assumption must be transparent, and each result must be tested through sensitivity analysis. Direct financial results and shadow-adjusted results should be presented separately. This will allow the monograph to show both narrow and extended economic efficiency.

The final methodological position of this subsection is as follows: the economic efficiency of digital environmental tools should be assessed by combining direct financial results with shadow-priced environmental, temporal, risk-related, and institutional effects. This makes it possible to evaluate digital tools not only as technologies, but as instruments for preventing losses, protecting natural resources, improving agricultural timing, and supporting sustainable land-use governance.

The previous subsections established three methodological pillars for determining the economic efficiency of digital environmental tools. Adapted cost-benefit analysis enables comparison of the full structure of costs and benefits, including data value and decision-support value. Multi-criteria decision analysis enables the comparison of alternatives when economic, temporal, environmental, spatial, risk-related, and institutional indicators interact. Shadow pricing enables assigning monetary values to prevent ecological damage, saved agronomic time windows, carbon emission reductions, and other non-market effects. The fourth methodological element is simulation and scenario-based evaluation.

Simulation and scenario-based evaluation are necessary because agriculture, land management, and environmental monitoring do not operate under stable laboratory conditions. They operate under volatile markets, changing weather, uncertain yields, variable fuel prices, data gaps, sensor failures, mobility restrictions, infrastructure risks, and institutional uncertainty. In Ukraine, these factors are further intensified by wartime and post-war conditions, changes in land access, damaged or restricted infrastructure, and the need for continuous replanning in peri-urban zones. The current monograph structure explicitly defines Subsection 2.4 as the methodological block for stress-testing and Monte Carlo simulations under volatile stochastic conditions.

In this monograph, simulation is not treated as a decorative technical instrument. It is considered a necessary method for determining whether digital tools remain economically efficient as the environment changes. A digital land-management system may look efficient under normal data availability but lose value when cadastral data is incomplete. A monitoring system may produce strong results under good sensor coverage but become less reliable when cloud cover, UAV restrictions, or sensor downtime occur. A routing system may reduce costs under normal fuel prices but become less or more valuable during a fuel shock, road closure, or an increase in transport risk. Therefore, a single deterministic calculation is not enough. The economic-efficiency model must be tested under alternative scenarios and repeated stochastic simulations.

This approach is consistent with the empirical logic of the Kyiv routing study, in which the platform was tested across Baseline, Stress, and Sustainability-adjusted scenarios using different fuel-price bands and varying weights for time, direct cost, CO_2e, and operational risk. The study showed that fuel-driven cost bands strongly affect weekly logistics costs, whereas routing feasibility and compliance with restricted edges remain stable when hard spatial masks are enforced. It also corresponds to the broader methodological logic of the monograph, in which digital tools must be evaluated not only by narrow financial returns but also by their ability to create measurable economic value, reduce environmental damage, improve institutional transparency, and increase resilience under uncertainty.

Table 2.19 Role of simulation and scenario-based evaluation in the methodological framework

Methodological component	Main question	Simulation role	Example in the monograph	Expected output
Adapted CBA	Do total benefits exceed total costs?	Tests whether NPV, EBCR, and payback remain stable under uncertain prices, yields, costs, and benefits	Digital monitoring was evaluated under different crop prices and input costs	Distribution of NPV and EBCR
MCDA	Which alternative is preferable under multiple criteria?	Tests on how rankings change when weights, constraints, or data reliability vary	Land parcel or route alternatives under different policy priorities	Robustness of ranking
Shadow pricing	What is the monetary value of non-market effects?	Tests the sensitivity of results to carbon price, restoration cost, delay-loss rate, and ecological-damage assumptions	CO_2ereduction valued under low/base/high carbon prices	Shadow-value range
Routing optimization	Which route or schedule is efficient and feasible?	Tests performance under fuel shocks, restrictions, delays, road closures, and weather	Baseline / Stress / Sustainability-adjusted scenarios	Cost, time, CO_2e, feasibility, violations
Monitoring and intervention	When should action be taken?	Tests on whether alerts remain valuable under sensor failure, cloud cover, weather variability, and uncertainty	Soil moisture and NDVI/EVI thresholds under variable conditions	Probability of successful intervention
Land management	Which land-use option is resilient?	Tests whether decisions remain feasible under regulatory, ecological, and market changes	Parcel suitability under hard masks and soft penalties	Feasible land-use scenarios

Source: *prepared by the authors.*

Simulation is a methodological approach that reproduces possible states of a system under different assumptions. In economic-efficiency evaluation, it helps answer not only what the result is under one set of conditions, but also how the result changes as the values of uncertain variables vary. For digital agritech and environmental management, this is essential because the economic impact of digital tools depends on many variables that are not fully under the researcher's or decision-maker's control.

In this monograph, simulation has four core functions. First, it tests robustness. A digital tool is robust if it remains economically useful when some input conditions change. For example, a routing system is robust if it maintains service-window feasibility even when fuel prices increase or several road segments become unavailable. Second, it tests resilience. A digital tool is resilient if it can continue to provide decision support under degraded operational conditions. For example, a monitoring system is resilient if it can fall back to satellite imagery and IoT telemetry when UAV flights are unavailable. The routing study explicitly uses such a resilience logic: under intermittent UAV availability and short-lived network outages, the middleware maintained advisory generation through store-and-forward buffers, asynchronous refresh, and provenance-preserving data exports.

Third, simulation tests sensitivity. A digital tool may be efficient only because of one assumption, such as a high carbon price, a high crop price, or a high fuel price. Sensitivity testing identifies which variables dominate the result. Fourth, simulation supports scenario comparison. It allows the researcher to compare normal, stressed, and sustainability-oriented operating conditions. This is especially important for the monograph because its empirical logic moves from land management to monitoring and then to routing. Each of these blocks depends on uncertain spatial, environmental, economic, and institutional variables.

The general simulation model may be expressed as:

$$Y_s = f(X_s, P_s, D_s, M) \backslash hfill (2.42)$$

, where:

- Y_S - output vector under scenario s;
- X_S - input variables under scenario s;
- P_S - parameter assumptions under scenario s;
- D_S - data availability and data-quality conditions under scenario s;
- M - model structure, including CBA, MCDA, shadow pricing, and routing logic.

For Monte Carlo simulation, the model is repeated for many iterations:

$$Y^{(k)} = f\left(X^{(k)}, P^{(k)}, D^{(k)}, M\right), \quad k = 1,2, \dots, N \backslash hfill (2.43)$$

, where:

- Y^k - output vector in iteration k;
- X^k - randomly sampled input variables in iteration k;
- P^k - randomly sampled parameters in iteration k;
- D^k - data-quality state in iteration k;
- N - total number of simulation iterations.

The purpose of this approach is to move from one deterministic result to a distribution of possible results. Instead of stating only that a digital tool has one expected NPV or one expected cost-saving level, the researcher can show the probability that the tool remains efficient under uncertainty. This is more appropriate for agriculture, where price, yield, weather, and operational variables are inherently stochastic.

Table 2.20 Main types of simulation used in the monograph

Simulation type	Definition	Best use in the monograph	Example output	Limitation
Deterministic baseline scenario	One fixed set of input assumptions	Establishes reference result	Baseline NPV, cost, route time, feasibility	Does not show uncertainty
Alternative deterministic scenarios	Several fixed scenarios with different assumptions	Compares Baseline, Stress, and Sustainability-adjusted logic	Scenario A/B/C comparison	Depends on selected scenarios
Stress testing	Extreme but plausible adverse conditions	Tests resilience under shocks	High fuel price, road closure, sensor failure	May not estimate probability
Monte Carlo simulation	Repeated random sample from probability distributions	Estimates the uncertainty distribution	Probability of EBCR > 1; cost range	Requires assumptions about distributions
Sensitivity analysis	Changes one variable or group of variables	Identifiesdominant drivers	Tornado chart of fuel, yield, carbon price	May ignore interactions
Scenario-MCDA simulation	Recalculates MCDA ranking under different weights and data conditions	Tests stability of land/route/intervention ranking	Robustness of top-ranked alternative	Requires transparent weighting logic
Scenario-CBA simulation	Recalculates NPV/EBCR under different price and benefit assumptions	Tests of investment efficiency	NPV distribution	Requires cost/benefit assumptions
Operational discrete-event simulation	Simulates task execution through time	Tests routing, queues, delays, service windows	% jobs completed on time	More data-intensive

Source: *prepared by the authors.*

Scenario-based evaluation begins by constructing realistic operating conditions. A scenario is not simply a random example. It is a logically consistent representation of a possible state of the system. In the context of this monograph, scenarios must reflect the main sources of uncertainty: market prices, weather, data availability, institutional restrictions, operational risk, and sustainability priorities.

The basic scenario structure includes at least three groups. The first group is the baseline scenario. It represents normal conditions. In routing, this may mean medium fuel prices, partial but acceptable UAV availability, standard road access, and regular task scheduling. In monitoring, it may mean normal sensor availability, typical weather variation, and standard intervention thresholds. In land management, it may mean available cadastral layers and known restrictions.

The second group is the stress scenario. It represents adverse but plausible conditions. In routing, this may include high fuel prices, increased transport risks, more restricted road segments, and safety slowdowns. In monitoring, it may include sensor failures, cloud cover, delayed UAV missions, or extreme weather. In land management, it may include incomplete data, uncertain parcel status, or new restrictions.

The third group is the sustainability-adjusted scenario. It represents conditions in which environmental performance receives a higher decision weight. In routing, this may mean assigning a higher weight to CO_2e or to low-emission corridors. In monitoring, it may prioritize reduced water, fertilizer, or agrochemical pressure. In land management, it may prioritize environmental sensitivity, protection of green cover, and restoration costs. The Kyiv routing case already follows this logic. It uses a Baseline scenario with fuel at 68 UAH/l and balanced time/cost weights, a Stress scenario with fuel at 92 UAH/l and higher cost weighting, and a Sustainability-adjusted scenario with fuel at 80 UAH/l and higher CO_2e weighting.

Table 2.21 Scenario templates for simulation-based evaluation

Scenario	Main logic	Typical assumptions	Recommended use	Key indicators
Scenario A: Baseline	Normal operating conditions	Average fuel/input prices, regular data availability, standard weather, known restrictions	Reference comparison	NPV, EBCR, cost, time, feasibility
Scenario B: Market stress	Economic pressure	High fuel price, high input price, higher labor cost, lower output price	Tests cost resilience	Cost increase, NPV decrease, payback delay
Scenario C: Weather stress	Agronomic pressure	Drought, excess rainfall, heat stress, shortened service windows	Monitoring tests and timing value	Yield protection, avoided delay loss
Scenario D: Data-degradation stress	Digital-system pressure	Sensor downtime, cloud cover, UAV unavailability, delayed updates	Tests data resilience	Decision continuity, data reliability
Scenario E: Mobility restriction	Spatial/logistical pressure	Road closures, safety restrictions, military zones, detours	Tests routing and land-use compliance	Feasibility, violations, travel time
Scenario F: Sustainability-adjusted	Environmental priority	Higher CO_2eweight, higher shadow carbon price, stronger ecological penalties	Tests sustainability-performance trade-off	CO_2e, ecological cost, EBCR_shadow
Scenario G: Combined stress	Multiple pressures together	High fuel price + weather stress + data gaps + road restrictions	Tests worst-case resilience	Probability of efficiency and service continuity

Source: prepared by the authors.

Table 2.22 Example scenario structure for the routing case study

Scenario	Fuel price	Cost band	MCDA weights: time / cost / CO_2e / risk	Operational meaning
Baseline A	68 UAH/l	60–120 UAH/km	0.35 / 0.35 / 0.20 / 0.10	Typical operating week
Stress B	92 UAH/l	120–250 UAH/km	0.25 / 0.45 / 0.20 / 0.10	High fuel price and higher transport risk
Sustainability-adjusted C	80 UAH/l	60–120 UAH/km	0.25 / 0.30 / 0.35 / 0.10	Higher priority for $CO_2e$and low-emission logic

Source: adapted from the Kyiv routing scenario structure.

Scenario analysis compares several defined cases. Monte Carlo simulation goes further. It treats uncertain variables as random variables and repeatedly recalculates the economic-efficiency model. The result is not a single NPV, EBCR, or route cost, but a distribution of possible outcomes. This is particularly useful for digital agriculture because many variables are uncertain: yield response, input prices, fuel prices, weather, sensor reliability, intervention timing, road availability, and market prices.

The general Monte Carlo procedure consists of the following steps:

1. Define the model output, such as NPV, EBCR, route cost, feasibility, CO_2e, or avoided loss.
2. Identify uncertain variables.
3. Assign probability distributions to uncertain variables.
4. Generate random samples.
5. Run the model for each iteration.
6. Store the outputs.
7. Analyze the distribution of results.
8. Calculate the probability of efficiency and risk metrics.
9. Interpret decision relevance.

The Monte Carlo model for digital tool economic efficiency can be written as:

$$NPV_D^{(k)} = \sum_{t=0}^{T} \frac{\left(B_{fin,t}^{(k)} + SV_{env,t}^{(k)} + SV_{time,t}^{(k)} + SV_{risk,t}^{(k)} + SV_{inst,t}^{(k)}\right) - C_{total,t}^{(k)}}{(1 + r^{(k)})^t} \backslash hfill(2.44)$$

, where:

- NPV_D^(k) - net present value in Monte Carlo iteration k;
- Bfin,t^(k) - sampled direct financial benefit;
- SVenv,t^(k) - sampled environmental shadow value;
- SVtime,t^(k) - sampled temporal shadow value;
- SVrisk,t^(k) - sampled risk-reduction shadow value;
- Vinst,t^(k) - sampled institutional value;
- Ctotal,t^(k) - sampled total cost;
- r^(k) - sampled discount rate;
- T - evaluation horizon.

The shadow-adjusted benefit-cost ratio for iteration k is:

$$EBCR_{shadow}^{(k)} = \frac{PV\left(B_{fin}^{(k)} + SV_{env}^{(k)} + SV_{time}^{(k)} + SV_{risk}^{(k)} + SV_{inst}^{(k)}\right)}{PV\left(C_{total}^{(k)}\right)} \backslash hfill(2.45)$$

The probability that the digital tool is economically efficient is then:

$$P_{eff} = \frac{1}{N} \times \sum_{k=1}^{N} \quad I\left(EBCR_{shadow}^{(k)} > 1\right) \backslash hfill(2.46)$$

, where:

- Peff - probability of economic efficiency;
- N - number of Monte Carlo iterations;
- I(·) - indicator function equal to 1 when the condition is true and 0 otherwise.

This probability is one of the most important outputs of the simulation. It is stronger than a single benefit-cost ratio because it shows how often the digital tool remains efficient under uncertainty.

Table 2.23 Recommended uncertain variables and probability distributions for Monte Carlo simulation

Variable	Why uncertain	Suggested distribution	Example parameters	Relevant case
Fuel price	Market volatility	Triangular or lognormal	min / mode / max	Routing
Input price	Fertilizer, agrochemical, and seed price volatility	Triangular or normal	mean and standard deviation	Monitoring / CBA
Crop price	Market uncertainty	Triangular or lognormal	low / expected / high	Monitoring / CBA
Yield response	Biological and weather variability	Normal or triangular	expected response ± error	Monitoring
Water savings	Depends on the weather and sensor accuracy	Triangular	low / most likely/high	IoT irrigation
Sensor uptime	Technical reliability varies	Beta	alpha/beta or expected uptime	Monitoring
UAV availability	Regulatory, weather, and safety constraints	Bernoulli or categorical	probability available	Monitoring/routing
Cloud cover	Affects optical satellite usability	Beta or empirical distribution	probability of a usable image	Monitoring
Road closure	Mobility and safety restrictions	Bernoulli	closure probability per segment	Routing
Travel time	Congestion and road condition variability	Normal or lognormal	mean and standard deviation	Routing
Delay-loss rate	Crop-stage sensitivity uncertainty	Triangular	low / mode / high	Monitoring/routing
Carbon price	Policy and valuation uncertainty	Scenario-based or triangular	low / base / high	Shadow pricing
Restoration cost	Site-specific ecological cost uncertainty	Triangular	low / mode / high	Land management
Data reliability coefficient	Depends on source quality and update frequency	Beta	expected reliability	All cases
Discount rate	Cost of capital and public-policy assumptions	Scenario-based or triangular	low / base / high	CBA

Source: *prepared by the author.*

Stress testing differs from Monte Carlo simulation because it does not require the researcher to define complete probability distributions. Instead, it asks what happens under adverse but plausible conditions. This is important for digital environmental tools because decision-makers often need to know whether a system can withstand shocks, not just what its average outcome will be.

For this monograph, stress testing should be applied to at least six categories of shocks:

1. fuel-price shock;
2. input-price shock;
3. weather and drought shock;
4. sensor and data-availability shock;
5. road-closure and mobility shock;
6. institutional or regulatory shock.

The general stress-test output can be expressed as:

$$\Delta Y_{stress} = \frac{Y_{stress} - Y_{base}}{Y_{base}} \times 100\% \backslash hfill(2.47)$$

where:

- ΔY_stress - percentage change in output under stress;
- Y_stress - output value under stress scenario;
- Y_base - output value under baseline scenario.

For cost:

$$\Delta_{Cost_{stress}} = \frac{Cost_{stress} - Cost_{base}}{Cost_{base}} \times 100\% \hfill (2.48)$$

For feasibility:

$$\Delta Feasibility_{stress} = Feasibility_{stress} - Feasibility_{base} \hfill (2.49)$$

For emissions:

$$\Delta_{CO_2e_{stress}} = \frac{CO_2e_{stress} - CO_2e_{base}}{CO_2e_{base}} \times 100\% \hfill (2.50)$$

The Kyiv routing study provides a clear example of stress testing. Under the stress scenario, direct logistics costs increased by 12.44% relative to the baseline, while in the sustainability-adjusted scenario, they increased by 6.22%. At the same time, travel time was protected, feasibility remained at or above 95%, and restricted-edge violations remained zero because hard masks excluded prohibited spatial segments before optimization.

Table 2.24 Stress-testing scenarios for digital environmental management

Stress category	Stress condition	Main affected variables	Expected output	Relevant empirical case
Fuel-price shock	Fuel increases by 20–50%	UAH/km, route cost, machinery cost	Cost increase; route re-weighting	Routing
Input-price shock	Fertilizer, agrochemical, seed prices increase	Input-use savings, intervention cost	Higher value of precision interventions	Monitoring
Crop-price decrease	Crop market price falls	Yield-protection value	Lower benefit from yield protection	Monitoring / CBA
Drought / heat stress	Higher evaporate inspiration, soil-moisture deficit	Water demand, yield risk, intervention timing	Higher value of monitoring and irrigation alerts	Monitoring
Excess rainfall	Field access reduced, delays increase	Route feasibility, machinery access	More missed windows and detours	Routing / monitoring
Sensor failure	Sensor uptime decreases	Data reliability, alert accuracy	Reduced monitoring benefit	Monitoring
UAV unavailability	UAV flights restricted	Spatial detail and validation quality	Fallback to Sentinel/IoT; lower data resolution	Monitoring / routing
Cloud cover	Optical imagery unavailable	NDVI/EVI update frequency	Delayed stress detection	Monitoring
Road closures	Road segments unavailable	Route length, travel time, risk	Higher cost and lower feasibility	Routing
New land-use restriction	Parcel or route segment becomes prohibited	Feasibility and compliance	Hard-mask exclusion	Land management / routing
Communication outage	Data transmission delayed	Real-time decision-support	Need for buffering and asynchronous refresh	All cases
Regulatory change	Compliance requirements increase	Administrative cost, reporting need	Higher institutional value of digital audit trails	Land management / policy

Source: prepared by the authors.

The goal of simulation is not only to calculate possible outcomes. The goal is to determine whether the digital tool is economically resilient. Economic resilience means the ability of a system to maintain acceptable efficiency, feasibility, compliance, and environmental performance under uncertainty and stress.

For the purposes of this monograph, economic resilience is evaluated through five groups of indicators:

1. financial resilience - whether NPV and EBCR remain positive under uncertainty;

2. operational resilience - whether service windows and tasks remain feasible;
3. environmental resilience - whether emissions and ecological impacts remain controlled;
4. data resilience - whether the system continues to work under partial data loss;
5. institutional resilience - whether compliance and auditability remain stable.

The expected value of NPV is:

$$E(NPV_D) = \frac{1}{N}\sum_{k=1}^{N} \quad NPV_D^{(k)} \backslash hfill(2.51)$$

The variance of NPV is:

$$Var(NPV_D) = \frac{1}{N-1}\sum_{k=1}^{N} \quad \left[NPV_D^{(k)} - E(NPV_D)\right]^2 \backslash hfill(2.52)$$

The coefficient of variation is:

$$CV_{NPV} = \frac{SD(NPV_D)}{E(NPV_D)} \backslash hfill(2.53)$$

, where:

- CV_{NPV} - coefficient of variation of NPV;
- $SD(NPV_D)$ - standard deviation of NPV.

A lower coefficient of variation indicates a more stable economic result, provided that the expected value is positive.

The probability of financial efficiency is:

$$P_{fin} = P(NPV_D > 0) \backslash hfill(2.54)$$

or:

$$P_{eff} = P(EBCR_{shadow} > 1) \backslash hfill(2.55)$$

Operational feasibility can be calculated as:

$$Feasibility = \frac{Jobs_{on\_time}}{Jobs_{total}} \times 100\% \backslash hfill(2.56)$$

Restricted-zone compliance can be calculated as:

$$Compliance = 1 - \left(\frac{Violations}{Total_{routes}}\right) \backslash hfill(2.57)$$

or, if violations are unacceptable:

Compliance = 1, if Violations = 0; Compliance = 0, if Violations > 0

A composite resilience index can be expressed as:

$$RI = w_1 \times P_{eff} + w_2 \times Feasibility + w_3 \times Compliance + w_4 \times DataReliability + w_5 \times EnvPerformance \backslash hfill(2.59)$$

, where:

- RI - resilience index;
- Peff - probability of economic efficiency;
- Feasibility - share of jobs completed within service windows;
- Compliance - restriction-compliance score;
- DataReliability - data-reliability coefficient;
- EnvPerformance - environmental-performance score;
- $w_1 \dots w_5$ - weights, where $\Sigma w_i = 1$.

This index can be adapted for each empirical case. In digital land management, compliance and data reliability may receive greater weight. For monitoring, data reliability and environmental performance may dominate. For routing, feasibility, cost, compliance, and emissions may be the dominant factors.

One of the main differences between digital-tool evaluation and traditional investment evaluation is the importance of data availability. A tractor, irrigation pump, or fertilizer spreader can be evaluated primarily based on purchase cost, operating cost, and productivity. A digital tool must also be evaluated based on the reliability of its data streams. If sensor data are unavailable, satellite imagery is cloud-covered, UAV flights are restricted, or cadastral layers are outdated, the digital tool may lose some of its value.

For this reason, simulation must include a data-quality layer. The routing case demonstrates this logic by combining EO, UAV, IoT, cadastral/land-use, road-network, market-signal, and restriction-notice data into one middleware pipeline. Where UAV operations were limited, the system used satellite and ground sensors as fallback sources.

The data availability state for a given simulation iteration can be expressed as:

$$D_{state}^{(k)} = \{EO^{(k)}, UAV^{(k)}, IoT^{(k)}, Cadastre^{(k)}, Road^{(k)}, Market^{(k)}, Restriction^{(k)}\}\backslash hfill(2.60)$$

, where each element may be represented by a binary variable, categorical state, or reliability score.

For example:

$$UAV^{(k)} \sim Bernoulli(p_{UAV})\backslash hfill(2.61) SensorUptime^{(k)} \sim Beta(\alpha_{sensor}, \beta_{sensor})\backslash hfill(2.62)$$

$$CloudCover^{(k)} \sim Beta(\alpha_{cloud}, \beta_{cloud})\backslash hfill(2.63) RoadClosure_e^{(k)} \sim Bernoulli(p_e)\backslash hfill(2.64)$$

The effective data reliability score may be calculated as:

$$Q_{data}^{(k)} = w_{EO} \times Q_{EO}^{(k)} + w_{UAV} \times Q_{UAV}^{(k)} + w_{IoT} \times Q_{IoT}^{(k)} + w_{Cad} \times Q_{Cad}^{(k)} + w_{Road} \times Q_{Road}^{(k)}\backslash hfill(2.65)$$

where:

- Qdata^(k) - total data reliability in iteration k;
- QEO^(k), Q_AV^(k), QIoT^(k), QCad^(k), QRoad^(k) - reliability scores for data sources;
- wEO, w_AV, wIoT, wCad, wRoad - source weights.

This score can then be used to adjust expected benefits:

$$B_{adj}^{(k)} = B_{raw}^{(k)} \times Q_{data}^{(k)}\backslash hfill(2.66)$$

This prevents overestimation of benefits when the digital system operates under poor data conditions.

Table 2.25 Data-reliability simulation variables

Data source	Reliability variable	Possible simulationstate	Distribution or rule	Effect on model
Sentinel-2 / EO	Usable image availability	Available / delayed / unavailable	Bernoulli or empirical cloud-cover probability	Affects NDVI/EVI update and stress detection
UAV imagery	Flight availability	Available / restricted / delayed	Bernoulli or categorical	Affects high-resolution diagnostics
IoT telemetry	Sensor uptime	0–1 reliability score	Beta distribution	Affects soil-moisture and microclimate alerts
Cadastral layers	Data completeness	Complete / partial / outdated	Expert score or categorical	Affects hard masks and legal feasibility
Road network	Road-data accuracy	Accurate / partially outdated	Reliability score	Affects routing time and feasibility
Market signals	Price update frequency	Current / delayed	Update-lag rule	Affects cost bands and scenario triggers
Safety restrictions	Restriction update availability	Current / delayed / missing	Event-based probability	Affects risk and compliance
System communication	Network status	Online / degraded / offline	Markov state or Bernoulli	Affects real-time advisory generation

Source: prepared by the authors.

Simulation becomes most valuable when it integrates all previous methodological components rather than standing separately. In this monograph, every simulation run should be able to recalculate:

1. direct financial costs and benefits;
2. shadow-priced environmental and temporal benefits;
3. MCDA scores and rankings;

4. route or intervention decisions;
5. resilience indicators.

The integrated model for one simulation iteration can be written as:

$$Result^{(k)} = \{CBA^{(k)}, MCDA^{(k)}, ShadowValue^{(k)}, RoutePlan^{(k)}, Resilience^{(k)}\}\backslash hfill(2.67)$$

The routing cost function for each route edge can be written as:

$$GC_e^{(k)} = w_t^{(k)} \times T_e^{(k)} + w_c^{(k)} \times C_e^{(k)} + w_{co2}^{(k)} \times \left[CO_2e_e^{(k)} \times SCP^{(k)}\right] + w_r^{(k)} \times R_e^{(k)} + P_e^{(k)}\backslash hfill(2.68)$$

, where:

- GCe^(k) - generalized cost of edge e in iteration k;
- Te^(k) - travel time;
- Ce^(k) - direct cost;
- CO2e_e^(k) - emissions;
- SCP^(k) - sampled carbon shadow price;
- Re^(k) - risk score or cost;
- Pe^(k) - soft penalty;
- wt^(k), wc^(k), wco2^(k), wr^(k) - scenario or simulation weights.

Hard masks are applied before optimization:

$$Feasible_e^{(k)} = 1 \; if \; H_e^{(k)} = 1; \quad 0 \; if \; H_e^{(k)} = 0\backslash hfill(2.69)$$

Feasible_e^(k) = 1, if H_e^(k) = 1

, where:

- H_e^(k) - hard-mask status of edge or spatial object.

The optimized route plan is then:

$$RoutePlan^{(k)} = argmin \sum_{e \in Route} GC_e^{(k)}, \quad subject \; to \; Feasible_e^{(k)} = 1 \; and \; ServiceWindow_i^{(k)} = 1\backslash hfill(2.70)$$

This equation expresses the main methodological bridge between MCDA, shadow pricing, and routing. It allows the route to be selected not only by distance or direct financial cost, but also by a generalized economic-environmental risk score.

For land-management simulation, the same logic applies to land-use alternatives:

$$LandScore_i^{(k)} = H_i^{(k)} \times \left[w_c \times C_i{}'^{(k)} + w_{env} \times E_i{}'^{(k)} + w_{acc} \times A_i{}'^{(k)} + w_{risk} \times R_i{}'^{(k)} + w_{inst} \times I_i{}'^{(k)} - P_i^{(k)}\right] \backslash hfill(2.71)$$

, where:

- LandScorei^(k) - score of parcel or land-use alternative i;
- Hi^(k) - hard feasibility mask;
- Ci'^(k) - normalized cost score;
- Ei'^(k) - environmental score;
- Ai'^(k) - accessibility score;
- Ri'^(k) - risk score;
- Ii'^(k) - institutional feasibility score;
- Pi^(k) - soft penalty.

For monitoring simulation, the intervention priority can be expressed as:

$$Priority_i^{(k)} = w_s \times Stress_i^{(k)} + w_y \times YieldRisk_i^{(k)} + w_w \times WaterDeficit_i^{(k)} + w_c \times CostScore_i^{(k)} + w_q \times Q_{data,i}^{(k)}\backslash hfill(2.72)$$

, where:

- Priorityi^(k) - intervention priority of field zone i;
- Stressi^(k) - crop-stress indicator;
- YieldRiski^(k) - expected yield-loss risk;
- WaterDeficiti^(k) - water deficit;
- CostScorei^(k) - normalized intervention cost score;
- Qdatai^(k) - data quality score.

Table 2.26 Integration of simulation with previous methodological components

Model component	Input to simulation	What is recalculated in each iteration	Output
Adapted CBA	Costs, benefits, discount rate, adoption cost, data cost	NPV, EBCR, payback, avoided cost	Financial-efficiency distribution
MCDA	Criteria, weights, normalized indicators, constraints	Alternative ranking, weighted scores	Ranking robustness
Shadow pricing	Carbon price, restoration cost, delay-loss rate, risk probability	Environmental and temporal shadow values	Shadow-value distribution
Routing	Road graph, fuel price, risk, service windows, hard masks	Route plan, travel time, cost, feasibility	Operational performance distribution
Monitoring	EO/IoT/UAV availability, thresholds, weather, crop risk	Intervention priority, detection delay, avoided loss	Monitoring-value distribution
Land management	Parcel data, restrictions, ecological sensitivity, legal feasibility	Land-use suitability and conflict risk	Spatial-governance resilience
Data reliability	Sensor uptime, cloud cover, data latency, source authority	Confidence-adjusted benefits and scores	Data-resilience profile

Source: prepared by the authors.

Simulation results should be presented in a way that supports decision-making. The researcher should not only report average values. It is necessary to report ranges, probabilities, and risk indicators. This is especially important for practical users: farms, cooperatives, local authorities, investors, and policymakers.

A minimum simulation output package should include:

1. baseline result;
2. stress result;
3. sustainability-adjusted result;
4. expected value under Monte Carlo simulation;
5. low and high percentile results;
6. probability of economic efficiency;
7. probability of service-window feasibility;
8. restricted-zone violation count;
9. data-reliability score;
10. sensitivity ranking of variables.

The Kyiv routing study provides an example of such interpretation. In the controlled scenario run, the same job set and masks produced identical weekly distance but different direct logistics costs: 76,582 UAH in Baseline A, 86,106 UAH in Stress B, and 81,344 UAH in Sustainability-adjusted C. The stress scenario increased direct logistics cost by 12.44% relative to baseline, while sustainability-adjusted routing increased it by 6.22%. Feasibility remained at 95–96%, and restricted-edge violations remained zero.

Table 2.27 Example routing scenario output based on Kyiv pilot logic

KPI	Scenario A: Baseline	Scenario B: Stress	Scenario C: Sustainability-adjusted	Interpretation
Distance, km	1,240	1,240	1,240	Same job set and masks
Direct logisticscost, UAH	76,582	86,106	81,344	Strong fuel-cost sensitivity
Average cost per km, UAH/km	61.76	69.44	65.60	Stress increases unit logisticscost
Total travel time, h	89.61	88.58	88.58	Tactical re-weighting protects time
CO_2e, kg	1,116.3	1,116.3	1,116.3	Stable under uniform emission factors
Feasibility, % jobs within windows	96%	95%	96%	Service-window feasibility remainshigh
Restricted-edge violations	0	0	0	Hard masks enforce compliance
Direct cost delta vs A	-	+12.44%	+6.22%	Stress and sustainability scenarios increase cost differently
Time delta vs A	-	−1.15%	−1.15%	Time performance remainsprotected
CO_2e delta vs A	-	0.00%	0.00%	Requires differentiated fleet/corridors for emission variation

Source: adapted from the Kyiv routing simulation results.

Monte Carlo simulation produces a distribution of possible outcomes, but the researcher must also explain why the outcomes change. Sensitivity analysis identifies which variables have the strongest influence on the result. This is essential for practical recommendations. If the model is most sensitive to fuel prices, then route optimization and fuel risk management become priorities. If it is most sensitive to yield response, then agronomic validation becomes more important. If it is most sensitive to sensor reliability, then system maintenance and redundancy become key.

Sensitivity can be calculated through several methods. The simplest method is a one-way sensitivity analysis, in which one variable is varied while the others remain fixed. A more advanced approach uses correlation or regression between sampled inputs and model outputs.

A simple sensitivity coefficient can be expressed as:

$$SC_x = \frac{\frac{\Delta Y}{Y_{base}}}{\frac{\Delta X}{X_{base}}} \backslash hfill(2.73)$$

, where:

- SC_x - sensitivity coefficient for variable x;
- ΔY - change in output;
- Y_{base} - baseline output;
- ΔX - change in input variable;
- X_{base} - baseline input variable.

A correlation-based sensitivity measure can be expressed as:

$$\rho_{x,Y} = Corr(X,Y) \backslash hfill(2.74)$$

, where:

- $\rho_{x,Y}$ - correlation between input X and output Y.

For scenario interpretation, the most important sensitivity outputs are:

- sensitivity of NPV to fuel price;
- sensitivity of EBCR to input savings;
- sensitivity of shadow-adjusted benefit to carbon price;
- sensitivity of feasibility to road closures;

- sensitivity of monitoring value to sensor uptime;
- sensitivity of yield protection to crop price and delay-loss rate;
- sensitivity of land-management value to restriction accuracy and conflict probability.

The simulation procedure must be transparent enough to be repeated by other researchers and practical users. For this reason, the monograph should present a clear algorithm that can be applied to each empirical case.

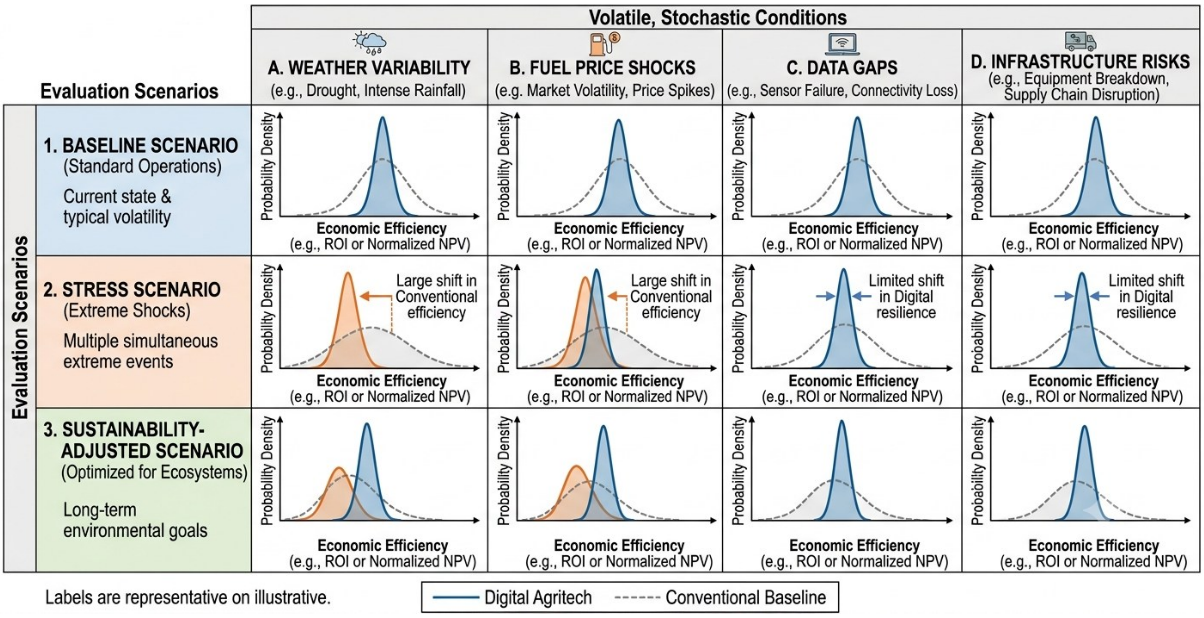


Figure 2.9 Sample visualization showcase of the scenario-based stress testing matrix under stochastic conditions

Table 2.28 Algorithm for simulation and scenario-based evaluation

Step	Action	Practical explanation	Output
1	Define the evaluation object	Digital land system, monitoring system, routing system, or integrated platform	Simulation object
2	Define baseline model	Establish standard costs, benefits, data, and operational conditions	Baseline scenario
3	Define scenario set	Build stress, sustainability, and combined scenarios	Scenario register
4	Select output indicators	NPV, EBCR, cost, CO_2e, feasibility, violations, data reliability	KPI list
5	Identify uncertain variables	Fuel, yield, input prices, weather, sensors, roads, restrictions, shadow prices	Uncertainty register
6	Assign distributions	Choose triangular, normal, beta, Bernoulli, categorical, or empirical distributions	Distribution table
7	Generate simulation samples	Run N iterations	Sample set
8	Recalculate CBA	Compute NPV, EBCR, payback, avoided costs	CBA output distribution
9	Recalculate MCDA	Update criteria, weights, constraints, rankings	Ranking distribution
10	Recalculate shadow values	Update CO_2e, delay, ecological damage, risk values	Shadow-value distribution
11	Recalculate operational decisions	Route plan, intervention plan, land-use alternative	Decision output
12	Calculate resilience indicators	Probability of efficiency, feasibility, compliance, data reliability	Resilience profile

Step	Action	Practical explanation	Output
13	Conduct sensitivity analysis	Identify dominant variables	Sensitivity report
14	Interpret results	Determine the conditions under which the tool remains efficient	Decision recommendation

Source: prepared by the authors.

The simulation methodology developed in this subsection will be applied differently in each empirical case study. In Case Study I, digital land management and cadastral systems should be tested under conditions of incomplete data, changing restrictions, different land-use priorities, and variable restoration or conflict costs. The main simulation outputs should include land-use suitability, the probability of legal feasibility, avoided-conflict cost, and sensitivity to data completeness. This is consistent with the author's previous information-system modeling logic, which holds that the economic assessment of land objects requires geographical, spatial, financial, taxation, assessment-output, and ecological data.

In Case Study II, IoT telemetry and environmental monitoring should be tested under uncertain sensor uptime, cloud cover, UAV availability, weather variability, crop price, intervention delay, and input price. The main simulation outputs should include expected yield protection, the range of input savings, avoided delay loss, data reliability, and the probability that the monitoring system remains economically justified.

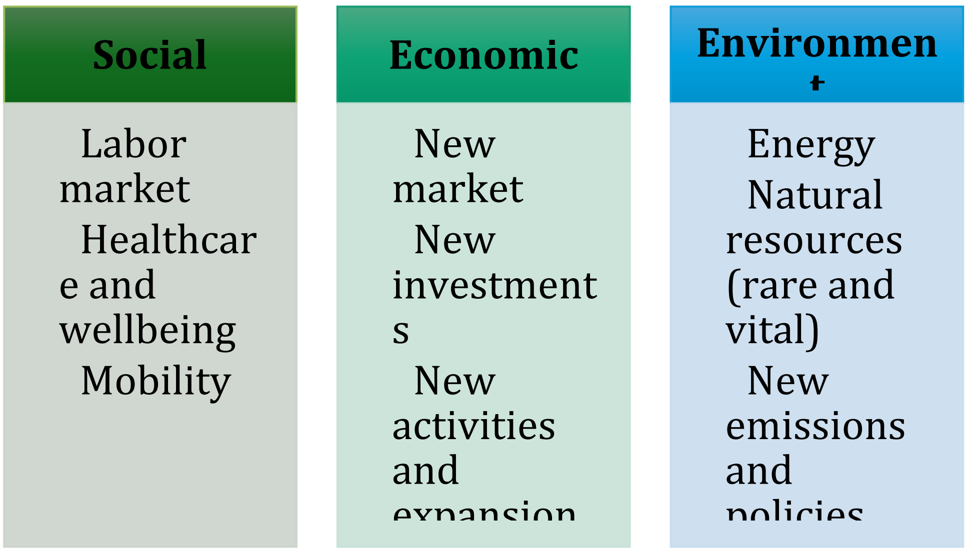


Figure 2.10 Three important components of the system and methodology framework

In Case Study III, spatio-temporal routing should be tested under fuel price volatility, road restrictions, safety risks, weather-related delays, heterogeneous fleet parameters, and service-window constraints. The main simulation outputs should include cost distribution, travel-time distribution, CO_2e range, service-window feasibility, restricted-edge violations, and resilience index. The Kyiv routing study already provides the methodological prototype for this block by showing how scenario testing can compare Baseline, Stress, and Sustainability-adjusted routing logic under shared spatial masks and job sets.

Table 2.29 Simulation application by empirical case study

Case study	Main simulation object	Main uncertainties	Main outputs	Recommended simulation method
Case I: Digital land management	Land-use alternatives, parcels, restriction layers	Data completeness, legal restrictions, restoration cost, conflict probability	Suitability robustness, avoided conflict cost, compliance probability	Scenario MCDA + Monte Carlo
Case II: IoT monitoring	Field zones, sensor networks, intervention decisions	Sensor uptime, cloud cover, UAV availability, weather, crop price, delay-loss rate	Yield protection, input savings, avoided delay loss, data reliability	Monte Carlo + stress testing
Case III: Routing	Routes, fleet schedules, service windows	Fuel price, road closures, risk, travel time, fleet parameters, weather	Cost, CO_2e, feasibility, violations, resilience index	Scenario optimization + Monte Carlo
Integrated platform	Combined land-monitoring-routing system	All above variables plus interoperability and institutional readiness	System-level EBCR, resilience index, policy audit metrics	Integrated simulation framework

Source: *prepared by the authors.*

Simulation and scenario-based evaluation complete the methodological framework of this monograph. Adapted CBA determines whether digital tools create economic value. MCDA structures decisions across heterogeneous criteria. Shadow pricing translates environmental and temporal effects into monetary terms. Simulation tests whether these results remain valid under uncertainty.

The main methodological contribution of this subsection is the transition from static evaluation to resilience-oriented evaluation. A digital environmental tool should not be considered economically efficient solely because it produces a positive result under a single fixed assumption. It should be considered economically efficient when it maintains acceptable financial, environmental, operational, and institutional performance across a range of plausible conditions.

For agriculture, this is especially important. Production decisions depend on weather, prices, biological processes, logistics, land access, machinery, labor, and data. For Ukraine, the need for simulation is even stronger because agricultural operations in peri-urban territories are exposed to wartime and post-war uncertainty, infrastructure restrictions, fuel volatility, and changing institutional conditions. Therefore, the economic-efficiency framework must include not only point estimates, but also probability, sensitivity, stress resistance, and resilience.

The final methodological position of this subsection is as follows: digital tools for sustainable environmental management should be evaluated through scenario comparison and stochastic simulation, because only this approach can demonstrate whether their economic benefits are stable, reproducible, and resilient under real-world uncertainty. This prepares the methodological foundation for the following empirical chapters, where digital land management, IoT telemetry and environmental monitoring, and spatio-temporal routing will be tested not only as technical systems, but as practical economic instruments for sustainable agricultural and peri-urban governance.

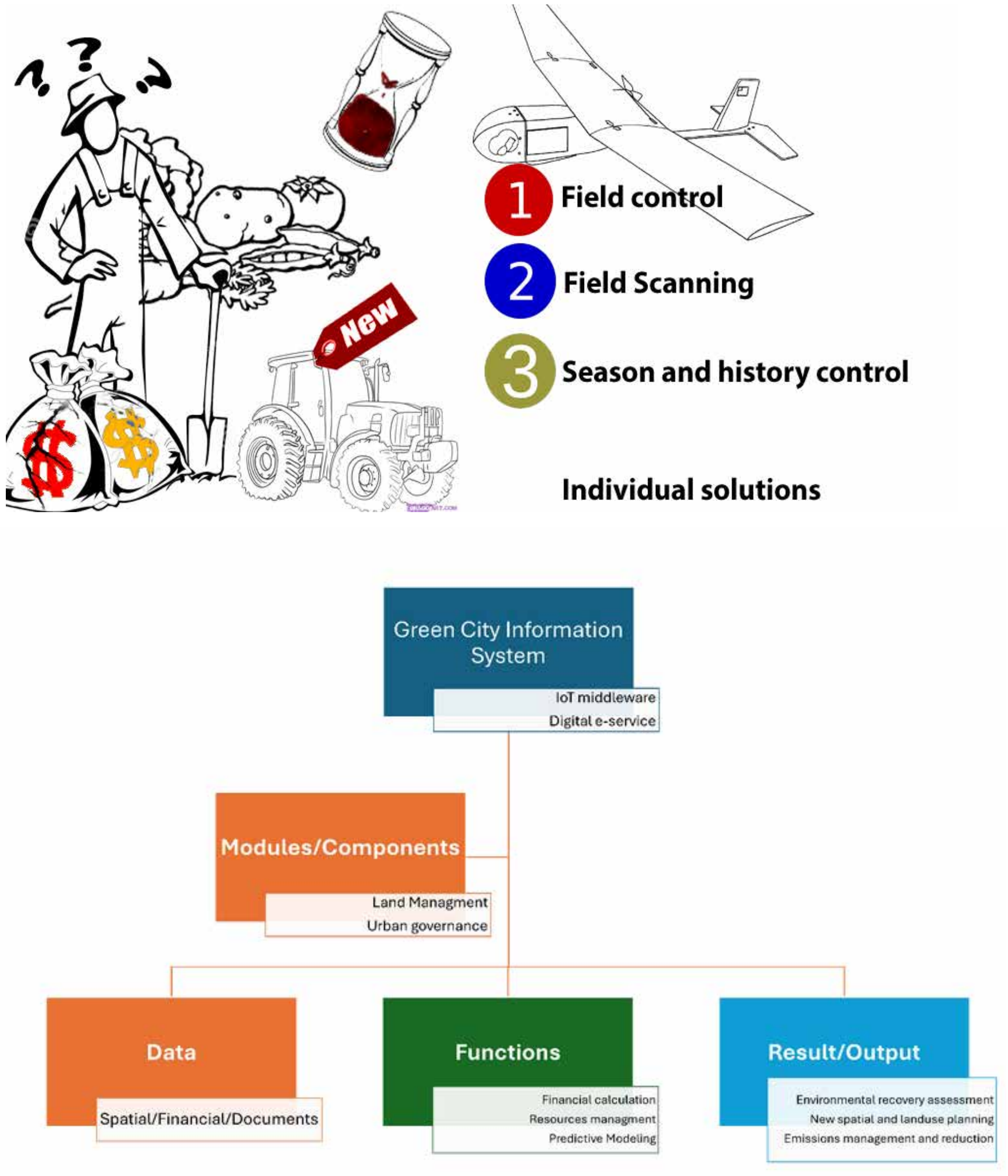


Figure 2.11 Simulation system and its technical and software components

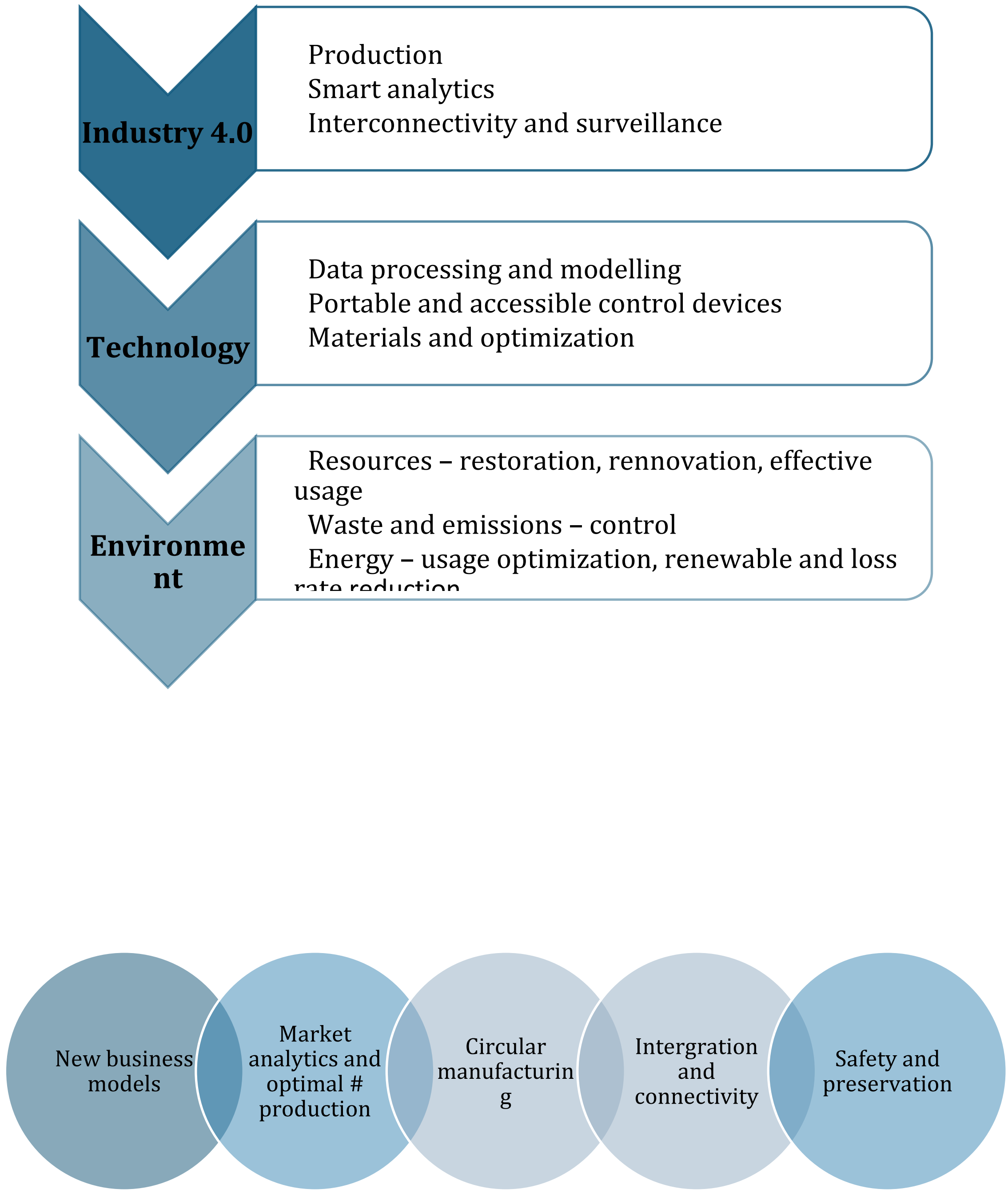


Figure 2.12 Industry 4.0 implications for the study

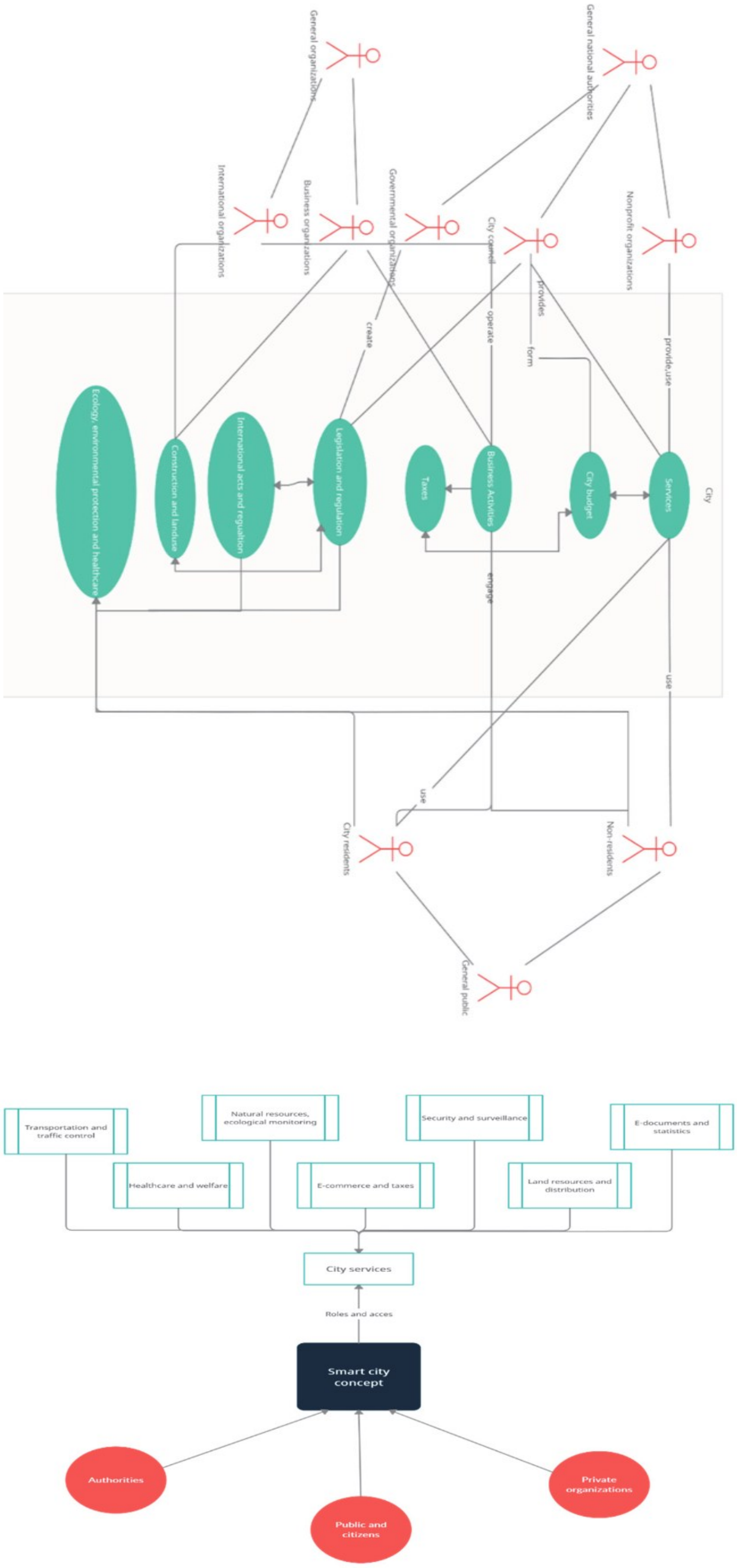


Figure 2.13 Urban and land governance system

CHAPTER 3

Case Study I - Economic Efficiency of Digital Land Management and Cadastral Systems

3.1. Digital Land Administration as Spatial-Economic Infrastructure: Dynamic Registries, FAIR Principles, and OGC-Aligned Data Services

This chapter develops the first empirical case study in the monograph by examining digital land management and cadastral systems as a specific class of digital environmental management infrastructure. The purpose of the chapter is not to repeat the methodological framework set out in Chapter 2, nor to anticipate the operational monitoring and routing cases that follow. Its task is narrower and more fundamental: to show how the economic efficiency of environmental management begins before any field sensor is installed, before any satellite anomaly is interpreted, and before any route is optimized. It begins with the quality of the official spatial-legal representation of land.

The central proposition of the chapter is that a digital cadastre is not merely a register of parcels. It is a spatial-economic infrastructure that converts land from a physically continuous and institutionally fragmented resource into a governable object of rights, obligations, restrictions, valuations, and decisions. In this sense, digital land administration is not a passive repository. It is enabling technology for agricultural investment, environmental compliance, land-market transparency, fiscal administration, infrastructure development, and peri-urban spatial allocation. Its economic effect is not exhausted by the price of cadastral extracts or by the administrative cost of registration. Its deeper value lies in reducing uncertainty, compressing verification time, preventing spatial conflicts, formalizing environmental restrictions, and enabling the repeated reuse of authoritative geodata by actors who may never interact directly with the cadastral authority.

The Ukrainian case is especially significant because the State Land Cadastre of Ukraine has evolved under conditions that are institutionally and politically more demanding than those of ordinary administrative modernization. It has had to support land reform, agricultural land markets, decentralization, spatial planning reform, wartime risk management, digital public services, and preparation for alignment with the European Union acquis. The added materials prepared for this monograph characterize the Ukrainian cadastre as a sovereign geospatial platform rather than a narrow land-record system: by 2030, it is expected to function as the spatial core connecting land parcels, buildings, addresses, rights, restrictions, valuation, taxation, planning regimes, and natural-resource cadastres (National University of Life and Environmental Sciences of Ukraine [NULES], 2026). This framing is consistent with the contemporary international understanding of land administration as infrastructure for sustainable development rather than as a technical registry function (Williamson et al., 2010; Enemark et al., 2014).

The European dimension is equally important. The EU has not built a single supranational cadastre. However, it has created a dense regulatory and technological environment in which public geodata must be interoperable, reusable, documented, and increasingly accessible through APIs. INSPIRE created the legal architecture for environmental spatial-data infrastructure; the Open Data Directive and the High-Value Datasets Regulation strengthened the expectation that geospatial and earth-observation data should be published for reuse; the Interoperable Europe Act translated interoperability into a general public-sector obligation; and the CAP relies on geospatial administration through IACS, LPIS, geospatial aid applications, and area monitoring. For Ukraine, EU integration therefore does not require copying a single cadastral model. It requires building a cadastral ecosystem whose data semantics, service interfaces, metadata, access rules, and evidentiary functions can interact with European systems.

The chapter's analytical logic is organized around three questions. First, how does digital land administration become spatial-economic infrastructure when cadastral objects are transformed into dynamic, FAIR, and OGC-aligned data services? Second, how can automated spatial constraints convert legal and ecological restrictions from after-the-fact administrative checks into ex ante decision rules in land-use planning? Third, what efficiency metrics allow digital land governance to be evaluated in terms of transaction-cost reduction, conflict prevention, compliance, and peri-urban allocation? Together, these questions form the first empirical link in the monograph's broader argument: digital environmental management is economically efficient only when the spatial base of decision-making is official, interoperable, auditable, and institutionally trusted.

Table 3.1. Analytical positioning of Chapter 3 within the monograph

Analytical boundary	Included in Chapter 3	Deliberately left to later chapters
Core object	Digital land administration, cadastral systems, parcel-level geodata, restrictions, zoning, valuation attributes, service interfaces.	IoT telemetry, crop stress monitoring, UAV diagnostics, spatio-temporal routing, fleet optimization.
Primary efficiency mechanism	Reduced information friction, lower transaction costs, conflict prevention, compliance-by-design, improved peri-urban allocation.	Input-use optimization, yield protection, fuel savings, and service-window feasibility.
Environmental connection	Spatial encoding of protected areas, water-protection zones, land-use regimes, functional zones, degraded or sensitive territories, and legal restrictions.	Real-time ecological monitoring, intervention thresholds, and operational emissions modeling.
EU alignment issue	INSPIRE, High-Value Datasets, Interoperable Europe, LADM, OGC APIs, IACS/LPIS compatibility.	Earth-observation processing chains, Sentinel-based agronomic analytics, and route-level emissions adjustment.
Ukrainian policy relevance	Transformation of the State Land Cadastre into the spatial core of real estate, natural-resource governance, recovery planning, fiscal administration, and agricultural support.	Farm-level decision support, operational monitoring, logistics under wartime constraints.

The transition from cadastral record-keeping to digital land administration should be understood as a change in the economic ontology of land information. In a traditional cadastral model, the state records an object that already exists in legal and physical space. In a digital infrastructure model, the cadastral system actively constitutes the informational conditions under which land can be exchanged, planned, valued, protected, financed, taxed, restored, and monitored. The economic role of the cadastre is therefore infrastructural because its benefits are realized not only in the registration transaction itself but in the many downstream decisions that depend on official parcel data.

Classical land-administration theory already moved beyond the narrow conception of the cadastre as a map-and-title archive. Williamson et al. (2010) define land administration as the processes by which information about land tenure, value, use, and development is implemented, managed, and disseminated. This definition is important because it places the cadastre at the intersection of property rights, land markets, spatial planning, taxation, and environmental governance. Enemark et al. (2014) then extend this logic through the fit-for-purpose approach: land-administration systems should be designed around societal needs, scalability, affordability, and usability rather than around overly rigid technical ideals. However, the digital phase adds further requirements. Fit-for-purpose systems must now be fit for machine use, cross-register linkage, legal traceability, environmental analytics, and service reuse.

A digital cadastre creates economic value through three infrastructural properties. The first is epistemic availability: the capacity to make spatial-legal facts knowable without repeated manual reconstruction. The second is legal reliability: the capacity to make those facts authoritative enough to support transactions, compensation, land-use restrictions, subsidies, permits, and dispute resolution. The third is operational calculability: the capacity to translate official geodata into inputs for engineering, fiscal, environmental, and agricultural workflows. A cadastral system that lacks any one of these properties remains institutionally incomplete. A visually attractive map without legal reliability does not reduce risk; a legally authoritative register without spatial serviceability does not support modern analytics; a data service without traceable sources and versioning cannot support compliance.

This is why the Ukrainian State Land Cadastre should be evaluated not only as a legal information system but also as a productive data infrastructure. The added engineering-economic study prepared for this monograph states that engineering projects in Ukraine require parcel geometry, intended use, rights, easements, restrictions, valuation attributes, and administrative location before construction begins, because these variables affect siting, corridor design, land acquisition, compensation, and schedule risk (Martyn et al., 2026). The same paper estimates that by the end of 2024, the cadastre contained 44.9 million hectares, or 74.4 percent of Ukraine's territory, including 33.0 million hectares of agricultural land, and that by early 2026, the system contained more than 26 million registered parcels (Martyn et al., 2026). The point is not only scale. Scale matters because a cadastral platform becomes economically powerful when a high fixed cost of system creation is spread across many repeated decisions.

The strategic framework on the cadastre of Ukraine to 2030 formulates this shift in explicit state-capacity terms. It argues that Ukraine should move from a model of a register of land-parcel information to a model of a spatial core for real estate and natural resources, linking land parcels, buildings, addresses, rights, restrictions, valuation, tax status, and planning decisions (NULES, 2026). This argument has direct economic implications. The more strongly the cadastral number, parcel geometry, building identifiers, address data, rights records, functional zoning, and valuation information are connected, the lower the cost of verifying an object for lending, investment, taxation, planning, environmental control, insurance, compensation, and recovery. Fragmentation increases the cost of search; integration lowers the cost of certainty.

The Ukrainian case also shows that digitalization is not equivalent to scanning paper. The 2030 vision document rightly warns that the most dangerous simplification is to reduce digitalization to scanned documents or online forms. True cadastral digitalization begins when a legally significant action produces a structured geospatial dataset, metadata, attributes, change logs, electronic signatures, timestamps, and machine-verifiable links to other registers (NULES, 2026). This distinction is central for economic efficiency. A scan preserves evidence but does not automatically become a decision-ready object. A structured parcel dataset can be validated, joined, queried, versioned, audited, and reused. The economic transition is from document circulation to data circulation.

The dynamic-registry concept follows from this logic. A static cadastre describes the current state of parcels; a dynamic cadastre records the life cycle of spatial-legal objects. It stores not only what the parcel is, but how it came into being, what version of geometry was used, which restrictions applied at the time of a decision, which source document created or changed the object, who acted, and how the object relates to adjacent parcels, planning regimes, easements, protected areas, valuation zones, buildings, and infrastructure networks. Dynamicity, therefore, means more than frequent updating. It means institutional memory encoded in a computable form.

Versioning is particularly important in transition economies because uncertainty often arises not from the absence of data but from the coexistence of several competing data histories. A parcel boundary may exist in a paper archive, a local GIS, a cadastral extract, a project plan, an orthophoto interpretation, a court case, or a land-use document. Without version control, the state cannot reliably explain why one representation is authoritative. Without provenance, the user cannot know whether a restriction is current, draft, historical, suspended, or superseded. Without temporal attributes, an investor cannot reconstruct which regime applied at the date of purchase or design. The economic cost of these gaps is not abstract: it manifests as due diligence fees, field visits, negotiation delays, redesign, disputes, and risk premiums.

In European terms, the digital cadastre must be read through the lens of spatial data infrastructure. INSPIRE was created to enable the sharing of environmental spatial information among public-sector organizations, public access to spatial information, and better cross-boundary policymaking. Its legal significance for cadastral modernization is that it treats spatial data as policy infrastructure rather than merely a technical asset. The High-Value Datasets Regulation strengthens this logic by identifying geospatial data, earth observation and environmental data, meteorological data, statistics, company information, and mobility data as categories with high socio-economic potential. The Interoperable Europe Act further shifts the focus from isolated digital services to cross-border and cross-sector interoperability of public-sector systems. For Ukraine, these frameworks imply that cadastral modernization cannot be complete if the cadastre remains a closed departmental database.

FAIR principles provide useful conceptual vocabulary for this transition. Originally formulated for scientific data management, the FAIR principles - findability, accessibility, interoperability, and reusability - are highly relevant to cadastral systems because the value of land data increases when users can discover, access, combine, and reuse it under clear conditions (Wilkinson et al., 2016). In land administration, however, FAIR cannot be interpreted as unrestricted openness. Cadastral data contains personal, security-sensitive, fiscal, and strategic information. Therefore, a FAIR cadastre is not necessarily an entirely open cadastre. It is a system in which each data class has defined metadata, access regimes, provenance, licensing, machine-readable semantics, and lawful reuse rules. Public base layers may be open; personal ownership details may require authentication; security-sensitive layers may require role-based access; analytical services may be provided through controlled APIs.

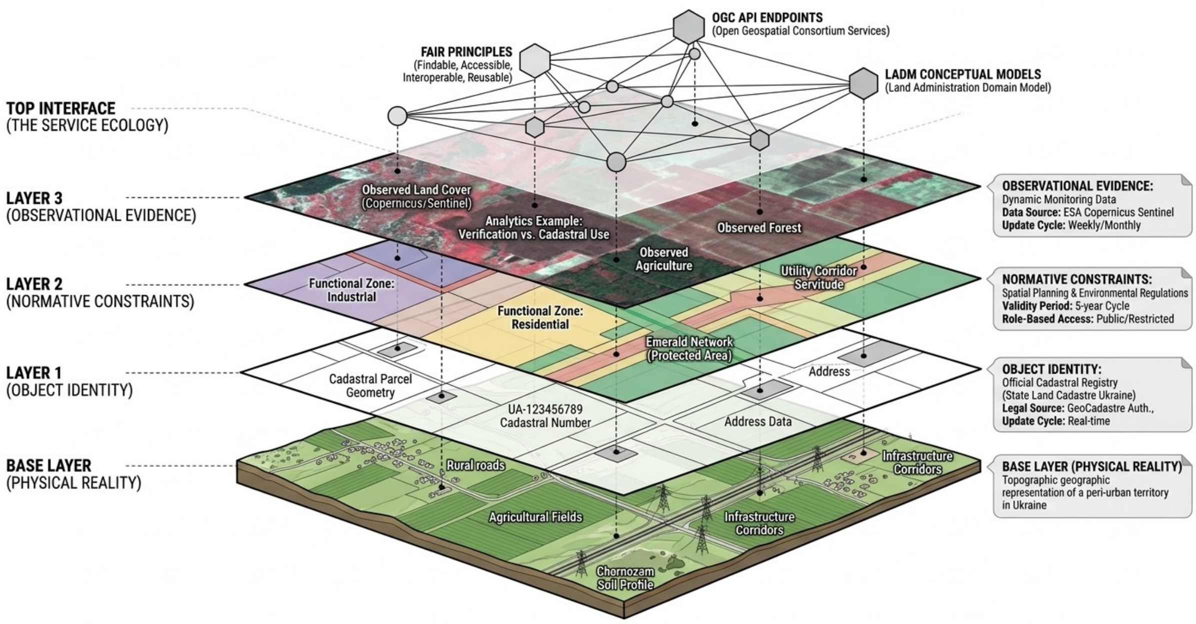


Figure 3.1 Digital Cadastre as an isometric multilayered decision system

This distinction is especially important for Ukraine under wartime and post-war conditions. The temporary restriction of some geospatial services during security threats does not invalidate the logic of openness; it demonstrates that modern cadastral infrastructure must support differentiated access. A mature cadastral system should not choose between total openness and total closure. It should support public transparency, where disclosure strengthens trust; controlled access, where legitimate use requires identification; and protected access, where national security or personal-data protection requires limitation. This layered-access model is economically efficient because it preserves the utility of cadastral data while reducing exposure to unacceptable risks.

OGC-aligned data services are the technical counterpart of the FAIR logic. Traditional download portals and map viewers are insufficient for high-frequency, cross-sector use. Engineering, agrarian, municipal, fiscal, and environmental systems require service interfaces capable of delivering object-level geospatial data, metadata, filters, coordinate reference handling, and stable identifiers. OGC API - Features is particularly relevant because it defines RESTful interfaces for discovering, querying, and retrieving geospatial feature data using modern Web API patterns. In practical terms, a parcel, a restriction zone, a valuation zone, or a functional zone should be accessible not merely as an image on a map but as a structured feature with attributes, provenance, geometry, and machine-readable relations.

The Land Administration Domain Model is equally important because it supplies a conceptual grammar for relating parties, rights, restrictions, responsibilities, spatial units, and source documents (Lemmen et al., 2015; ISO, 2024). The updated ISO 19152-1:2024 extends the land-administration domain toward georegulation, which is particularly relevant for Chapter 3. A modern cadastre is no longer only about ownership and parcel geometry. It must represent restrictions, responsibilities, planning regimes, natural-resource constraints, utility corridors, environmental zones, and the legally significant spatial facts that determine what can and cannot be done with land. This is why the Ukrainian vision of the cadastre as the future spatial core of real estate and natural resources is not merely a national aspiration; it is aligned with the direction of international standardization.

The Ukrainian State Land Cadastre already contains several features that can support this infrastructural transformation. It operates as a single state geoinformation system; it has a public map history; it provides electronic services; it supports extraction and cadastral procedures; it is connected to spatial planning reform; it has begun incorporating functional zones; and it is increasingly linked to public monitoring and mass valuation. The official reporting cited in the added materials notes the growth of electronic services, the registration of restrictions and functional zones, the development of mass land valuation, and the digitization of archival land-management documentation (NULES, 2026; StateGeoCadastre, 2026). These are not isolated administrative improvements. Together, they indicate a shift from cadastral information as a static record to a reusable service environment.

However, the case also reveals unresolved design tensions. The first is the tension between legal conclusiveness and analytical usability. Cadastral data must be authoritative enough to support rights and obligations, but flexible enough to be reused in analytics. The second is the tension between openness and security. Public access increases transparency, but wartime conditions and personal-data protection require restrictions. The third is the tension between centralization and local relevance. A national cadastre ensures uniformity, but communities need localized analytical services for planning, taxation, and recovery. The fourth is the tension between good public provision and sustainable financing. Basic cadastral data should support public trust, while value-added services may require a cost-recovery model. The 2030 vision recognizes this by proposing that core public information remain open while high-value cadastral analytics, historical data, SLA-based API access, mass extracts, and verification services can support the financing of the service and analytical layer (NULES, 2026).

The economic-efficiency implication is that the cadastre should not be evaluated solely based on the administrative costs of cadastral maintenance. A narrow cost-center view would treat the cadastre as a budget burden. An infrastructure view treats it as a public asset whose value is realized through reuse. If the same parcel geometry supports land-bank management, irrigation planning, servitude design, compensation, taxation, environmental compliance, mortgage underwriting, municipal planning, and post-war recovery, then the marginal value of the dataset grows with each additional legally meaningful use. The primary efficiency question is therefore not whether the cadastre is inexpensive to operate, but whether it reduces the total cost of land-related decisions across the economy.

Table 3.2. From cadastral record to spatial-economic infrastructure

Layer of transformation	Conventional registry function	Digital infrastructure function	Economic effect
Object identity	Assign a cadastral number and record parcel geometry.	Maintain a stable spatial identifier linking parcel, building, address, rights, restrictions, valuation, and planning regime.	Lower search costs and fewer object-matching errors across registers.
Data structure	Store records and documents for administrative use.	Produce structured geodata, metadata, source links, timestamps, and change logs.	Lower cost of verification and reuse in engineering, fiscal, agricultural, and compliance workflows.
Access model	Provide extracts and map viewing.	Provide role-based access, public layers, controlled layers, APIs, and auditable requests.	Higher service throughput while preserving security and personal data protection.
Regulatory content	Record selected restrictions as attributes or documents.	Represent restrictions, responsibilities, functional zones, servitudes, environmental regimes, and valuation zones as computable spatial objects.	Earlier detection of infeasible decisions and reduced conflict exposure.
Temporal logic	Show the current state of parcel information.	Maintain a versioned life cycle of parcel geometry, status, restrictions, valuation, and source documents.	Lower evidentiary uncertainty in disputes, compensation, recovery, and investment due diligence.
Service ecology	Operate as a departmental information system.	Function as part of a national spatial-data infrastructure aligned with INSPIRE, LADM, OGC APIs, and FAIR principles.	Reduced duplication and greater cross-sector data productivity.

Table 3.3. Selected empirical signals of cadastral digitalization in Ukraine

Indicator	Reported value or event	Interpretation for economic efficiency
Start of the modern State Land Cadastre	The State Land Cadastre began functioning as a unified state geoinformation system on 1 January 2013.	Created a national parcel-based spatial layer for land markets, public services, planning, and land-related investment.
Registered land coverage	By the end of 2024, 44.9 million ha, or 74.4 percent of the country, were recorded in the cadastre, including 33.0 million ha of agricultural land.	extensive coverage increases the return on fixed digital-infrastructure investment and supports agricultural decision-making at scale.
Registered parcel inventory	By early 2026, public reporting indicated that more than 26 million registered parcels existed.	High parcel density makes object-level verification, cross-register linkage, and service reuse economically meaningful.
Functional zones in the cadastre	In 2025, Ukraine first entered information on functional zones into the cadastre based on comprehensive spatial development plans.	Planning restrictions are beginning to move from documents into official, computable geodata.
Normative monetary valuation services	Public reporting for 2025 indicates record-scale issuance of extracts on normative monetary valuation.	Mass digital service throughput reduces administrative friction for taxation, rent, compensation, and investment appraisal.

Indicator	Reported value or event	Interpretation for economic efficiency
Digitization of land-management archives	The 2030 vision reports millions of digitized copies of land-management and valuation documentation and calls for a national repository of spatially referenced archives.	Historical documents serve as evidence assets for dispute prevention, recovery, and the reconstruction of spatial-legal histories.

3.2. Automated Spatial Constraints in Land-Use Planning: Hard Masks, Soft Penalties, and Compliance-Aware Allocation

The second layer of economic value in digital land management arises when cadastral and planning data are used not merely to describe parcels, but to constrain decisions before costly errors occur. Environmental management fails when restrictions are discovered late - after a parcel has been purchased, an investment project has been designed, a route has been selected, an irrigation network has been planned, a construction permit has been prepared, or a subsidy claim has been submitted. Digital land administration becomes economically efficient when it shifts compliance from ex post correction to ex ante prevention.

Land-use planning is a normative activity expressed in spatial form. It allocates permitted, prohibited, conditional, and discouraged use across territory. In paper-based or weakly interoperable systems, however, these spatial norms are often separated from the operational decisions that they should control. A protected area may exist in one map, a water-protection zone in another, a cultural-heritage restriction in a local plan, a servitude in a legal document, a mining or military restriction in a separate database, and a parcel boundary in the cadastre. The user must manually reconstruct the regulatory surface. Economic losses arise not because restrictions do not exist, but because they are not available as official, machine-verifiable spatial constraints at the time of decision.

Automated spatial constraints change this logic. A hard mask removes an alternative from the feasible set because it conflicts with a binding rule: a legally protected area, a water-protection zone, a military exclusion zone, an unresolved parcel status, a dangerous contamination area, a strictly prohibited land-use category, a registered easement incompatible with the proposed use, or another non-negotiable restriction. A soft penalty does not remove the alternative. However, it reduces its attractiveness because the spatial condition creates costs, risks, risks, delays, environmental pressures, or institutional uncertainty: distance from infrastructure, fragmented land-bank structure, moderate ecological sensitivity, uncertain archive quality, lower road accessibility, possible conflict with neighboring land uses, or a higher probability of public opposition.

The conceptual distinction between hard masks and soft penalties is crucial because environmental and land-use governance should not pretend that all values are commensurable. Some restrictions are legal thresholds and cannot be traded against economic gain. Other spatial conditions are economically relevant but negotiable. Treating everything as a soft trade-off makes the model legally unsafe; treating everything as a hard prohibition makes planning rigid and inefficient. Compliance-aware allocation requires a hierarchical reading of spatial constraints: first, legality; then, ecological and social risk; and finally, economic optimization. In other words, the cadastre should not only answer where a parcel is; it should answer whether a proposed action can be considered at all, and under what penalty or condition it should be evaluated.

This is where the Ukrainian transition to functional zones becomes important. The 2030 cadastral vision proposes incorporating functional zones, restrictions, and planning layers into the State Land Cadastre as a decisive step toward a system in which land-use decisions are linked to official spatial regimes (NULES, 2026). Official reporting in 2025 on the first entry of functional-zone information into the cadastre, based on a comprehensive community spatial development plan, illustrates this shift. The significance is not only administrative. Functional zoning in the cadastre makes planning rules computable. Once a functional zone has an official geometry, a source document, a legal status, and a temporal record, it can be used in automated pre-checks, investment due diligence, subsidy eligibility control, compensation planning, ecological compliance, and municipal development analytics.

The EU context reinforces this direction. INSPIRE's environmental spatial-data infrastructure does not merely encourage publication of maps; it requires metadata, harmonization, and services that allow environmental spatial information to be shared across public authorities. The CAP's geospatial administration demonstrates a related logic in the agricultural sector. IACS and LPIS do not function as ordinary cadastral systems; they are administrative-geospatial systems for eligibility, payment, control, and monitoring. The EU Area Monitoring System increasingly uses Sentinel-1 and Sentinel-2 data to support systematic satellite-based monitoring of agricultural parcels. For Ukraine, the policy challenge is to avoid creating a separate agricultural control geography that is disconnected from authoritative cadastral parcels. A more efficient strategy is to establish semantic and spatial bridges between the cadastral parcel, agricultural reference parcels, declared crop areas, restrictions, and remote-sensing evidence.

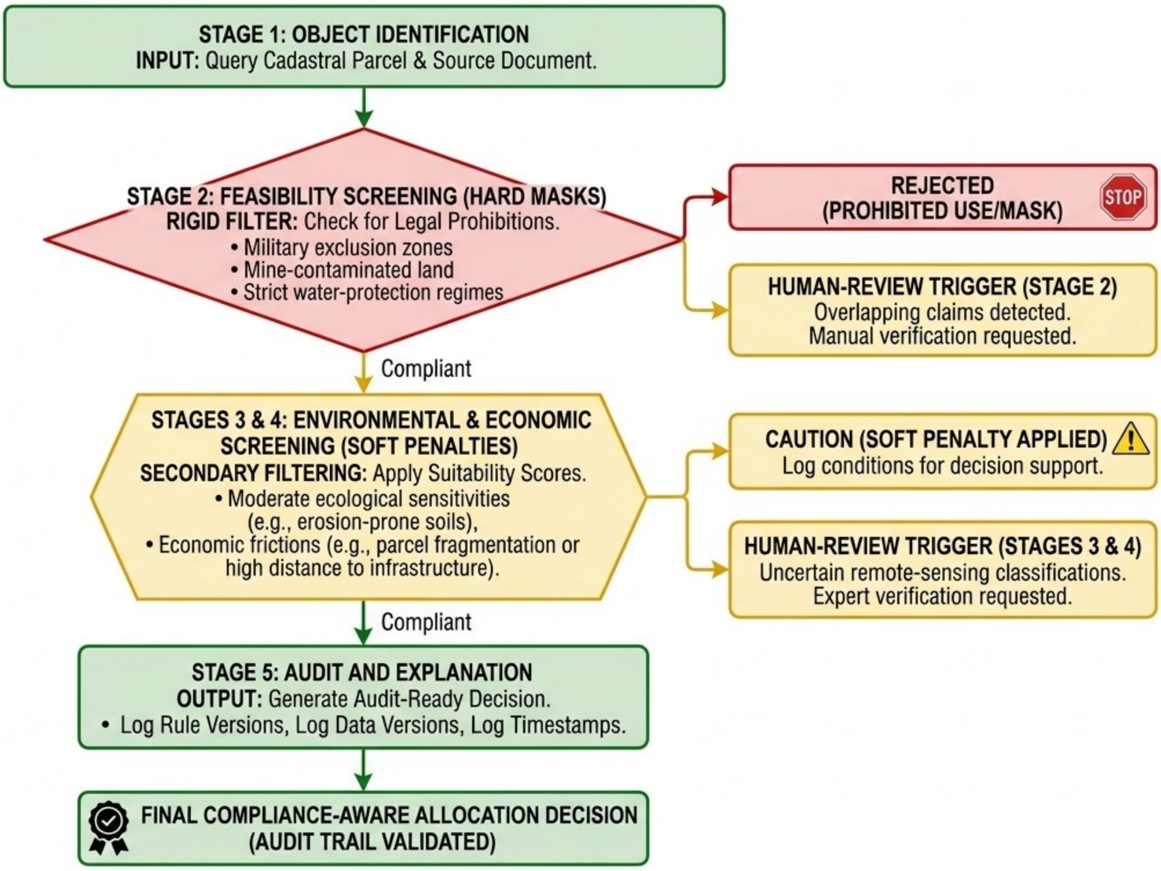


Figure 3.2 Automated Spatial Constraints in Land-Use Planning System Flowchart

The added article by Martyn, Trevoho, and Yevsiukov (2024) is directly relevant here. It argues that modernizing state control over land use and land protection in Ukraine should shift from manual inspection to the intensive use of remote-sensing information products to identify land-use violations. The authors note that remote-sensing data can support comparisons between intended land use and actual land cover, detect unauthorized deviations from land-management documentation, identify plowing of meadows, pastures, forest belts, and protective zones, verify crop structures, support subsidy control, and reveal shadow leasing. These functions are not developed in this chapter as a separate environmental-monitoring system; they are used here to show how cadastral constraints can become evidence-aware. A restriction layer becomes more effective when it can be periodically compared with observed land cover and land use.

The same article identifies a legal subtlety that is often underestimated: remote-sensing products used for legally significant purposes must be embedded in evidentiary procedures. Satellite data are technically powerful, but public authorities need rules for admissibility, provenance, quality, resolution, interpretation, and responsibility (Martyn et al., 2024). This is a key point for digital land governance. Automation does not remove law from administration. It requires the law to become more explicit, because automated checks must know which data source is authoritative, which rule is binding, which threshold is sufficient, and which actor is accountable for interpreting ambiguous evidence.

A compliance-aware cadastral system, therefore, requires a rule architecture rather than a simple map overlay. The first component is an official register of spatial norms: protected areas, water-protection zones, sanitary zones, cultural-heritage regimes, servitudes, functional zones, land-use categories, restrictions from planning documentation, and other legally significant regimes. The second component is a metadata and provenance layer: legal source, adoption date, authority, validity period, version, update cycle, and relation to other spatial objects. The third component is a rule engine that classifies each restriction as prohibitive, conditional, advisory, or risk-creating. The fourth component is a decision interface that explains not only the result of a check but the reason for it. The fifth component is an audit trail documenting the data and rule versions used at the time of the decision.

Such a system changes the economics of land-use planning. It reduces the cost of legal screening by automatically detecting preliminary infeasibility. It reduces the cost of environmental compliance by making protected or sensitive zones visible before intervention. It reduces the cost of dispute resolution because decisions can be reconstructed from versioned data and rules. It reduces corruption risk by replacing discretionary interpretation, where possible, with transparent, reproducible checks. It reduces investment risk because the user can identify constraints before project design becomes expensive. Most importantly, it changes the timing of knowledge. In land governance, early knowledge is cheaper than late knowledge.

The Ukrainian post-war and EU-integration context increases the importance of this timing effect. Recovery projects, infrastructure reconstruction, agricultural modernization, irrigation rehabilitation, renewable-energy siting, housing reconstruction, and community spatial planning will all involve land parcels with overlapping rights, restrictions, environmental risks, security constraints, and compensation requirements. A non-digital or weakly linked system pushes these constraints into later stages, where they become conflicts. A digital, compliance-aware cadastral system moves them into the first stage of site selection, where they are decision parameters.

Peri-urban territories are the most demanding testing ground for such systems. In and around Kyiv and other large Ukrainian cities, agricultural parcels, residential expansion, logistics infrastructure, industrial sites, green areas, forests, water bodies, roads, utility corridors, and local budgets interact within a compressed spatial field. Land that looks economically attractive for development may be environmentally sensitive; agriculturally valuable land may be fragmented by infrastructure; land suitable for logistics may trigger conflict with settlement expansion or green infrastructure; land with high fiscal potential may impose high external costs. Compliance-aware allocation does not solve all political conflicts, but it makes the spatial premises of decisions explicit.

In this chapter, compliance-aware allocation is understood not as a final automated choice but as a disciplined narrowing of the feasible decision space. The system first removes legally prohibited options, then ranks the remaining alternatives by risk and suitability, and finally presents the residual trade-offs to decision-makers. This is a different administrative philosophy from manual approval after project preparation. It is a shift from gatekeeping to governance by transparent spatial rules.

Figure 3.3 Digital Cadastre as spatial-economic infrastructure

The concept also clarifies how digital land management differs from general smart-city or smart-farming rhetoric. The digital cadastre does not create value because it is technologically modern. It creates value by providing a legally trusted spatial ontology for automated and semi-automated decision-making rules. A drone image may reveal land-cover change, but without cadastral geometry, it is unclear whose parcel is affected. A planning map may show a functional zone, but without cadastral linkage, it is difficult to test parcel-level compliance. A subsidy declaration may indicate crop area, but without cadastral and LPIS-compatible spatial logic, it is difficult to control eligibility. A public monitoring portal may display market indicators, but without a parcel-level structure, it cannot fully support local fiscal and land-use decisions. The cadastre is the spatial grammar that enables these systems to communicate with one another.

The most advanced form of automated constraints is not a single prohibition layer but a layered decision fabric. In such a fabric, the legal geometry of the parcel is intersected with planning regimes, environmental restrictions, infrastructure corridors, valuation zones, historical documents, observed land cover, administrative boundaries, and risk layers. Each intersection has a status: prohibitive, conditional, informative, uncertain, or requiring human review. The economic function is to reduce the number of cases requiring expensive expert attention and to direct human attention to the cases where interpretation is necessary.

This is the principal institutional value of automation. It does not abolish professional judgment; it reallocates it from routine searches to difficult cases. Certified land surveyors, planners, local authorities, environmental inspectors, cadastral registrars, and courts remain important. However, their time is no longer consumed by reconstructing basic facts that should be available as official data. The value of expertise increases when routine verification is automated.

Table 3.4. Hard masks and soft penalties in digital land-use planning

Type of spatial rule	Examples in land governance	Digital-cadastral representation	Economic rationale
Hard mask: legal prohibition	Protected areas, strict water-protection regimes, military exclusion zones, legally impossible intended use, unresolved object status.	Official geometry with source act, validity period, legal status, and prohibition code.	Prevents investment in infeasible options and reduces late-stage cancellation or litigation.
Hard mask: safety or public-interest exclusion	Mine-contaminated land, damaged infrastructure zones, restricted wartime access, and dangerous contamination.	Spatial risk layer with authority, update cycle, and role-based access regime.	Protects users and institutions from high-consequence decisions under unacceptable risk.
Conditional rule	Servitudes, utility corridors, reconstruction conditions, compensation obligations, and heritage consultation zones.	Constraint geometry is linked to procedural requirements and the responsible authority.	Allow feasible projects to proceed with known procedures and budgeted obligations.
Soft penalty: environmental sensitivity	Erosion-prone soils, fragmented ecological corridors, buffer areas, and moderate biodiversity sensitivity.	Suitability score or penalty attribute derived from official and analytical layers.	Internalizes ecological risk without treating all sensitivities as absolute prohibitions.
Soft penalty: economic or spatial friction	Parcel fragmentation, poor access, high distance to infrastructure, unclear archive history, and complex ownership patterns.	Attribute-based scores are linked to cadastral, valuation, road, and archive data.	Improves allocation by accounting for transaction costs and implementation risk.
Human-review trigger	Conflicting source documents, outdated geometry, overlapping claims, and uncertain remote-sensing classification.	Flagged spatial object with provenance conflict and audit requirement.	Directs professional expertise to cases where automation cannot safely decide.

Table 3.5. Compliance-aware allocation sequence for cadastral decision support

Stage	Main question	Relevant data layers	Governance output
1. Object identification	Which parcel or spatial unit is being evaluated?	Cadastral parcel, administrative boundary, address, building link, source document.	Stable object identity and spatial extent.
2. Feasibility screening	Is the proposed use legally possible?	Land category, intended use, functional zone, protected areas, registered restrictions, servitudes.	Allowed, prohibited, conditional, or requires human review.
3. Environmental screening	What ecological constraints or sensitivities apply?	Water zones, soil, forests, green infrastructure, degraded land, and remote-sensing evidence.	Environmental risk profile and possible mitigation requirements.
4. Economic screening	What are the transaction and implementation costs are likely?	Ownership/use rights, parcel fragmentation, valuation, access, archive quality, and dispute indicators.	Indicative cost and risk profile.
5. Audit and explanation	Why was the decision result produced?	Rule version, data version, source documents, responsible authority, timestamp.	Traceable decision evidence for appeals, reporting, and accountability.

3.3. Efficiency Metrics for Digital Land Governance: Transaction Costs, Conflict Prevention, Compliance, and Peri-Urban Land Allocation

The final question is how the efficiency of digital land governance should be measured in the specific case of cadastral systems. The methodological chapter of this monograph establishes the broader logic of extended economic evaluation. The present section applies logic in a cadastral setting without repeating the formulas. It identifies the substantive channels through which digital cadastral systems create value: transaction-cost reduction, conflict prevention, compliance efficiency, fiscal and valuation support, and improved peri-urban allocation.

Transaction costs are the most immediate efficiency channel. Land-related decisions require actors to search for information, verify it, negotiate with rights holders, check restrictions, obtain extracts, compare documents, conduct field visits, prepare technical documentation, and manage uncertainty. In fragmented systems, these costs multiply because each actor independently reconstructs the same facts. A bank verifies a parcel for collateral; a municipality verifies it for taxation; an investor verifies it for acquisition; an engineer verifies it for project siting; an environmental inspector verifies it for compliance; a farmer verifies it for land-bank management. When official data is reusable, the same cadastral facts serve many workflows. The value of the system, therefore, lies not only in administrative efficiency but also in avoiding repeated reconstruction.

The engineering-economic paper added to the monograph provides a useful applied illustration. It compares a digital-official-data scenario with a fragmented-information scenario in agricultural land-bank and irrigation planning, energy infrastructure sitting, and transport corridor development. In the agricultural case, digital cadastral data reduced parcel search, legacy-plan digitization, repeated ownership checks, and unnecessary field reconciliation; in the energy case, they reduced servitude screening, owner identification, overlap checks, and redesign loops; in the transport case, they reduced corridor parcel reconstruction, acquisition-package preparation, and late alignment changes (Martyn et al., 2026). The reported avoided costs range from EUR 28,000-63,000 for a representative agricultural campaign, EUR 92,000-211,000 for an energy project, and EUR 0.43-1.06 million for a transport corridor interface (Martyn et al., 2026). These numbers should not be read as universal coefficients. Their importance is theoretical: they demonstrate that cadastral data have project-level economic value by compressing the time and uncertainty of land-related workflows.

The same evidence supports a more general proposition: the value of a digital cadastre is cumulative. A database query may look cheap, but its result can prevent a field visit, a repeated survey, a failed negotiation, a design correction, a compensation dispute, or a court case. Even if each cost avoided is modest, repeated use across thousands of transactions and hundreds of projects can exceed the historical cost of system development. Martyn et al. (2026) relate historical international financing for the 2003-2013 cadastre-development project to the current inventory and derive an indicative cost of only a few US dollars per parcel or per recorded hectare. This is not a full cost-benefit account; it is an infrastructure benchmark showing that the unit cost of creating authoritative geodata can be low relative to the value generated through repeated reuse.

Conflict prevention is the second efficiency channel. Land conflicts often arise when different actors rely on different representations of the same territory: a cadastral boundary, a lease map, a local plan, a field boundary, an archive plan, an orthophoto interpretation, a utility corridor, or a protected-area regime. Digital land governance reduces conflict when it provides a shared official reference, but only if the reference is accurate, versioned, and connected to source documents. If a cadastral system merely publishes disputed or outdated geometry, it may reproduce conflict in digital form. Therefore, the quality of conflict prevention depends on data completeness, correction procedures, audit trails, and the ability to link spatial objects to legal evidence.

Conflict prevention is especially valuable in peri-urban agricultural territories. The peri-urban belt is neither purely rural nor purely urban. It is a zone of competing rents, accelerated conversion pressure, fragmented ownership, infrastructure expansion, informal expectations, ecological tension, and administrative overlap. Agricultural land may be attractive for logistics or residential expansion; green belts may be pressured by development; community budgets may prefer high tax-yield uses; farmers may need land consolidation; roads and utility corridors may fragment fields; environmental restrictions may be poorly understood. In such conditions, the cadastre becomes a conflict-prevention infrastructure when it allows actors to see not only parcels but the spatial relations among parcels, rights, restrictions, functional zones, ecological sensitivity, valuation, and planned development.

The Bilotserkiv data used in the added engineering-economic paper illustrates the practical importance of cadastral completeness in an intensive agricultural region of the Kyiv oblast. The district-level analysis identifies 164,685 parcels covering 485,166.84 ha, of which 88.81 percent are agricultural land; the Bilotserkiv community contains 10,989 parcels covering 28,844.66 ha, with 77.30 percent agricultural land and additional industrial, energy, water, and forest categories relevant for irrigation routing androutesty siting (Marsitting al., 2026). Such a territory is not simply a set of fields. It is a spatial portfolio in which agricultural production, infrastructure, water access, environmental restrictions, ownership patterns, and local development priorities interact. Digital cadastral analytics turn this portfolio into an object of governance.

The third efficiency channel is compliance. Compliance is frequently treated as a cost imposed on economic actors. In a digital cadastral system, however, compliance can serve as a cost-saving mechanism by preventing violations and reducing the cost of proving lawful behavior. If a farm can verify that its operations comply with land categories, restrictions, and environmental zones, it reduces exposure to sanctions and disputes. If a community can verify functional-zone consistency before approving a land-use decision, it lowers legal risk. If an infrastructure project can identify servitudes and compensation obligations early, it lowers redesign risk. If a future IACS/LPIS-compatible agricultural administration system can link declared land use with cadastral and earth observation data, it reduces control costs and strengthens trust in subsidy administration.

The added article on remote sensing and state land-control modernization is important because it connects compliance with evidentiary modernization. It argues that remote-sensing products can shorten the time between a land-use violation and its identification, improve legal culture among landowners and users, and reduce corruption risks in control activities (Martyn et al., 2024). From the perspective of Chapter 3, this argument should be interpreted in a cadastral-infrastructural sense. Remote sensing alone cannot determine legal compliance; it must be compared with cadastral parcels, intended use, restrictions, and source documents. Conversely, a cadastre without observational evidence may record formal legality while missing actual misuse. The efficiency frontier lies in combining official spatial-legal objects with evidence layers under clear rules of admissibility and interpretation.

The fourth channel is fiscal and valuation efficiency. Land valuation, taxation, rent calculation, compensation, and local budget planning depend on accurate parcel identification, area, land category, location, restrictions, and valuation attributes. The 2030 cadastral vision treats mass valuation as a permanent function of the cadastre based on CAMA models rather than as an episodic administrative project (NULES, 2026). This is a major shift. If mass valuation is integrated with dynamic cadastral data and market evidence, the cadastre becomes a fiscal intelligence system. It can support more equitable taxation, better compensation planning, more transparent rent calculation, and more credible local public finance. In Ukraine, where communities depend on land-related revenues and recovery will require substantial compensation and reconstruction decisions, valuation integration is a core economic function rather than a secondary technical module.

The fifth channel is allocation efficiency. The cadastre improves allocation by allowing decision-makers to compare land-use options under spatial, legal, environmental, and economic constraints. Allocation efficiency does not mean maximizing land-market price alone. A peri-urban parcel with high market value may produce negative environmental externalities if converted; a low-priced parcel may be strategically important for ecological connectivity; a fragmented agricultural field may impose machinery and irrigation costs; a parcel close to infrastructure may be valuable but constrained by servitudes. Digital land governance supports allocation by making these characteristics visible now of choice.

Ukraine's EU integration makes the allocation more demanding. Alignment with the EU agricultural administration will require reliable geospatial data for support eligibility, monitoring, land-use declarations, environmental conditionality, and audit. Alignment with EU environmental policy requires reliable data on protected areas, water regimes, soil conditions, and ecological restrictions. Alignment with the EU open data and interoperability policy requires the publication and reuse of high-value geodata under defined conditions. These requirements are often discussed separately, but in practice they converge on the same cadastral question: can the state represent land as a legally reliable, environmentally meaningful, and machine-usable spatial object?

The answer depends on data governance. Economic efficiency can be undermined if cadastral data are incomplete, outdated, internally inconsistent, semantically incompatible, inaccessible through APIs, insufficiently documented, weakly linked to rights and restrictions, or legally ambiguous. Therefore, efficiency metrics must include not only outputs, such as the number of parcels or extracts, but also quality and usability indicators. A million extracts are less valuable if users still need manual verification; a public map is less valuable if it cannot be queried; a restriction layer is less valuable if its legal source is unclear; a valuation model is less credible if its inputs are not traceable.

For this reason, the metrics proposed in this chapter are grouped by the type of value they measure. Service-efficiency metrics measure time, cost, and throughput of cadastral procedures. Data-quality metrics measure completeness, positional consistency, attribute accuracy, update frequency, provenance, and versioning. Transaction-efficiency metrics measure reductions in search time, field reconciliation, resurvey, document requests, and repeated legal checks. Conflict-prevention metrics measure reductions in boundary overlaps, disputed parcels, late restrictions, litigation, and redesign triggered by land-information failures. Compliance metrics measure automated pre-checks, detection of mismatches between actual and intended use, restriction-violation flags, and audit-ready decisions. Peri-urban allocation metrics measure land-use compatibility, accessibility, ecological sensitivity, fragmentation, fiscal implications, and consistency with functional zones.

A key feature of these metrics is that they should be evaluated at multiple scales. At the parcel scale, the question is whether a specific object is identifiable, legally reliable, and constraint-aware. At the farm or land-bank scale, the question is whether parcels form a coherent production and investment portfolio. On the community scale, the question is whether cadastral information supports planning, taxation, public services, and conflict prevention. At the regional scale, the question is whether cadastral data support infrastructure, logistics, environmental corridors, and recovery planning. At the national scale, the question is whether the cadastre supports EU integration, land-market transparency, fiscal capacity, and digital sovereignty.

The notion of digital sovereignty is not rhetorical. A cadastral system is one of the few digital infrastructures in which territorial sovereignty is literally represented as geometry. It records the spatial objects through which the state administers property, obligations, restrictions, valuation, and planning. In wartime and post-war conditions, such infrastructure must be resilient: it needs cybersecurity, geographically distributed backups, differentiated access, disaster recovery, and controlled continuity of critical services. The 2030 vision's emphasis on cyber protection, backup, access segmentation, emergency scenarios, and role-based access during martial law is therefore an economic condition, not merely a security measure (NULES, 2026). If cadastral services fail, land markets, planning, compensation, taxation, and recovery processes suffer.

The comparative European perspective should be used carefully. Some EU countries have long-established cadastral traditions, but the relation between cadastral parcels, legal boundaries, land registers, planning data, and agricultural support parcels varies significantly. The EU LPIS is primarily an agricultural support and control system; it does not necessarily substitute for a legally authoritative cadastre. This distinction is important for Ukraine. Ukraine should not interpret EU alignment as requiring it to replace its cadastral parcel system with an LPIS-based logic. Instead, it should build interoperability between the legal cadastral parcel and the agricultural reference parcel. The former protects rights and obligations; the latter supports eligibility and control. Their integration can give Ukraine a stronger geospatial governance model than a system in which legal, agricultural, and environmental geographies remain separate.

This is also where OGC APIs, LADM, and FAIR principles become practical rather than decorative. If parcel data, restriction data, functional zones, valuation data, and monitoring evidence are represented through common identifiers, metadata, service interfaces, and conceptual models, they can be reused across systems without losing legal meaning. If they are displayed on separate portals, users still face high integration cost. The economic efficiency of a digital cadastre, therefore, depends on its ability to become a service fabric. The target is not a single giant application but a governed ecosystem of interoperable services.

The main risk is that cadastral modernization becomes an accumulation of digital modules without a coherent spatial-legal architecture. A public map, electronic extracts, mass valuation, functional zones, remote-sensing analytics, archive digitization, and agricultural support systems can all be useful. However, their value is limited if they do not share object identifiers, metadata rules, data-quality standards, access regimes, and audit trails. The cadastral system must therefore be designed as an architecture of relations: land parcel to building, land parcel to right, land parcel to restriction, land parcel to valuation, land parcel to functional zone, land parcel to agricultural declaration, land parcel to observed land cover, land parcel to public decision.

The final theoretical implication of the case study is that digital land governance creates efficiency through institutional compression. It compresses the distance between map and law, between plan and parcel, between restriction and decision, between valuation and taxation, between observation and compliance, between local planning and national data infrastructure, and between Ukrainian reform and European interoperability. This compression does not eliminate politics, professional judgment, or conflict. It reduces the cost of understanding the conflict and shifts decisions from opaque negotiation to traceable spatial evidence.

Accordingly, the Ukrainian digital cadastre should be interpreted as a strategic infrastructure for sustainable environmental management. It is the first empirical case in the monograph because land serves as the base layer for the other digital tools. Monitoring needs parcels to attach observations to accountable objects. Routing needs to account for parcels and restrictions to avoid spatial conflicts. Environmental valuation needs land categories, soil, water, restrictions, and land-use history. Policy scaling needs auditable indicators. Without digital cadastral infrastructure, other digital tools remain technically impressive but institutionally underpowered.

The case also demonstrates a broader lesson for transitioning economies. Digitalization is most valuable when it changes the cost structure of governance, not merely the interface of administration. A digital cadastre becomes economically efficient when it reduces search costs, prevents errors, reduces discretion, improves trust, enables cross-sector reuse, and creates a reliable spatial memory of rights and responsibilities. For Ukraine, this is simultaneously a land reform, environmental management, recovery, and EU integration task.

Table 3.6. Efficiency metrics for digital cadastral governance

Metric group	Representative indicators	Primary data source	Interpretive value
Service efficiency	Average time for extracts, share of automated extracts, API response time, service uptime, and number of procedures completed electronically.	Cadastral service logs, e-service portal statistics, and SLA records.	Measures administrative speed and user-facing friction.
Data quality and completeness	Parcel coverage; attribute completeness; restriction coverage; functional-zone coverage; positional consistency; versioned updates; archive linkage.	State Land Cadastre, NSDI metadata, archival repository, quality-control reports.	Measures whether data can be trusted and reused without repeated reconstruction.
Transaction-cost reduction	Reduced search hours; avoided field visits; reduced resurvey; fewer duplicate document requests; reduced due diligence cycles.	Workflow studies, engineering project records, survey logs, and user time records.	Captures the economic value of authoritative geodata in real workflows.
Conflict prevention	Boundary-overlap rate; disputes caused by late restrictions; redesign events; compensation disputes; corrected errors before approval.	Cadastral correction logs, court data, project redesign records, and local government records.	Measures whether digital land information prevents costly spatial conflicts.
Compliance efficiency	Automated pre-checks; mismatches between intended and actual use; restriction-violation flags; audit-ready decisions; remote-sensing evidence linked to parcels.	Cadastre, functional zones, restriction layers, Copernicus/Sentinel products, and inspection records.	Measures movement from manual inspection toward evidence-aware compliance.
Peri-urban allocation	Land-use compatibility; infrastructure access; ecological sensitivity; agricultural fragmentation; fiscal impact; conflict probability.	Cadastre, planning documentation, valuation data, transport data, and environmental layers.	Measures how well land allocation balances agricultural, urban, fiscal, and ecological objectives.

Table 3.7. Empirical interpretation of added-value channels from official cadastral geodata

Project environment	Dominant cadastral inputs	Avoided activities in the fragmented-information scenario	Reported efficiency effect
Agricultural land bank and irrigation planning	Parcel geometry, area, intended use, ownership/use rights, land category, missing-data flags.	Parcel search, legacy-plan digitization, repeated ownership checks, and unnecessary field reconciliation.	Avoided cost estimated at EUR 28,000-63,000 and schedule gain of 2-5 weeks in the analyzed campaign.
Energy infrastructure and servitudes	Parcel boundaries, rights holders, servitudes, restrictions, land-use compatibility, temporary and permanent right needs.	Servitude screening, owner identification, overlap checks, repeated documentation cycles, and redesign loops.	Avoided cost estimated at EUR 92,000-211,000 and probable schedule gain of 1.7-4.0 months.
Transport corridor interface	Long-corridor parcel inventory, land-take areas, ownership categories, subdivision needs, valuation, and compensation data.	Corridor parcel reconstruction, acquisition-package preparation, late alignment changes, and repeated negotiation evidence.	Avoided cost estimated at EUR 0.43-1.06 million and schedule gain of 3-7 months.

The economic efficiency of digital land management and cadastral systems is best understood as the efficiency of spatial certainty. Digital cadastres reduce the cost of making land knowable, legally reliable, environmentally constrained, and economically calculable. Their benefits are realized not only inside cadastral procedures but across the wider land economy: agriculture, infrastructure, taxation, compensation, planning, environmental control, and recovery.

The case of Ukraine demonstrates that the State Land Cadastre has already moved beyond the minimal logic of parcel registration. It functions as a national geoinformation system with significant coverage, mass digital services, increasing integration of restrictions and functional zones, a developing mass valuation function, and strategic potential to become the spatial core of real estate and natural resource governance. At the same time, its next efficiency gains depend on deeper interoperability, dynamic versioning, archive linkage, controlled APIs, FAIR metadata, OGC-aligned services, LADM-consistent conceptual modeling, differentiated access, and stronger integration with planning, environmental, agricultural, and fiscal systems.

For the EU-Ukraine context, the key issue is not formal imitation of European cadastral arrangements. The EU itself contains diverse cadastral and land-register traditions. The relevant benchmark is functional: data must be interoperable, reusable, legally traceable, environmentally meaningful, and serviceable for public administration and market actors. INSPIRE, the High-Value Datasets Regulation, the Interoperable Europe Act, IACS/LPIS, and Copernicus-based monitoring all point toward a governance environment in which spatial data are not simply published but operationalized. Ukraine's cadastral modernization should therefore be seen as a central infrastructure of European integration.

The chapter also clarifies why land management is the first case study in the monograph. Without reliable cadastral data, environmental monitoring cannot be attached to accountable spatial objects, routing cannot avoid legally meaningful constraints, and sustainability indicators cannot be audited. Digital land administration is the base layer upon which other digital environmental tools acquire institutional force. Its economic efficiency is not the sum of cadastral fees or IT expenditures. It is the economy-wide reduction of uncertainty, conflict, delay, and discretionary decision-making in land governance.

CHAPTER 4

Case Study II - Economic Efficiency of IoT Telemetry and Environmental Monitoring

4.1. Cyber-Physical Architecture of Agrarian Monitoring: IoT Telemetry, Sentinel-2, UAV Diagnostics, and Data Fusion

The second empirical case study in the monograph examines the economic efficiency of IoT telemetry and environmental monitoring. In the monograph's general logic, this case study occupies an intermediate position between digital land management and spatio-temporal routing. Digital land management, analyzed in Section 3, provides the spatial and institutional basis: parcel boundaries, restrictions, land-use categories, protection zones, and other spatial constraints. The present section adds the environmental and agronomic observation layer. Section 5 then uses the outputs of both previous cases - land constraints and monitoring signals - as inputs for operational routing, machinery scheduling, and agronomic service-window planning. This sequence corresponds to the current monograph structure, in which Case Study II is explicitly focused on transforming IoT telemetry, Sentinel-2 imagery, and UAV diagnostics into an economic evaluation of environmental monitoring.

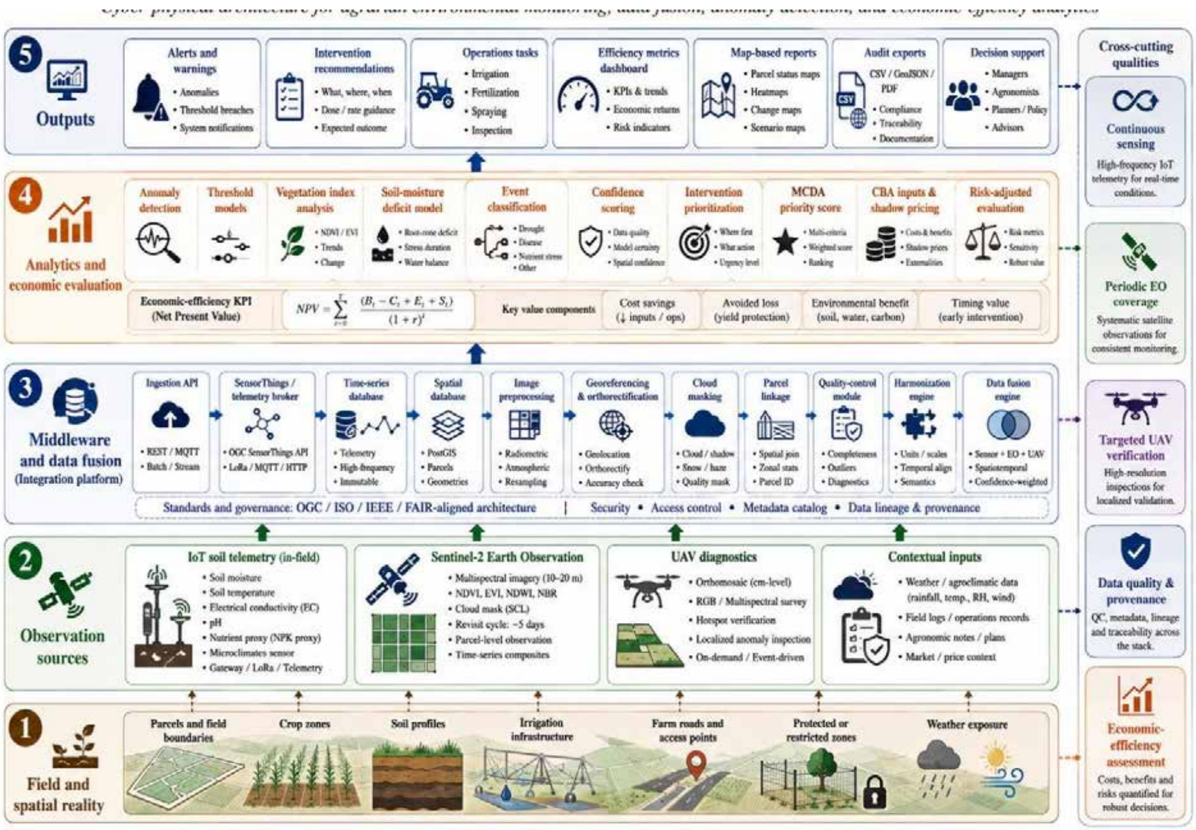


Figure 4.1 Integrated IoT-Sentinel2-UAV monitoring architecture

The central methodological problem of this subsection is architectural. Before evaluating the economic efficiency of precision interventions, it is necessary to define how the monitoring system collects, synchronizes, validates, stores, processes, and interprets heterogeneous data. In digital agriculture, the value of monitoring is not created by a single sensor, a single satellite image, or a single UAV flight. It is enabled by the system's ability to combine different observation modes into a stable decision-support workflow. IoT telemetry provides continuous point-based field observations. Sentinel-2 provides regular multispectral coverage across the territory. UAV imagery provides high-resolution local diagnostics when permitted and operationally feasible. The economic value appears only when these data streams are integrated into a common architecture that supports agronomic decisions, economic accounting, environmental assessment, and auditability.

The need for a multi-source architecture stem from the author's previous research on web service models for ecological and economic monitoring. In that model, ecological monitoring requires the collection, processing, and analysis of large volumes of heterogeneous data through databases, data repositories, user interfaces, external APIs, notification systems, sensor inputs, and cloud deployment components. The same logic is transferred here from urban ecological-economic monitoring to agrarian monitoring. The monitoring system must not be designed as a simple dashboard. It must be designed as a cyber-physical system in which field sensors, satellite observations, UAV imagery, geospatial databases, middleware services, and economic models operate as parts of one decision-support environment.

This approach is also consistent with the author's earlier IoT middleware model. In that work, the platform is presented as a multi-layer architecture connecting endpoint devices, hardware abstraction, core services, event systems, service management, web services, APIs, and application connectors. For the purposes of this monograph, this software architecture is adapted to agrarian monitoring. The endpoint device layer becomes the soil and environmental sensor layer. The middleware layer becomes the telemetry ingestion, quality control, event detection, and data fusion layer. The application layer becomes the agronomic dashboard, economic-efficiency calculator, intervention planner, and reporting interface.

The architecture proposed in this subsection is therefore based on the principle of complementarity of observation sources. IoT telemetry, Sentinel-2, and UAV imagery should not be treated as competing sources. They solve different monitoring problems. IoT sensors provide temporal continuity but limited spatial coverage. Sentinel-2 provides spatial coverage and multispectral consistency but is periodic and affected by cloud cover. UAV imagery provides very high spatial detail but is episodic, more expensive, and, under wartime conditions in Ukraine, may be restricted by security and regulatory factors. For this reason, the monitoring system must be designed with a flexible, resilient architecture that prevents the failure or degradation of any single source from halting the entire decision-support process. The current routing article applies the same resilience principle: when UAV data are intermittent, the system must be able to roll back to satellite and ground-sensor data while preserving advisory generation, event queues, metadata lineage, and asynchronous updates.

Table 4.1 General architecture of the agrarian IoT–EO–UAV monitoring system

Architectural layer	Main components	Primary data handled	Main function	Economic role in the monograph
Field sensing layer	Soil moisture sensors, soil temperature sensors, electrical conductivity sensors, microclimate sensors, irrigation meters	Continuous in-situ telemetry	Measures local field conditions in near-real time	Reduces uncertainty about irrigation, soil stress, and local field status
Satellite Earth Observation layer	Sentinel-2 L1C/L2A imagery, derived NDVI/EVI, cloud masks, vegetation anomaly products	Periodic multispectral raster data	Provides spatially continuous vegetation and land-surface observation	Supports field prioritization and reduces inspection costs
UAV diagnostic layer	UAV RGB/multispectral imagery, orthomosaics, local crop-stress maps	High-resolution project imagery	Provides detailed local verification of detected anomalies	Reduces false positives and supports targeted intervention
Weather and agroclimatic layer	ERA5, NASA POWER, local weather stations, precipitation and temperature records	Time-series climate and weather data	Contextualizes stress, irrigation, and service-window timing	Supports interpretation of whether the anomaly is agronomic, weather-driven, or data-driven
Spatial governance layer	Parcel boundaries, land-use categories, protection zones, restrictions, farm boundaries	Vector GIS data	Connect observations to legal and operational land units	Make monitoring outputs parcel-specific and auditable
Middleware and data-fusion layer	APIs, message broker, ETL pipelines, time-series database, spatial database, event manager	Harmonized EO/IoT/UAV/weather/ GIS data	Aligns data in space, time, units, metadata, and quality level	Converts raw signals into decision-ready indicators
Analytics and decision-support layer	Threshold models, anomaly detection, MCDA, CBA modules, dashboards	Processed indicators and decision rules	Produces alerts, intervention priorities, and economic-efficiency inputs	Links monitoring to measurable cost savings and avoided losses

Architectural layer	Main components	Primary data handled	Main function	Economic role in the monograph
Reporting and audit layer	Reports, GeoJSON/CSV exports, metadata, provenance logs, sustainability indicators	Decision outputs and evidence trails	Documents about what was observed, when, how, and why action was recommended	Supports certification, policy reporting, subsidies, and reproducible evaluation

Source: prepared by the authori based on the monograph methodology, IoT middleware architecture, and ecological-economic monitoring models.

The architecture of the agrarian monitoring system must be evaluated not only from an engineering standpoint, but also from an economic standpoint. The system is useful only if it improves the economic quality of decisions. Therefore, in this monograph, the monitoring architecture is treated as an economic infrastructure. It collects environmental and agronomic signals, reduces uncertainty, supports timely intervention, lowers unnecessary input use, and provides data for later calculation of avoided losses and environmental benefits.

In Section 2, the economic-efficiency framework was defined in terms of four methodological components: adapted cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario-based evaluation. The monitoring architecture must provide data for all four components. For CBA, it must generate measurable before-and-after indicators: water saved, fertilizer saved, crop loss avoided, field inspection costs reduced, and intervention time improved. For MCDA, it must provide normalized criteria: crop-stress score, soil-moisture deficit, intervention cost, data reliability, environmental sensitivity, and yield-loss risk. For shadow pricing, it must provide physical changes that can be monetized: avoided water stress, avoided runoff, avoided soil damage, and saved agronomic time window. For simulation, it must provide uncertainty parameters: sensor uptime, cloud cover, UAV availability, weather variability, detection delay, and data-reliability coefficients.

The monitoring architecture, therefore, has a double function. Technically, it is a data-fusion and decision-support system. Economically, it is a measurement system for efficiency analysis. Without this architecture, it would be impossible to prove whether a precision intervention actually reduces costs, protects yield, saves resources, or mitigates ecological damage.

The general monitoring-output vector for parcel or field zone p in period t may be expressed in MS Word-compatible linear equation format as:

$$M_{p,t} = \{NDVI_{p,t}, EVI_{p,t}, SM_{p,t}, Tsoil_{p,t}, EC_{p,t}, W_{p,t}, UAV_{p,t}, Q_{p,t}, R_{p,t}\}\backslash hfill(4.1)$$

, where:

- M{p,t} - monitoring state vector for parcel or field zone p in period t;
- NDVI{p,t} - normalized difference vegetation index;
- EVI{p,t} - enhanced vegetation index;
- SM{p,t} - soil moisture;
- Tsoil{p,t} - soil temperature;
- EC{p,t} - electrical conductivity or salinity proxy;
- W{p,t} - weather and agroclimatic context;
- UAV{p,t} - UAV-derived local diagnostic indicator;
- Q{p,t} - data-quality or reliability score;
- R{p,t} - risk or stress score derived from combined indicators.

The role of architecture is to regularly update this vector, preserve its provenance, and make it available for later intervention and economic evaluation.

Table 4.2 Monitoring outputs required for economic-efficiency evaluation

Monitoring output	Main source	Spatial unit	Temporal unit	Economic interpretation	Later use in a monograph
NDVI	Sentinel-2, UAV multispectral	Pixel, field zone, parcel	Image date / composite period	Vegetation vigor and stress proxy	Intervention prioritization and yield-protection estimation

Monitoring output	Main source	Spatial unit	Temporal unit	Economic interpretation	Later use in a monograph
EVI	Sentinel-2, UAV multispectral	Pixel, field zone, parcel	Image date / composite period	Vegetation condition with improved sensitivity in high-biomass areas	Crop-stress confirmation and productivity proxy
Soil moisture	IoT soil sensors, optional satellite soil-moisture products	Sensor point, interpolated field zone	Hourly/daily	Irrigation need and drought-stress indicator	Water-saving and avoided-stress valuation
Soil temperature	IoT sensors	Sensor point, field zone	Hourly/daily	Crop-growth and stress-context indicator	Timing of interventions and agronomic window analysis
Electrical conductivity	IoT sensors / field sampling	Sensor point, field zone	Daily/weekly/seasonal	Salinity, nutrient, or soil-condition proxy	Soil-quality and localized damage analysis
Precipitation and weather	Weather station, ERA5, NASA POWER	Grid / station / parcel aggregate	Hourly/daily	Agronomic context for interpreting telemetry and EO	Scenario and stress-testing variables
UAV anomaly map	UAV RGB/multispectral imagery	Sub-field zone	Mission date	Local verification of stress, weeds, disease, erosion, waterlogging	False-positive reduction and targeted intervention
Data reliability score	Metadata from all sources	Parcel / field zone / source	Each processing cycle	Confidence in monitoring output	Adjustment of benefits and risk calculations
Alert status	Middleware event engine	Parcel / field zone	Event-based	Convert monitoring into action	Entry point for 4.2 intervention economics
Audit trail	Metadata, logs, provenance records	System-level / parcel-level	Continuous	Evidence for reporting, certification, and policy	Institutional value and sustainability reporting

Source: prepared by the authors.

IoT telemetry is the continuous observation layer of the monitoring system. Its main role is to measure field conditions at a frequency that satellite and UAV observations cannot provide. While Sentinel-2 and UAV imagery are periodic, IoT sensors can report hourly, sub-hourly, or daily measurements, depending on power, connectivity, and data storage constraints. This makes IoT especially important for variables that change quickly, such as soil moisture, soil temperature, air temperature, relative humidity, precipitation, irrigation events, and local microclimate conditions.

In this case study, IoT telemetry should be treated as locally generated operational data. It is not a replacement for satellite imagery. It provides point-based field evidence that helps interpret satellite vegetation signals. For example, a low NDVI value may indicate drought stress, disease, poor emergence, waterlogging, soil problems, or simply a crop-stage difference. Soil moisture and local weather telemetry help distinguish between these possible explanations. This is economically important because misinterpretation may lead to unnecessary irrigation, fertilizer application, delayed field inspection, or ineffective spraying.

A single IoT observation may be represented as:

$$O_{s,t} = \{SensorID_s, x_s, y_s, z_s, t, v_{s,t}, u_s, q_{s,t}, b_{s,t}\}\backslash hfill(4.2)$$

, where:

- O{s,t} - observation from sensor s at time t;
- SensorIDs - unique sensor identifier;
- xs, ys, zs - spatial coordinates and depth or installation level;
- t - time stamp;
- v{s,t} - observed value;
- us - unit of measurement;
- q{s,t} - quality flag;
- b{s,t} - battery or device-status indicator.

For soil moisture, a normalized soil-moisture deficit indicator can be calculated as:

$$SMD_{s,t} = \frac{SM_{ref,s,t} - SM_{s,t}}{SM_{ref,s,t}} \hfill(4.3)$$

, where:

- SMD{s,t} - soil-moisture deficit at sensor s and time t;
- SM{ref,s,t} - reference or target soil-moisture level for the crop, soil type, and growth stage;
- SM{s,t} - observed soil moisture.

If field-level aggregation is required, point measurements can be converted into a parcel or field-zone indicator:

$$SM_{p,t} = \frac{\sum_{s=1}^{n} \quad w_s \times SM_{s,t}}{\sum_{s=1}^{n} \quad w_s} \hfill(4.4)$$

, where:

- SM{p,t} - aggregated soil moisture for parcel or field zone p;
- SM{s,t} - soil moisture measured by sensor s;
- ws - spatial, reliability, or representativeness weight of sensor s;
- n - number of sensors assigned to parcel or field zone p.

In practice, the weight w_s may reflect distance to the field-zone centroid, representativeness of the sensor location, sensor reliability, soil-type similarity, or installation depth. This is necessary because a single field sensor cannot automatically represent the entire field when the field is heterogeneous. For irrigated fields, additional weighting may be linked to irrigation zones.

The IoT telemetry layer should include not only raw sensor readings but also device metadata. Battery level, last communication time, calibration date, firmware version, installation depth, sensor type, and measurement unit are important for data reliability. This follows the logic of IoT middleware design, in which endpoint devices, hardware abstraction, core services, service management, web services, and API layers must be connected via communication protocols and data formats. It also aligns with the OGC SensorThings API, which provides a geospatial-enabled framework for connecting IoT devices, data, and applications over the web, including standardized ways to manage observations and metadata from heterogeneous sensor systems.

Table 4.3 IoT telemetry layer for agrarian monitoring

IoT variable	Sensor / source	Recommended frequency	Main agronomic meaning	Economic meaning	Data-quality concern
Soil moisture	Capacitive / TDR / FDR soil sensor	Hourly or daily	Water availability and drought stress	Prevents over-irrigation and delayed irrigation	Calibration, depth, soil-type sensitivity
Soil temperature	Soil temperature probe	Hourly or daily	Germination and root-zone condition	Supports timing of sowing, irrigation, and intervention	Sensor depth and local microclimate effects
Electrical conductivity	EC sensor / soil probe	Daily or weekly	Salinity and nutrient proxy	Supports targeted soil correction and avoids unnecessary inputs	Requires interpretation with soil moisture
Air temperature	Microclimate sensor	Hourly	Heat stress and disease-risk context	Supports stress interpretation and intervention timing	Station placement
Relative humidity	Microclimate sensor	Hourly	Disease-risk and evapotranspiration context	Supports crop-protection timing	Sensor exposure and maintenance
Precipitation	Rain gauge / weather station	Event-based / daily	Water balance	Avoids unnecessary irrigation after rainfall	Local representativeness

IoT variable	Sensor / source	Recommended frequency	Main agronomic meaning	Economic meaning	Data-quality concern
Irrigation flow	Flow meter / pump sensor	Event-based	Water applied	Measures water-use efficiency	Meter calibration
Battery voltage	Sensor diagnostic	Each transmission	Device health	Reduces data-loss risk	Low battery can distort continuity
Communication status	Gateway / telemetry platform	Each transmission	Data availability	Determines reliability of decision-support	Network loss and delayed upload
Calibration status	Maintenance log	Periodic	Sensor trustworthiness	Reduces false alerts	Human maintenance discipline

Source: prepared by the authors.

Sentinel-2 imagery forms the periodic spatial observation layer of monitoring architecture. Its main strengths are not point-level continuity but spatial completeness and spectral consistency. Sentinel-2 enables the monitoring system to observe the entire field, farm, municipality, or peri-urban agricultural belt rather than only individual sensor locations. This is essential for detecting spatial heterogeneity: uneven emergence, drought patches, crop stress, waterlogging, field access damage, edge effects, and land-cover change.

The Sentinel-2 mission is a European wide-swath, high-resolution multispectral imaging mission. The Copernicus SentiWiki documentation states that the twin-satellite configuration was designed for a 5-day revisit frequency at the equator, and that the MSI sensor samples 13 spectral bands: four at 10 m, six at 20 m, and three at 60 m spatial resolution, with a 290 km swath width. These characteristics make Sentinel-2 well-suited to the monograph monitoring case, as it can support regular crop and vegetation analysis over the Kyiv agglomeration and adjacent peri-urban agricultural territories.

For this case study, Sentinel-2 should be used mainly for Level-2A surface reflectance products where available, because vegetation indices and anomaly detection require atmospherically corrected reflectance. The main vegetation indicators are NDVI and EVI. NDVI is simple, interpretable, and widely used. EVI is useful where the researcher wants a vegetation index that can be more stable in high-biomass conditions and partly correct for atmospheric and soil-background effects.

The NDVI equation is:

$$NDVI_{p,t} = \frac{\rho_{NIR,p,t} - \rho_{RED,p,t}}{\rho_{NIR,p,t} + \rho_{RED,p,t}} \backslash hfill(4.5)$$

For Sentinel-2:

$$NDVI_{p,t} = \frac{\rho_{B8,p,t} - \rho_{B4,p,t}}{\rho_{B8,p,t} + \rho_{B4,p,t}} \backslash hfill(4.6)$$

, where:

- ρ{B8,p,t} - Sentinel-2 near-infrared reflectance for parcel or pixel p at time t;
- ρ{B4,p,t} - Sentinel-2 red reflectance.

The EVI equation may be written as:

$$EVI_{p,t} = G \times \frac{\rho_{NIR,p,t} - \rho_{RED,p,t}}{\rho_{NIR,p,t} + C_1 \times \rho_{RED,p,t} - C_2 \times \rho_{BLUE,p,t} + L} \backslash hfill(4.7)$$

For Sentinel-2:

$$EVI_{p,t} = 2.5 \times \frac{\rho_{B8,p,t} - \rho_{B4,p,t}}{\rho_{B8,p,t} + 6 \times \rho_{B4,p,t} - 7.5 \times \rho_{B2,p,t} + 1} \backslash hfill(4.8)$$

, where:

- ρ{B2,p,t} - blue reflectance;
- G - gain factor;
- C_1 and C_2 - aerosol correction coefficients;
- L - canopy background adjustment.

The satellite layer must include cloud masking, atmospheric correction, clipping to parcel boundaries, resampling where needed, and temporal compositing. Since cloud cover may prevent useful optical observations, the architecture should not assume that every nominal acquisition produces usable data. Instead, the processing pipeline should calculate a usability score for each parcel and acquisition date.

A basic cloud-adjusted usability indicator can be expressed as:

$$U_{S2,p,t} = 1 - CloudShare_{p,t} \backslash hfill(4.9)$$

, where:

- U{S2,p,t} - usability of Sentinel-2 observation for parcel pat time t;
- CloudShare{p,t} - share of parcel area affected by cloud, cloud shadow, or unusable pixels.

If only valid pixels are used:

$$NDVI_{p,t}^{valid} = \frac{1}{n_{valid}} \sum_{i=1}^{n_{valid}} \quad NDVI_{i,t} \backslash hfill(4.10)$$

, where:

- n_{valid} - number of valid pixels inside parcel p.

The Copernicus Data Space Ecosystem is the preferred access and processing environment for this monograph because it supports catalogue discovery, product download, STAC, openEO, Sentinel Hub, and OGC API access. The official CDSE API page states that CDSE provides APIs for catalogue, download, visualization, and processing services, including STAC, openEO, and Sentinel Hub APIs. The same page explains that openEO enables access to and processing of EO datasets using programming libraries, with processing automatically scaled on the cloud infrastructure hosting the data. This is important for research reproducibility: the monograph should not rely only on manual image download, but on a repeatable processing workflow that can be documented and rerun.

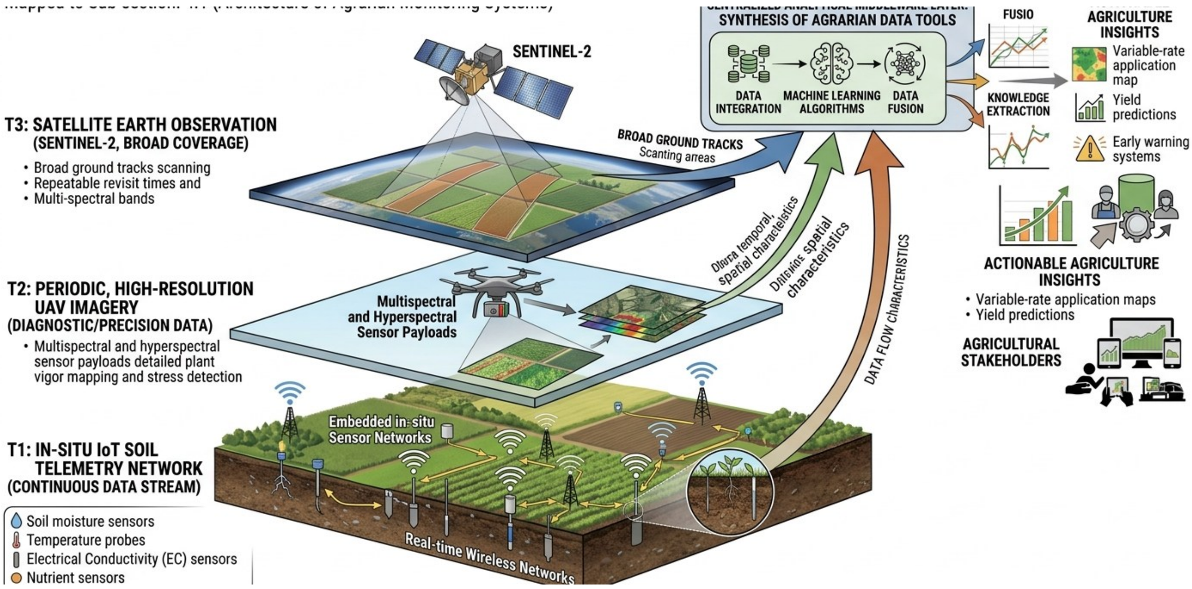


Figure 4.2 Multi-tier architecture of agrarian monitoring systems

Table 4.4 Sentinel-2 data layer for agrarian monitoring

Sentinel-2 component	Recommended use in the monograph	Main output	Processing requirement	Economic interpretation
B2 - Blue	EVI calculation and atmospheric context	Blue reflectance	Surface reflectance, cloud masking	Improves vegetation-index reliability
B4 - Red	NDVI/EVI calculation	Red reflectance	Surface reflectance	Detects vegetation absorption and crop stress
B8 - NIR	NDVI/EVI calculation	NIR reflectance	Surface reflectance	Detects vegetation vigor
B5, B6, B7, B8A - Red edge / narrow NIR	Crop stress, chlorophyll-related diagnostics	Red-edge indicators	Resampling and calibration	Supports advanced anomaly interpretation
B11, B12 - SWIR	Moisture stress, water content, soil/crop condition	SWIR reflectance	Atmospheric correction, resampling	Supports water-stress interpretation
Cloud mask	Usability control	Valid-pixel mask	Cloud and shadow removal	Avoids false monitoring conclusions
NDVI	Basic vegetation condition indicator	Parcel/zone vegetation score	Valid-pixel aggregation	Supports intervention prioritization

Sentinel-2 component	Recommended use in the monograph	Main output	Processing requirement	Economic interpretation
EVI	Enhanced vegetation condition indicator	Parcel/zone vegetation score	Blue/red/NIR reflectance	Supports high-biomass monitoring
Time-series composite	Multi-date observation	Trend and anomaly	Temporal harmonization	Detects deviation from normal field behavior
Parcel-level summary	Field-level index	Mean, median, percentiles, anomaly	Spatial join with parcel boundary	Converts raster data into economic decision unit

Source: prepared by the authors based on Sentinel-2 mission characteristics and the monitoring requirements of the monograph.

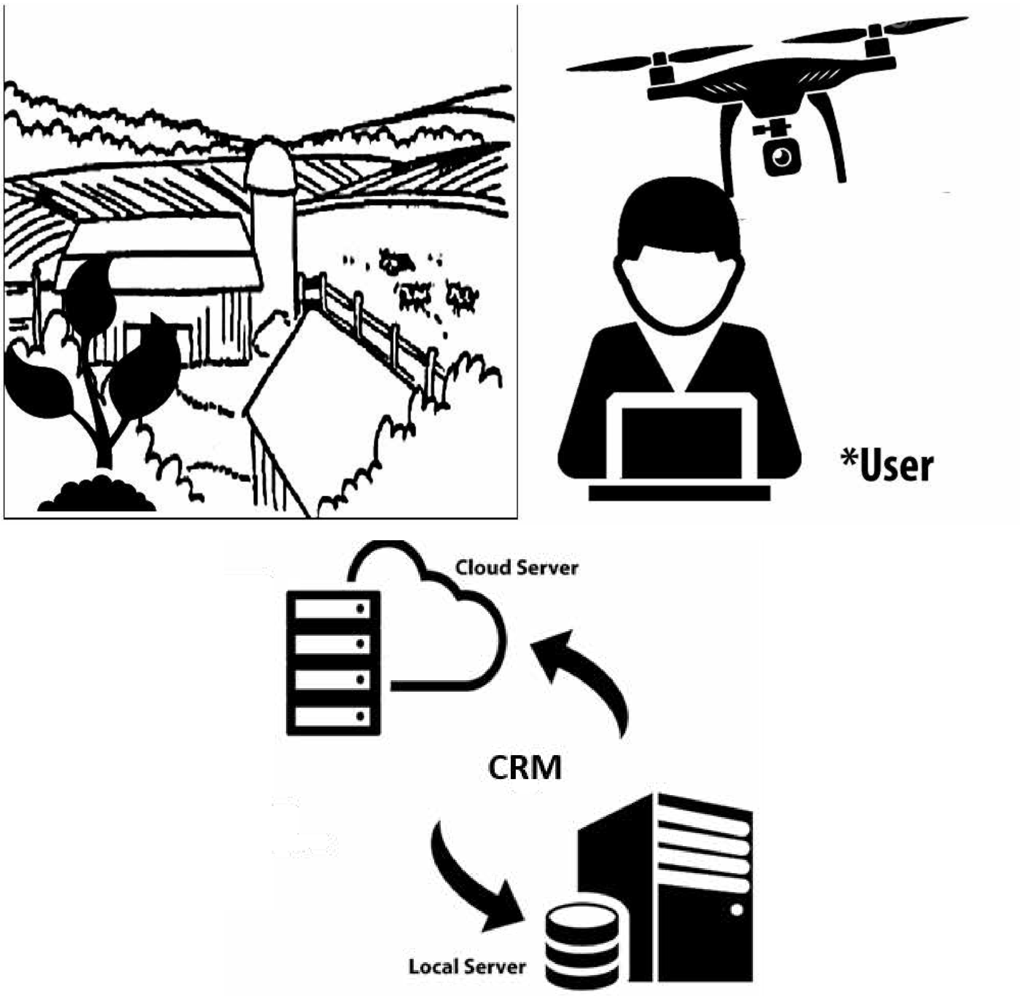


Figure 4.3 Conceptual visualization of UAV real-time surveillance

UAV imagery is the high-resolution diagnostic layer of the monitoring system. Its role is not to replace Sentinel-2 or IoT telemetry, but to verify, localize, and explain anomalies detected by broader or continuous sources. If Sentinel-2 shows a vegetation anomaly and IoT telemetry suggests water stress, UAV imagery can help determine whether the problem is distributed across the field, concentrated in low zones, linked to irrigation infrastructure, associated with weeds, disease, erosion, machinery damage, or soil heterogeneity.

The economic value of UAV data, therefore, depends on diagnostic precision. UAV imagery can reduce unnecessary whole-field interventions by identifying the actual affected area. It can also reduce false positives and support targeted field inspection. However, UAV imagery incurs higher operational costs and may be subject to legal, security, weather, and mission-planning constraints. The digital agronomy research by Nazarenko and Martyn explicitly notes that UAV use in Ukraine under wartime conditions must be handled cautiously due to safety restrictions, regulatory oversight, and risks associated with aerial data collection. In such cases, satellite imagery, ground-based IoT sensors, and administrative and economic datasets can help compensate for limited UAV availability.

For the monitoring architecture, this means UAV data must be integrated as an optional diagnostic service, not as a mandatory always-on layer. The system should support UAV imagery when it is available and permitted but maintain a functional monitoring workflow without it. This principle is important for resilience and cost control.

UAV diagnostic value may be represented as:

$$UAVD_{p,t} = f(Ortho_{p,t}, MS_{p,t}, RGB_{p,t}, GCP_{p,t}, Q_{uav,p,t}) \backslash hfill(4.11)$$

, where:

- UAVD{p,t} - UAV diagnostic output for parcel or field zone p at time t;
- Ortho{p,t} - orthomosaic;
- MS{p,t} - multispectral UAV data, if available;
- RGB{p,t} - RGB imagery;
- GCP{p,t} - georeferencing or ground-control quality;
- Q{uav,p,t} - UAV data-quality score.

For affected-area estimation:

$$A_{affected,p,t} = \sum_{i=1}^{n} a_i \times I(Anomaly_{i,t} = 1) \backslash hfill(4.12)$$

, where:

- A{affected,p,t} - affected area in parcel p;
- ai - area of pixel or grid cell i;
- I(Anomaly_{i,t} = 1) - indicator equal to 1 if cell i is classified as anomalous.

This equation is important because subsection 4.2 will use affected area to calculate intervention cost, input savings, and avoided yield loss. If the monitoring system can reduce the treated area from the whole field to the affected zone, the economic effect becomes directly measurable.

Table 4.5 UAV diagnostic layer in the monitoring architecture

UAV output	Main use	Required processing	Integration with other data	Economic role
RGB orthomosaic	Visual diagnosis of field heterogeneity	Image stitching, orthorectification	Compare with Sentinel-2 anomaly and parcel boundary	Reduces field-inspection uncertainty
Multispectral orthomosaic	Local vegetation-index mapping	Radiometric calibration, vegetation-index calculation	Compare with Sentinel-2 NDVI/EVI	Confirms or refines satellite anomaly
Thermal imagery, if available	Water stress and heat anomaly detection	Thermal calibration	Compare with soil moisture and weather	Improves irrigation-decision accuracy
Digital surface model, if available	Terrain, drainage, erosion, local morphology	Photogrammetry	Compare with waterlogging and soil conditions	Supports localized damage mitigation
Weed/disease patch map	Targeted intervention planning	Object detection / classification	Compare with scouting and field logs	Reduces unnecessary agrochemical use
Affected-area polygon	Spatial boundary of intervention zone	Segmentation, vectorization	Input into CBA and MCDA	Converts diagnosis into cost-saving calculation
UAV data-quality score	Reliability of UAV output	Blur, overlap, GSD, geolocation accuracy	Used in data-fusion reliability score	Prevents overconfidence in poor-quality imagery

Source: prepared by the authors.

The main architectural challenge is data fusion. IoT, Sentinel-2, UAV imagery, weather, and spatial governance data differ by spatial resolution, temporal frequency, measurement unit, uncertainty, and reliability. The monitoring system must therefore harmonize these data into a common parcel-level or field-zone-level structure.

The basic fusion unit in this monograph is the field zone. A field zone may be a parcel, management zone, irrigation block, or monitoring grid cell. This choice is important because economic evaluation is rarely performed at the individual pixel level. Costs and benefits are calculated at the level of field operations: irrigation event, spraying event, fertilizer application, field inspection, machinery route, or parcel-level planning decision. Therefore, all monitoring data must eventually be converted into decision units that match operational and economic accounting.

A fused monitoring vector may be expressed as:

$$X_{z,t} = [NDVI_{z,t}, EVI_{z,t}, SM_{z,t}, SMD_{z,t}, Tsoil_{z,t}, Rain_{z,t}, UAVD_{z,t}, Q_{z,t}] \backslash hfill(4.13)$$

, where:

- X{z,t} - fused state vector for field zone z at time t;
- NDVI{z,t} and EVI_{z,t} - satellite or UAV vegetation indicators;
- SM{z,t} - soil moisture;
- SMD{z,t} - soil-moisture deficit;
- Tsoil{z,t} - soil temperature;
- Rain{z,t} - precipitation or weather context;
- UAVD{z,t} - UAV diagnostic indicator;
- Q{z,t} - combined data-quality score.

The combined quality score may be calculated as:

$$Q_{z,t} = w_{IoT} \times Q_{IoT,z,t} + w_{S2} \times Q_{S2,z,t} + w_{UAV} \times Q_{UAV,z,t} + w_W \times Q_{W,z,t} + w_G \times Q_{G,z,t} \backslash hfill(4.14)$$

, where:

- Q{IoT,z,t} - IoT telemetry quality;
- Q{S2,z,t} - Sentinel-2 usability and processing quality;
- Q{UAV,z,t} - UAV diagnostic quality;
- Q{W,z,t} - weather-data quality;
- Q{G,z,t} - geospatial/governance data quality;
- w - weights assigned to each source, where Σw = 1.

If one source is unavailable, the model should reallocate weights or reduce confidence rather than stop monitoring workflow. For example:

$$Q_{z,t} = w_{IoT} \times Q_{IoT,z,t} + w_{S2} \times Q_{S2,z,t} + w_W \times Q_{W,z,t} + w_G \times Q_{G,z,t} \quad if\ Q_{UAV,z,t} = 0 \backslash hfill(4.15)$$

This is not merely a technical detail. It is a condition of economic resilience. If the monitoring system depends entirely on a single source, the economic benefit becomes fragile. If the system remains functional despite partial data loss, its value increases.

Table 4.6 Data-fusion logic for IoT, Sentinel-2, UAV, weather, and spatial layers

Data source	Spatial character	Temporal character	Main strength	Main limitation	Fusion role
IoT soil telemetry	Point-based	Continuous/high-frequency	Captures rapid field dynamics	Limited spatial representativeness	Temporal anchor and local truth signal
Sentinel-2	Raster / parcel coverage	Periodic	Broad and consistent spatial observation	Cloud cover and revisit constraints	Spatial field condition baseline
UAV imagery	High-resolution local raster	Episodic / mission-based	Detailed diagnostic verification	Cost, regulation, weather, mission planning	High-resolution confirmation layer
Weather data	Point or grid time-series	Hourly/daily	Agronomic context	Spatial mismatch and model uncertainty	Explaining whether stress is weather-driven
Parcel and land-use data	Vector boundaries and attributes	Slow-changing / event-updated	Defines legal and economic decision units	Incomplete or outdated records	Spatial aggregation and audit basis
Field logs	Operational record	Event-based	Records actual intervention	Incomplete human entry	Connects monitoring to economic outcomes
Economic records	Costs, prices, yields, input use	Seasonal / event-based	Enables economic-efficiency calculation	Confidentiality and data gaps	Converts monitoring into CBA indicators

Source: prepared by the authors.

The monitoring system requires a middleware layer because the data sources are heterogeneous and updated at different speeds. IoT telemetry may arrive every hour. Sentinel-2 images may be processed every several days or when cloud conditions allow. UAV imagery may be uploaded after a specific mission. Weather data may arrive hourly or daily. Field logs may be entered manually. Economic records may be available only at the end of an operation or season.

The middleware layer performs five functions.

First, it ingests data from different sources through APIs, file uploads, device gateways, or batch jobs. Second, it validates the data by checking units, timestamps, coordinates, missing values, and sensor status. Third, it harmonizes the data into a common spatial and temporal structure. Fourth, it stores raw and processed data in appropriate repositories: a time-series database for telemetry, a spatial database for GIS data, object storage for imagery, and a relational database for economic records. Fifth, it publishes decision-ready outputs through dashboards, reports, and machine-readable exports.

The author's research on smart city microservices provides a directly relevant model for this architecture. It argues that a middleware platform serves as the medium connecting existing software and hardware systems, and that complex service systems should be decomposed into microservices across software abstraction layers from hardware to end-user applications. The agrarian monitoring system follows this logic. Instead of building one monolithic application, it should be built as a set of interoperable services: sensor ingestion, EO processing, UAV processing, weather ingestion, spatial aggregation, alert generation, economic calculation, dashboard visualization, and reporting.

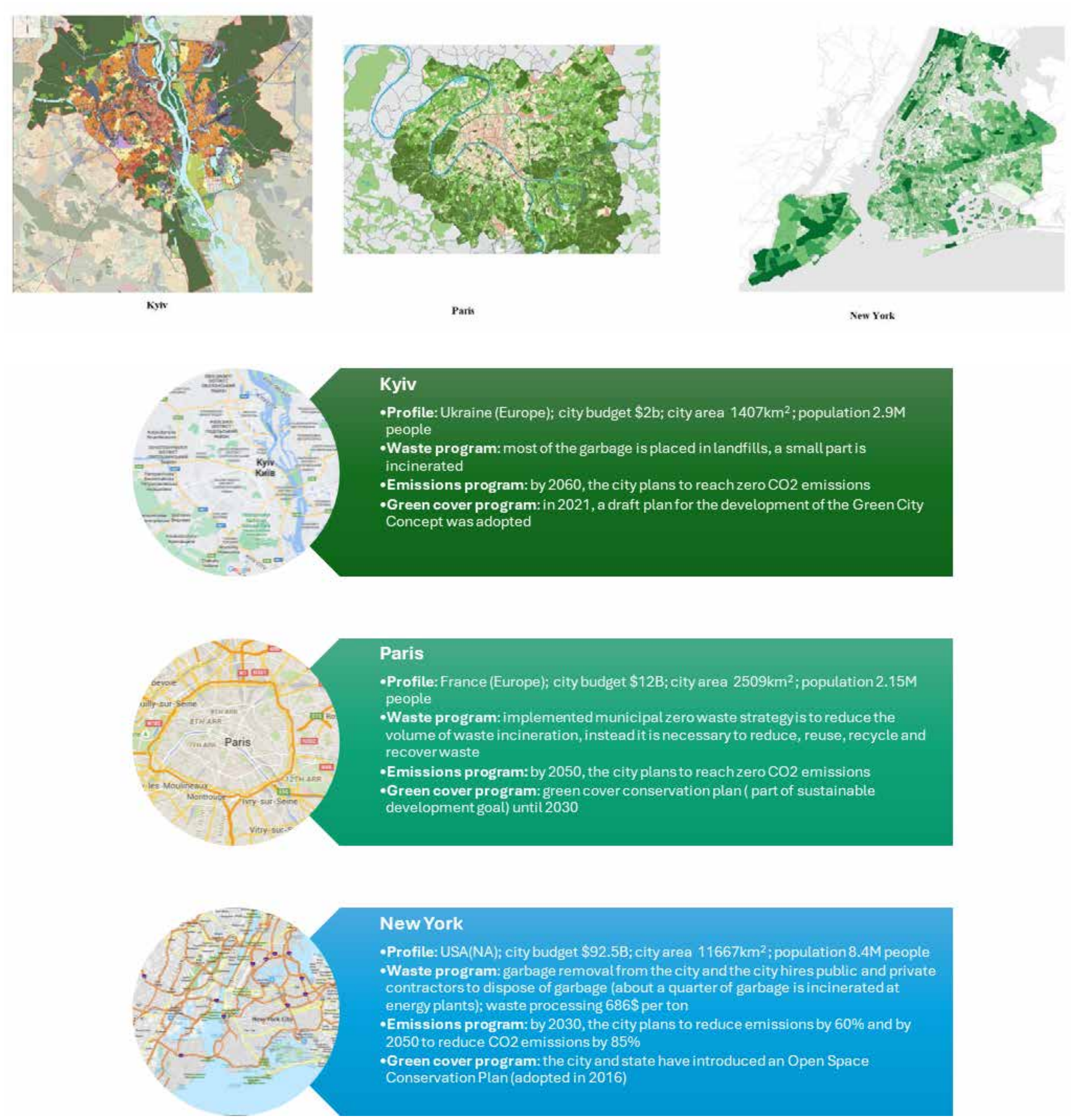


Figure 4.4 Three cities environmental profiles

The middleware service model may be expressed as:

$$D_{raw} \rightarrow Ingest \rightarrow Validate \rightarrow Harmonize \rightarrow Store \rightarrow Analyze \rightarrow Alert \rightarrow Report \backslash hfill(4.16)$$

More formally:

$$Y_{z,t} = A\left(H\left(V\left(I\left(D_{raw,z,t}\right)\right)\right)\right) \backslash hfill(4.17)$$

, where:

- D{raw,z,t} - raw data for zone z and time t;
- I - ingestion function;
- V - validation function;
- H - harmonization function;
- A - analytics function;
- Y{z,t} - decision-ready monitoring output.

The database architecture should include at least four storage components:

1. Time-series storage for IoT telemetry.
2. Spatial database for parcels, field zones, restrictions, and derived indicators.
3. Raster/object storage for Sentinel-2 and UAV imagery.
4. Relational/economic database for costs, operations, inputs, yields, and reports.

The OGC SensorThings API may serve as a reference model for IoT observation interoperability because it provides an open, geospatial-enabled standard for connecting IoT devices, data, and applications, and its sensing component manages and retrieves observations and metadata from heterogeneous IoT systems. For Earth Observation, the Copernicus Data Space Ecosystem supports catalog and processing services, including STAC and openEO, while OGC API access enables use of WMS/WMTS/WFS/WCS services in GIS applications.

Table 4.7 Recommended middleware services for monitoring architecture

Service	Main function	Data handled	Recommended implementation logic	Output
Sensor ingestion service	Receives IoT telemetry	Soil moisture, temperature, EC, device status	MQTT/HTTP/API gateway; SensorThings-compatible model	Validated time-series observations
EO discovery service	Searches and loads Sentinel-2 products	Sentinel-2 metadata and imagery	CDSE STAC / openEO / Sentinel Hub	Selected image collection
EO processing service	Calculates indices and masks	Reflectance, cloud mask, NDVI/EVI	openEO, Python/R, raster processing	Parcel-level vegetation indicators
UAV processing service	Processes local imagery	RGB/multispectral images, orthomosaics	Photogrammetry and image-analysis workflow	Affected-area polygons and diagnostics
Weather ingestion service	Loads of weather and agroclimatic data	Temperature, precipitation, ET, wind	ERA5, NASA POWER, local stations	Weather context layer
Spatial aggregation service	Links observations to field zones	Raster, point, vector layers	PostGIS/QGIS/spatial overlay	Field-zone monitoring vector
Data-quality service	Compute's reliability scores	Metadata, missing values, cloud share, sensor status	Rule-based scoring	Q_{z,t} reliability indicator
Event engine	Converts signals into alerts	Thresholds, anomalies, risk scores	Event-driven middleware	Monitoring events for 4.2
Economic connector	Sends monitoring outputs to CBA/MCDA	Input use, affected area, risk score	Structured data export	Economic-efficiency variables
Reporting and audit service	Produces traceable outputs	Logs, metadata, indicators	CSV/GeoJSON/PDF/dashboard	Audit-ready evidence

Source: prepared by the authors.

Spatial and temporal harmonization is one of the most important technical steps because each data source has a different native structure. IoT sensors are points. Sentinel-2 data are raster pixels. UAV imagery is a high-resolution raster or orthomosaic. Parcels are vector polygons. Weather may be at a grid point or a station point. Economic data are usually tabular. These structures cannot be compared directly without harmonization.

The purpose of this harmonization is not only technical correctness. It also prevents false economic conclusions. For example, if soil moisture is measured today but Sentinel-2 imagery is from ten days ago, the system must not treat both values as simultaneous without noting the temporal mismatch. Similarly, a UAV mission after irrigation should not be used to explain a pre-irrigation stress signal unless the timing is explicitly documented.

Monitoring architecture cannot be economically reliable if it does not measure its own data quality. Digital monitoring systems may create an illusion of accuracy if every data stream is treated as equally valid. Each source has limitations. IoT sensors can fail, lose power, drift, or transmit delayed values. Sentinel-2 imagery can be clouded or affected by atmospheric conditions. UAV imagery may be unavailable, poorly georeferenced, or collected under unsuitable lighting conditions. Weather data can be spatially coarse. Parcel data can be outdated or incomplete.

For this reason, the monitoring system must calculate data-reliability indicators and use fallback logic. Fallback logic means that if the highest-resolution data source is unavailable, the system continues to operate using lower-resolution but reliable alternatives. For example, if UAV imagery is unavailable, the system uses Sentinel-2 and IoT. If Sentinel-2 is cloud-covered, the system uses IoT and weather data to delay vegetation-index confirmation. If IoT sensors fail, Sentinel-2 and weather data can still support broad monitoring, but confidence is reduced.

The monitoring architecture should be event oriented. This means the system should not only store data but also detect situations that require attention. In the context of this monograph, an event is an agronomically or economically meaningful change in the monitoring state of a parcel or field zone. Examples include soil moisture below threshold, NDVI anomaly, rapid decline in vegetation index, possible water stress, suspected disease patch, possible over-irrigation, or data-quality warning.

The event structure can be expressed as:

$$E_{z,t} = \{EventID, ZoneID_z, t, Type, Severity, Evidence, Q_{z,t}, RecommendedAction\} \backslash hfill(4.18)$$

, where:

- E{z,t} - monitoring event for field zone z at time t;
- Type - event type, such as drought stress, vegetation anomaly, possible disease, or data-quality issue;
- Severity - event intensity;
- Evidence - supporting IoT/EO/UAV/weather indicators;
- Q{z,t} - reliability score;
- RecommendedAction - inspection, irrigation, spraying, fertilization, wait, or no action.

The event severity can be calculated as:

$$Severity_{z,t} = w_1 \times NDVI\_anom_{z,t} + w_2 \times SMD_{z,t} + w_3 \times WeatherStress_{z,t} + w_4 \times UAVD_{z,t} \backslash hfill(4.19)$$

, where:

- NDVIanom{z,t} - vegetation-index anomaly;
- SMD{z,t} - soil-moisture deficit;
- WeatherStress{z,t} - weather-derived stress indicator;
- UAVD{z,t} - UAV diagnostic indicator;
- $w_1 \dots w_4$ - weights.

This equation is a bridge to subsection 4.2. In 4.1, the event architecture is defined. In 4.2, the economic value of acting on these events will be evaluated. This separation is important. The architecture creates the event; the economic model evaluates whether the intervention triggered by that event is efficient.

Table 4.8 Monitoring event types generated by architecture

Event type	Main trigger	Supporting source	Recommended action	Economic variable
Soil-moisture deficit	SM < SM_threshold	Weather, Sentinel-2, crop stage	Irrigation inspection or irrigation event	Avoided water stress; irrigation timing
Vegetation-index anomaly	NDVI/EVI below expected range	IoT, UAV, field log	Field inspection / diagnostic verification	Affected area and yield-loss risk
Rapid vegetation decline	Negative NDVI/EVI change over time	Weather, UAV	Disease/pest/water-stress check	Avoided crop damage
Waterlogging risk	Low vegetation + high moisture/rainfall	Weather, topography	Drainage/inspection	Localized damage mitigation
Over-irrigation risk	High irrigation volume + adequate moisture	IoT flow meter, weather	Stop/delay irrigation	Water and energy savings
Fertilizer inefficiency risk	Poor vegetation response after application	EO/UAV, field records	Soil or nutrient check	Avoided wasted input
Sensor failure	Missing or abnormal telemetry	Device status	Maintenance task	Data reliability and system OPEX
Clouded EO cycle	Cloud share above threshold	Metadata	Wait for next image / use IoT fallback	Reduced confidence in EO-driven benefit
UAV diagnostic request	High anomaly severity	EO + IoT	UAV mission if permitted	Cost of verification vs avoided loss
Compliance-sensitive anomaly	Event intersects restricted or protected zone	GIS constraints	Notify planner / avoid intervention	Avoided ecological/legal risk

Source: prepared by the authors.

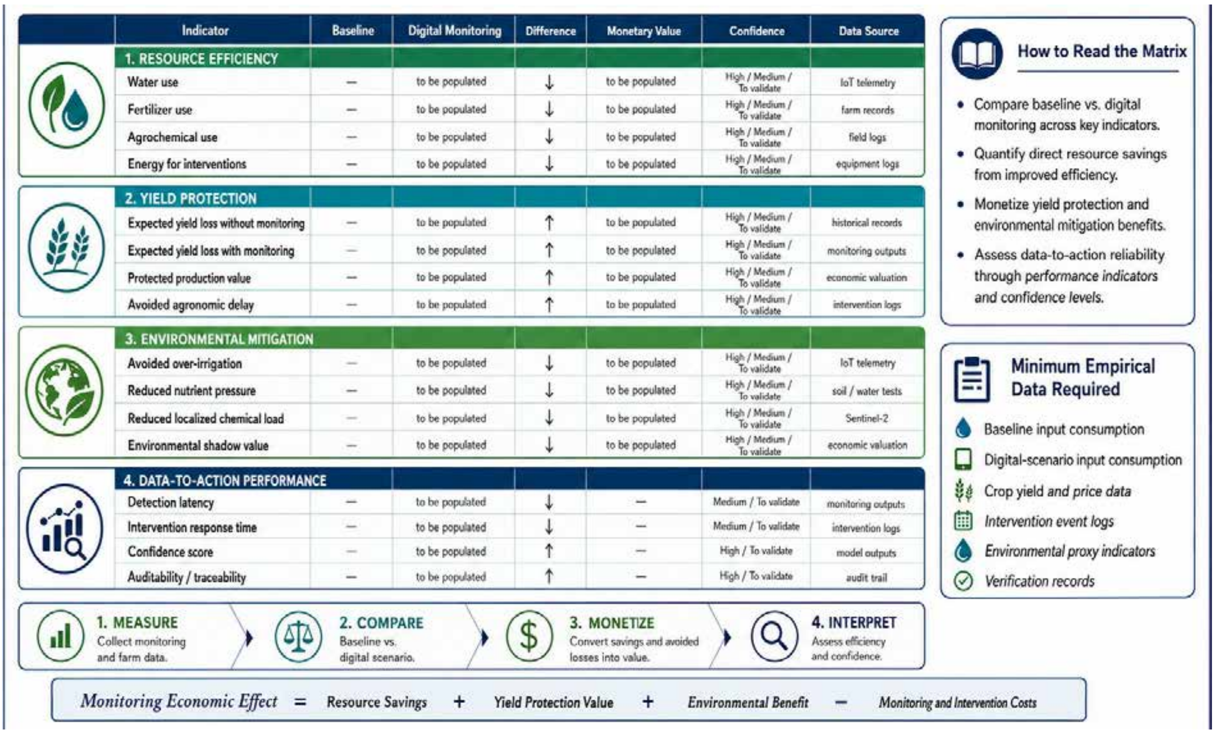


Figure 4.5 Monitoring efficiency matrix

The architecture described above prepares the empirical foundation for evaluating economic efficiency in subsections 4.2 and 4.3. It does this by transforming environmental and agronomic data into structured, auditable, and economically interpretable variables.

The monitoring system must generate at least five groups of economic inputs.

First, it must generate input-use variables: water applied, water saved, fertilizer applied, agrochemical use, labor for inspection, and machinery time. Second, it must generate yield-protection variables: affected area, crop stress duration, intervention timing, and expected yield-loss risk. Third, it must generate environmental variables: water stress, runoff risk, soil degradation risk, localized ecological damage, and emissions proxies where relevant. Fourth, it must generate temporal variables: detection time, decision time, intervention time, and delay relative to the agronomic window. Fifth, it must generate data-quality variables: reliability, completeness, latency, source availability, and provenance.

The general architecture-to-economics transformation can be written as:

$$EconomicInput_{z,t} = g\left(X_{z,t}, E_{z,t}, Q_{z,t}, CostData_{z,t}, FieldLog_{z,t}\right)\backslash hfill(4.20)$$

, where:

- EconomicInput{z,t} - structured economic input for zone z and time t;
- X{z,t} - fused monitoring vector;
- E{z,t} - monitoring event;
- Q{z,t} - data-quality score;
- CostData{z,t} - prices, costs, and resource-use data;
- FieldLog{z,t} - record of actual intervention.

This equation shows that the economic model is not separated from the monitoring architecture. It depends on it. If the architecture does not preserve field-zone identity, timestamp, affected area, intervention status, and data quality, then later calculations of efficiency will be weak or impossible to verify.

The basic monitoring benefit categories prepared by this architecture can be expressed as:

$$B_{monitoring} = B_{water} + B_{fertilizer} + B_{agrochemical} + B_{yield} + B_{time} + B_{environment} + B_{data}\backslash hfill(4.21)$$

, where:

- Bwater - avoided water and energy cost;
- Bfertilizer - avoided fertilizer waste;
- Bagrochemical - avoided agrochemical waste;
- Byield - protected yield value;
- Btime - value of saved agronomic time window;
- Benvironment - avoided environmental damage;
- Bdata - value of generated reusable data.

These benefit categories are not fully calculated in 4.1. They are prepared here architecturally and evaluated in 4.2 and 4.3.

For empirical implementation, the architecture should be developed in a stepwise way. The system does not have to begin as a full national-scale platform. It can start as a pilot system for selected parcels, a single cooperative, a single hromada, or a single peri-urban agricultural belt. The important condition is that the pilot architecture already follows the same data logic that can later be scaled: common identifiers, field-zone structure, metadata, quality flags, reproducible EO processing, and traceable event outputs.

Table 4.9 Implementation algorithm for the IoT–Sentinel-2–UAV agrarian monitoring architecture

Step	Action	Practical explanation	Output
1	Define monitoring territory	Select farm, cooperative, hromada, or peri-urban agricultural zone	Area of interest
2	Define field zones	Create parcel/field-zone layer linked to land-management data	Spatial decision units
3	Select monitoring variables	Choose soil moisture, soil temperature, NDVI/EVI, weather, UAV diagnostics, input records	Monitoring variable register
4	Install or register IoT sensors	Define sensor location, depth, ID, calibration, and communication mode	Sensor inventory
5	Configure EO processing	Define Sentinel-2 collection, date range, cloud mask, NDVI/EVI formulas, aggregation rules	EO workflow

Step	Action	Practical explanation	Output
6	Define UAV protocol	Specify when UAV is used, what imagery is collected, and how diagnostics are produced	UAV diagnostic protocol
7	Build ingestion services	Connect IoT, EO, UAV, weather, GIS, and field-log inputs	Data-ingestion layer
8	Build storage architecture	Set up time-series, spatial, raster/object, economic, and metadata stores	Monitoring database
9	Harmonize data	Align coordinate systems, timestamps, units, and field-zone IDs	Harmonized dataset
10	Compute reliability scores	Calculate completeness, latency, accuracy, and provenance indicators	Q_{z,t}
11	Generate monitoring events	Convert thresholds and anomalies into decision events	Event register
12	Export economic variables	Send affected area, timing, input use, data quality, and field logs to CBA/MCDA models	Economic-evaluation dataset
13	Test fallback logic	Simulate cloud cover, sensor failure, and UAV unavailability	Resilience profile
14	Prepare dashboard and reports	Visualize monitoring status, alerts, and audit trail	Decision-support interface

Source: prepared by the authors.

4.2 From Monitoring Signals to Precision Interventions: Thresholds, Event Classification, and Economic Decision Rules

The architecture of the agrarian monitoring systems proposed in this subsection is based on integrating continuous IoT soil telemetry, periodic Sentinel-2 Earth Observation, and episodic UAV imagery. Its scientific and practical value lies in treating monitoring as active data collection rather than passive data collection. It treats monitoring as a structured cyber-physical system that converts heterogeneous observations into decision-ready economic variables.

IoT telemetry gives the system temporal continuity. Sentinel-2 gives the system spatial completeness and multispectral comparability. UAV imagery provides the system with high-resolution diagnostic capabilities when such data collection is permitted and economically justified. Weather and agroclimatic data provide contextual explanation. Parcel and land-use data provide the spatial and institutional decision unit. Middleware and databases integrate these sources into one operational environment. The event engine converts data into agronomic alerts. The economic connector prepares variables for cost-benefit analysis, MCDA, shadow pricing, and simulation.

The main methodological conclusion is that the economic efficiency of environmental monitoring cannot be evaluated without first designing a reliable monitoring architecture. If the data are not harmonized, data quality is not measured, parcel-level aggregation is not performed, and events are not linked to field logs and cost records, later economic calculations will be speculative. Conversely, if the architecture preserves spatial identity, timing, source reliability, affected area, and intervention records, then monitoring can be evaluated as a real economic instrument.

This prepares the transition to subsection 4.2, where the monograph evaluates how raw monitoring data - NDVI/EVI anomalies, soil-moisture thresholds, UAV diagnostic outputs, and weather-context indicators - are translated into actionable agronomic events and economically justified precision interventions.

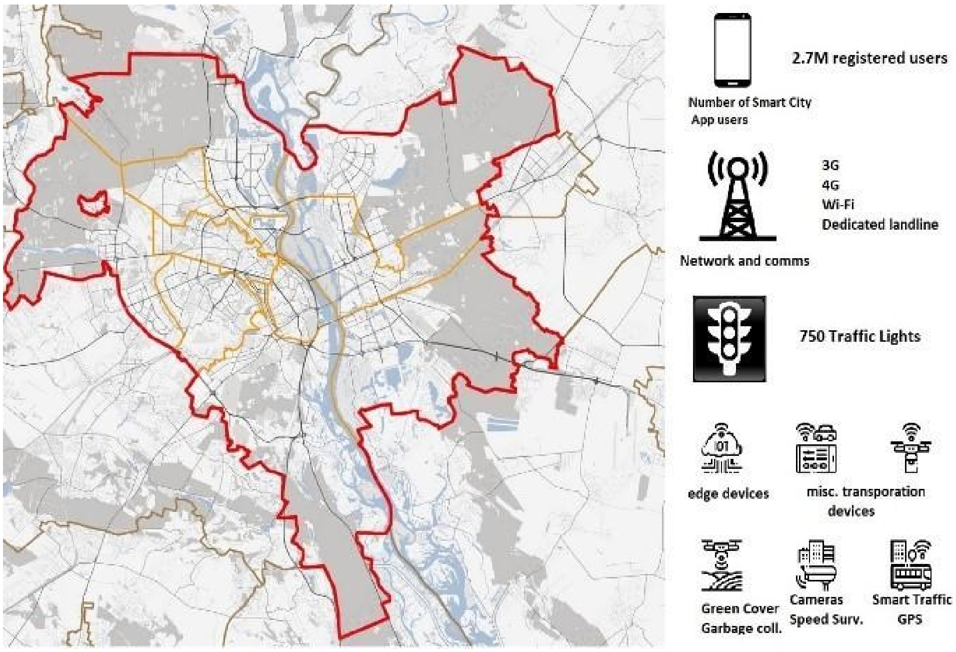


Figure 4.6 Kyiv city IoT profile

4.2. Evaluating the Efficiency of Precision Interventions: The economics of translating raw monitoring data (e.g., NDVI/EVI, soil moisture thresholds) into actionable agronomic events.

Subsection 4.1 defined the architecture of agrarian monitoring as a cyber-physical system that integrates continuous IoT soil telemetry, periodic Sentinel-2 Earth Observation, UAV diagnostics, weather data, cadastral/spatial layers, and economic records. The present subsection moves from architecture to economic action. Its central question is not whether a monitoring system can collect data, but whether the collected data can be transformed into economically justified agronomic events.

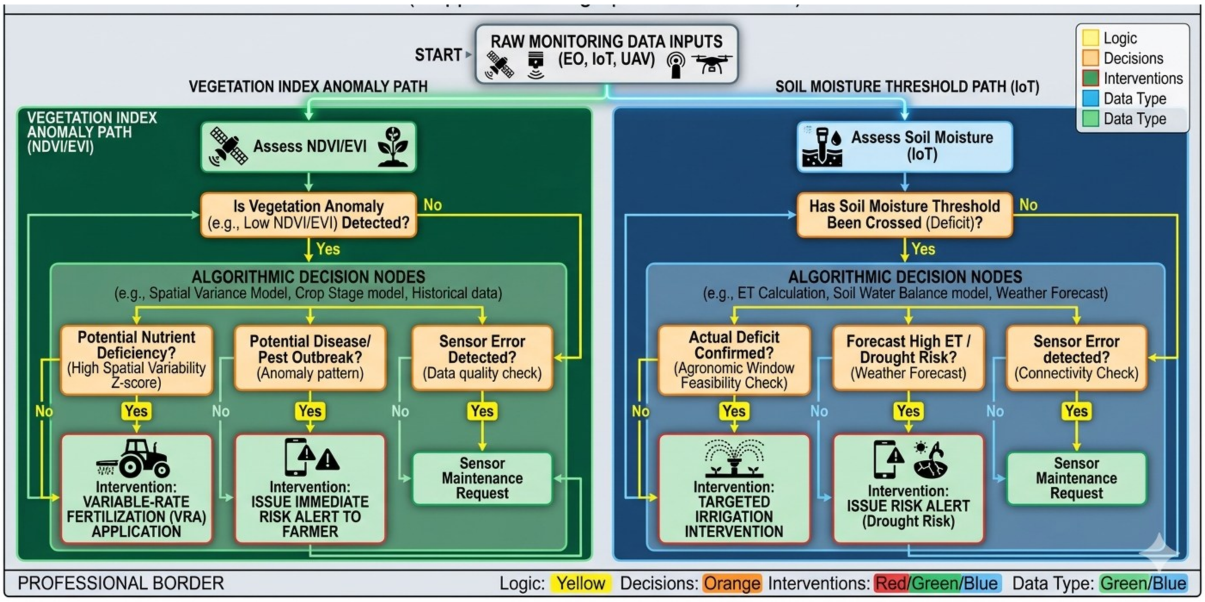


Figure 4.7 Decision tree for precision interventions and agronomic events

This distinction is fundamental. A sensor reading, a vegetation index, a UAV orthomosaic, or a weather record has no independent economic value if it does not change the decision of the farm, cooperative, local authority, or service provider. Economic value appears when monitoring changes the timing, location, scale, or type of intervention. In practical terms, raw data becomes valuable when they help answer questions such as: Should irrigation be started now or delayed? Should fertilizer be applied uniformly or only in a stressed zone? Should a field be inspected? Should a UAV mission be launched?

Should spraying be triggered, postponed, or avoided? Should a route or machinery schedule be adjusted because an agronomic service window is closing?

The author's digital agronomy workflow for the Kyiv agglomeration already formulates this transition from multisource data to action: UAV/satellite imagery, in-field IoT, and climate/crop data are fused with administrative-economic layers, and the system translates these inputs into stress detection, irrigation timing, and input allocation recommendations. The same logic is extended here into a formal economic model: each monitoring signal must be converted into an event, each event into a feasible intervention option, and each intervention option into a measurable expected economic result.

In this monograph, a precision intervention is defined as an agronomic or operational action whose location, timing, intensity, or necessity is determined by digital monitoring data rather than by uniform, calendar-based, or purely visual decision-making. The intervention may be physical, such as irrigation, spraying, fertilization, drainage correction, field inspection, or machinery operation. It may also be informational, such as issuing an alert, creating a risk note, delaying action, requesting additional verification, or updating a route. The economic evaluation must include both action and non-action because sometimes the most efficient intervention is to avoid unnecessary input use.

This subsection, therefore, develops a structured methodology for evaluating the economic efficiency of precision interventions. The logic is sequential:

1. Raw monitoring data are converted into indicators.
2. Indicators are converted into anomalies or thresholds.
3. Anomalies are converted into agronomic events.
4. Agronomic events are converted into intervention options.
5. Intervention options are evaluated through expected net benefit, MCDA, risk adjustment, and data reliability;
6. Selected interventions are recorded as economic events for later efficiency metrics in subsection 4.3.

The current monograph already defines Case Study II as the block where raw environmental and agronomic data are transformed into actionable decisions and then evaluated through reduced input waste, yield protection, improved timing, and mitigation of localized environmental damage. This subsection provides the operational and economic mechanism for that transformation.

Table 4.10 Transformation chain from monitoring data to economically justified precision intervention

Stage	Input	Processing logic	Output	Economic meaning
Raw monitoring data	IoT soil moisture, Sentinel-2 NDVI/EVI, UAV imagery, weather data, field logs	Data cleaning, harmonization, spatial and temporal alignment	Valid monitoring dataset	Creates reliable evidence-based
Indicator calculation	Reflectance bands, sensor telemetry, and weather variables	Vegetation indices, soil-moisture deficit, anomaly scores, weather-stress indicators	Agronomic indicators	Converts raw data into interpretable variables
Threshold/anomaly detection	Indicator values and historical/crop-stage baselines	Dynamic thresholds, z-scores, percentile deviations, rule-based triggers	Candidate anomaly	Identifies possible agronomic problem
Event generation	Candidate anomaly + field zone + crop stage + data quality	Event classification, severity scoring, confidence scoring	Agronomic event	Creates a decision object
Intervention mapping	Event type, severity, timing, field zone, available resources	Irrigation, spraying, fertilization, inspection, UAV verification, no-action option	Intervention alternatives	Defines feasible response options
Economic evaluation	Intervention cost, input price, yield-risk estimate, delay cost, environmental value	Expected net benefit, risk-adjusted benefit, MCDA priority	Intervention value	Determines whether action is justified
Decision and execution	Best-ranked intervention option	Action scheduling, task assignment, routing, audit log	Executed or postponed intervention	Converts digital recommendation into operational result
Efficiency recording	Action record, input use, affected area, observed result	Before/after comparison and CBA/MCDA feed	Economic-efficiency dataset	Provides empirical basis for subsection 4.3

Source: prepared by the authors.

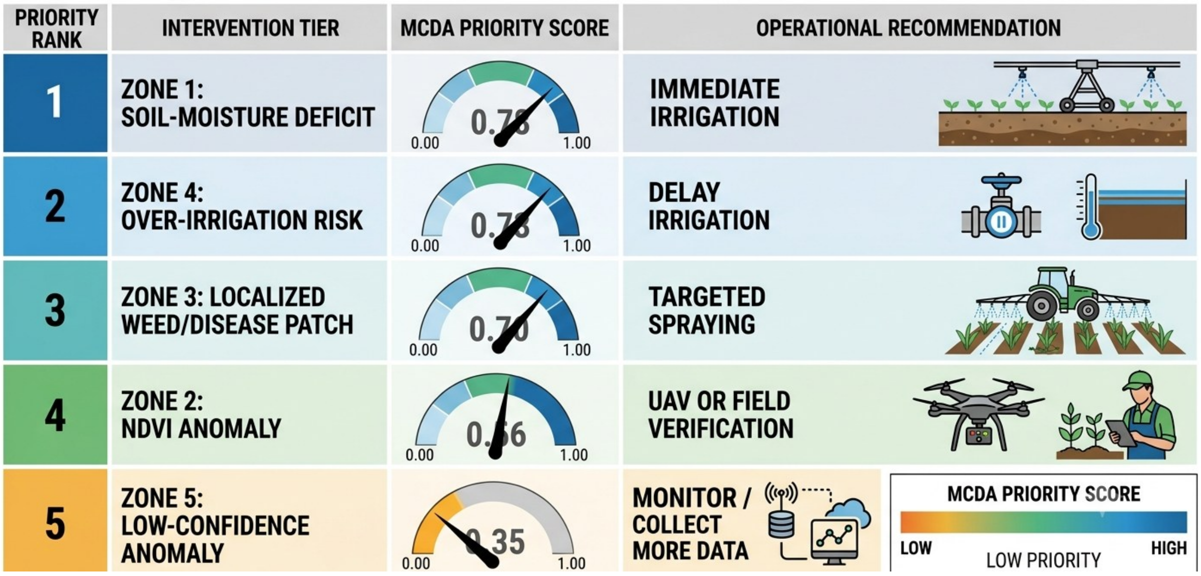


Figure 4.8 MCDA-based prioritization of precision interventions

The first methodological step is to distinguish an indicator from an event. An indicator is a measured or calculated value. Examples include NDVI, EVI, soil moisture, soil temperature, soil-moisture deficit, precipitation, evapotranspiration, or UAV-derived affected-area share. An event is a decision-relevant interpretation of one or more indicators. For example, "NDVI is low" is an indicator result. "Potential drought stress in Zone 3 requiring irrigation verification within 24 hours" is an agronomic event.

This distinction is important because economic evaluation should not be based directly on raw values. If every low-index value triggers immediate action, the system will generate false interventions and incur unnecessary costs. If the system waits for perfect certainty, it may miss time-sensitive agronomic windows. Therefore, event generation must balance sensitivity, specificity, timeliness, and cost.

The general event function can be written in in a linear equation format as:

$$E_{z,t} = F\left(X_{z,t}, B_{z,g}, CROP_{z,t}, W_{z,t}, Q_{z,t}, R_{z,t}\right) \backslash hfill(4.22)$$

, where:

- E(z,t) - agronomic event for field zone z at time t;
- X(z,t) - fused monitoring vector;
- B(z,g) - baseline or reference behavior for zone z and crop-growth stage g;
- CROP(z,t) - crop type and growth stage;
- W(z,t) - weather and agroclimatic context;
- Q(z,t) - data-quality and reliability score;
- R(z,t) - risk context, including field access, environmental sensitivity, and operational constraints.

The event function should not use a single universal threshold across all fields. It should be calibrated by crop type, soil type, growth stage, weather conditions, and local historical behavior. A soil-moisture value that is acceptable for one crop stage may be dangerous at another. A decline in NDVI may be normal during maturation but alarming during vegetative growth. A low vegetation index at a field edge may reflect road dust or trampling, whereas a similar pattern within the field may indicate disease, water stress, or nutrient deficiency.

$$Event_{z,t} = \{1\ if\ Score_{z,t} \geq \theta_{event}\ and\ Q_{z,t} \geq Q_{min}\ 0\ if\ Score_{z,t} < \theta_{event}\ or\ Q_{z,t} < Q_{min}\ \backslash hfill(4.23)$$

, where:

- Score(z,t) - composite agronomic stress or opportunity score;
- θevent - event threshold;
- Qmin - minimum reliability threshold.

If the data quality is too low, the system should not generate a direct intervention. It should generate a verification event or data-quality event. This avoids economically unjustified actions based on weak evidence.

Table 4.11 Difference between monitoring indicators, anomalies, events, and interventions

Analytical object	Definition	Example	Economic role
Raw value	Direct measurement or observation	Soil moisture = 16%; Sentinel-2 B8 reflectance; UAV RGB pixel	No direct economic meaning until interpreted
Indicator	Processed agronomic variable	NDVI, EVI, soil-moisture deficit, weather-stress index	Supports comparison across zones and time
Anomaly	Deviation from expected baseline	NDVI 18% below same-stage historical median	Signals possible problem or opportunity
Event	Decision-relevant interpretation	Moderate drought-stress event in Zone 2 with high confidence	Creates a management decision object
Intervention option	Possible response to event	Irrigate, inspect, UAV verification, spray, fertilize, delay	Defines cost and expected benefit alternatives
Executed intervention	Actual action taken	Irrigation applied to 12 ha; UAV mission completed	Produces empirical record for efficiency calculation
Economic result	Measured or estimated effect	Water saved, yield protected, cost avoided, environmental damage reduced	Used in 4.3 efficiency metrics

Source: prepared by the authors.

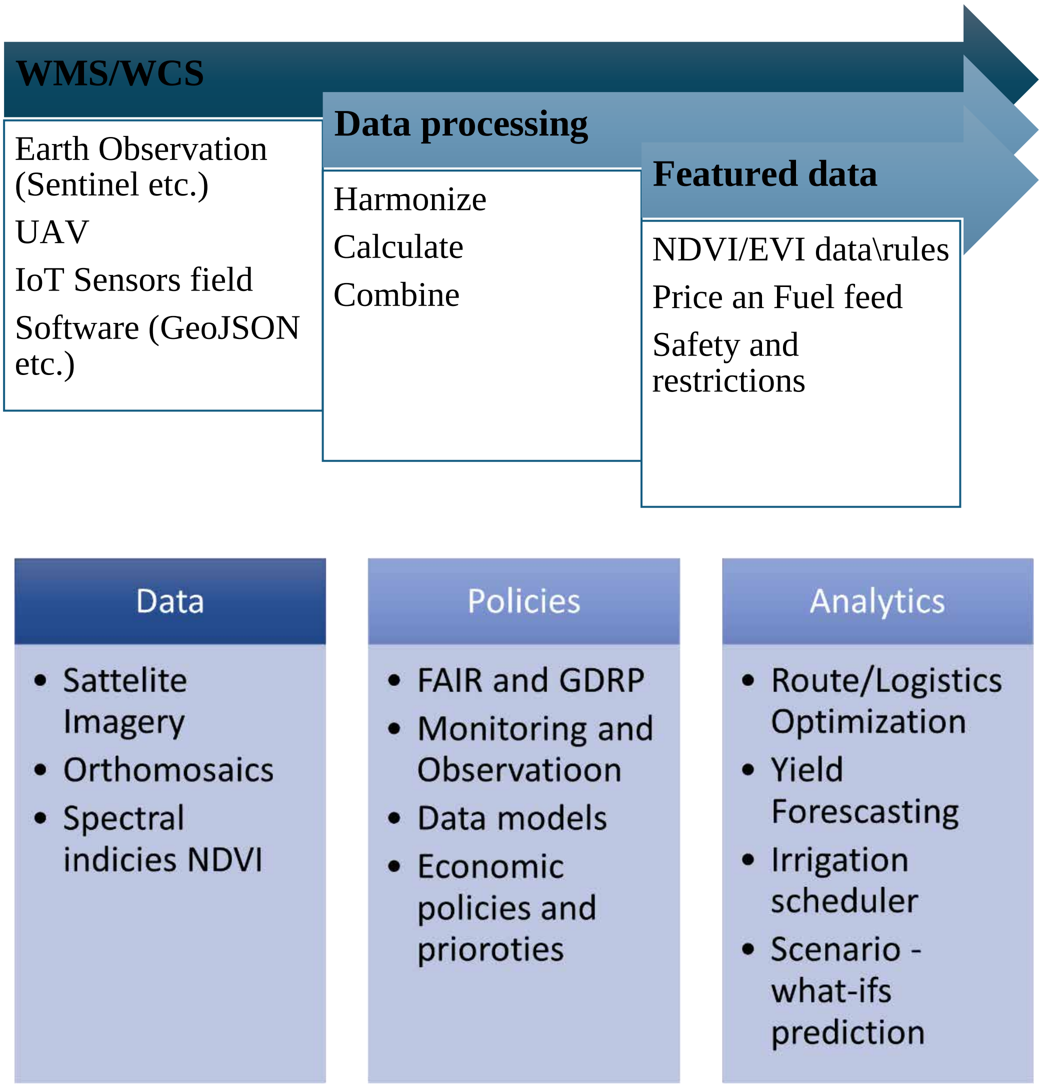


Figure 4.9 Observation system data processing flow

Vegetation indices are among the most practical monitoring indicators because they provide spatial evidence of crop condition. NDVI and EVI are especially useful because they can be derived from Sentinel-2 and, where available, UAV multispectral imagery. However, the economic interpretation of NDVI/EVI must be approached with caution. These indices do not directly measure profit, yield, disease, or water stress. They indicate vegetation conditions, and the economic model must interpret them in relation to crop stage, weather, soil moisture, management history, and field heterogeneity.

The NDVI formula is:

$$NDVI_{z,t} = \frac{\rho_{NIR,z,t} - \rho_{RED,z,t}}{\rho_{NIR,z,t} + \rho_{RED,z,t}} \backslash hfill(4.24)$$

For Sentinel-2:

$$NDVI_{z,t} = \frac{\rho_{B8,z,t} - \rho_{B4,z,t}}{\rho_{B8,z,t} + \rho_{B4,z,t}} \backslash hfill(4.25)$$

The EVI formula is:

$$EVI_{z,t} = 2.5 \times \frac{\rho_{B8,z,t} - \rho_{B4,z,t}}{\rho_{B8,z,t} + 6 \times \rho_{B4,z,t} - 7.5 \times \rho_{B2,z,t} + 1} \backslash hfill(4.26)$$

, where:

- ρ(B8,z,t) - near-infrared reflectance;
- ρ(B4,z,t) - red reflectance;
- ρ(B2,z,t) - blue reflectance;
- z - field zone or parcel;

- t - observation date or monitoring cycle.

A vegetation-index anomaly may be calculated using a reference value:

$$VI\_anom_{z,t} = \frac{VI_{ref,z,g} - VI_{z,t}}{VI_{ref,z,g}} \hfill (4.27)$$

, where:

- VIanom(z,t) - vegetation-index anomaly;
- VI(z,t) - current NDVI or EVI value;
- VIref(z,g) - reference value for the same zone or comparable field at growth stage g.

A standardized anomaly score may also be used:

$$Z\_VI_{z,t} = \frac{VI_{z,t} - \mu_{VI,z,g}}{\sigma_{VI,z,g}} \hfill (4.28)$$

, where:

- μVI(z,g) - expected mean vegetation index for zone z at growth stage g;
- σVI(z,g) - standard deviation of historical or comparable values.

The event logic can then be written as:

$$VI\_Event_{z,t} = 1 \quad if\ Z\_VI_{z,t} \le -\theta_{VI}\ and\ Q_{S2,z,t} \ge Q_{min} \hfill (4.29)$$

, where:

- θVI - vegetation anomaly threshold;
- QS2(z,t) - Sentinel-2 or EO data-quality score.

If the anomaly is spatially localized, the system should calculate the affected area:

$$A_{affected,z,t} = A_z \times Share\_anom_{z,t} \hfill (4.30)$$

, where:

- Az - total area of zone z;
- Shareanom(z,t) - share of valid pixels classified as anomalous.

The affected area is economically important because it determines whether an intervention should cover the whole field or only a part of it. A uniform intervention across 100 hectares has a different cost structure than a targeted intervention across 12 hectares. This is one of the main ways in which digital monitoring creates economic value: it reduces the treated area when the problem is spatially localized.

Table 4.12 Vegetation-index triggers and economic interpretation

Indicator	Trigger logic	Event type	Supporting data required	Possible intervention	Economic interpretation
Low NDVI	NDVI below growth-stage reference	General vegetation stress	Crop stage, weather, soil moisture	Inspection, UAV verification, irrigation check	Prevents delayed response to crop stress
Low EVI	EVI below reference, especially in dense canopy	Vegetation condition anomaly	Crop stage, EO quality, field history	Inspection or targeted diagnostic	Improves anomaly detection in high-biomass conditions
Rapid NDVI decline	Negative change over a short time period	Sudden stress/disease / water issue	Weather, soil moisture, field log	Urgent inspection or crop-protection check	Protects yield by shortening detection delay
Patchy NDVI anomaly	Localized low-value cluster	Local field heterogeneity	UAV or field scouting	Targeted treatment or localized correction	Reduces unnecessary whole-field input use
NDVI low + soil moisture low	Combined vegetation and water stress	Probable drought or irrigation deficit	IoT, weather, irrigation records	Irrigation event or irrigation inspection	Avoids water-stress yield loss

Indicator	Trigger logic	Event type	Supporting data required	Possible intervention	Economic interpretation
NDVI low + soil moisture high	Possible waterlogging/disease/other issue	Non-drought anomaly	Weather, UAV, field inspection	Diagnostic inspection before action	Prevents wrong irrigation decisions
NDVI normal + soil moisture low	Early water-stress risk	Preventive irrigation warning	Crop stage, forecast	Timed irrigation	Prevents future vegetation decline
NDVI anomaly + low EO quality	Uncertain anomaly	Verification event	Cloud mask, valid pixel share	Wait, UAV, field check	Avoids false-positive intervention

Source: prepared by the authors.

Soil-moisture telemetry is especially important because water stress can develop faster than satellite monitoring cycles can detect. IoT sensors provide continuous evidence of whether a field is moving toward a critical threshold. However, soil-moisture thresholds must also be interpreted carefully. A single threshold cannot be applied mechanically across all soils, crops, root depths, and crop stages. The threshold should be calibrated based on crop water demand, soil type, rooting depth, irrigation system, weather forecast, and the economic costs of water and energy.

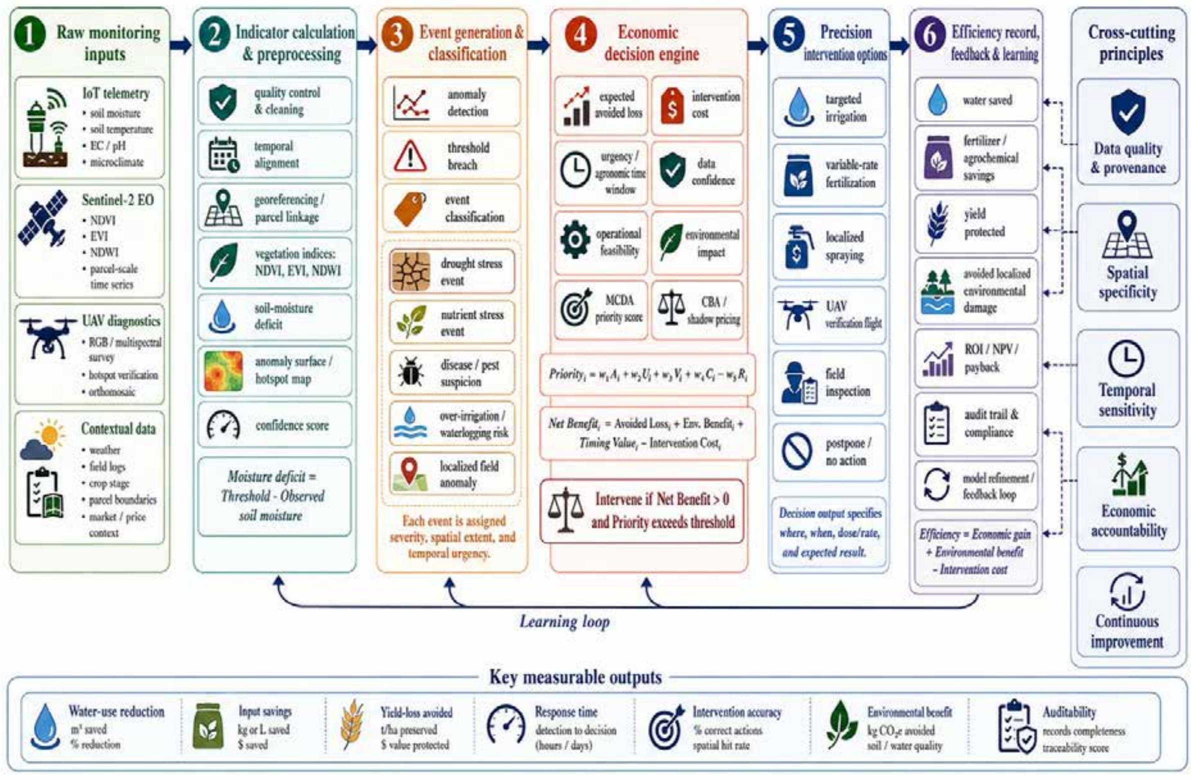


Figure 4.10 System data and process flow diagram for monitoring and decision support

The basic soil-moisture deficit indicator was introduced in subsection 4.1 and can be used here as an event trigger:

$$SMD_{z,t} = \frac{SM_{target,z,g} - SM_{z,t}}{SM_{target,z,g}} \backslash hfill(4.31)$$

, where:

- SMD(z,t) - soil-moisture deficit;
- SMtarget(z,g) - target soil moisture for zone z and growth stage g;
- SM(z,t) - observed soil moisture.

An irrigation event may be generated when the deficit exceeds a threshold:

$$Irr\_Event_{z,t} = 1 \quad if\ SMD_{z,t} \geq \theta_{SMD}\ and\ Q_{IoT,z,t} \geq Q_{min} \backslash hfill(4.32)$$

, where:

- θSMD - soil-moisture deficit threshold;
- QIoT_(z,t) - IoT data-quality score.

However, the event should also consider forecast precipitation and existing vegetation conditions. If rain forecasts in the next short window, immediate irrigation may not be economically justified. If NDVI/EVI remains normal while soil moisture declines, the event may be preventive rather than corrective. If NDVI/EVI is already declining and soil moisture is low, the event becomes more urgent.

A weather-adjusted irrigation urgency score can be expressed as:

$$IU_{z,t} = w_1 \times SMD_{z,t} + w_2 \times VI\_anom_{z,t} + w_3 \times ET\_risk_{z,t} - w_4 \times RainProb_{z,t} \backslash hfill(4.33)$$

, where:

- IU(z,t) - irrigation urgency score;
- ETrisk_(z,t) - evapotranspiration or heat-stress risk;
- RainProb(z,t) - probability or expected amount of near-term precipitation;
- $w_1 \ldots w_4$ - weights.

The irrigation event becomes economically actionable when expected avoided loss exceeds the cost of irrigation:

$$Action\_Irr_{z,t} = 1 \quad if\ EAL_{water,z,t} - C_{irrig,z,t} > 0 \backslash hfill(4.34)$$

, where:

- EALwater(z,t) - expected avoided loss from timely irrigation;
- Cirrig(z,t) - cost of irrigation, including water, energy, labor, machinery, and system operation.

The cost of irrigation can be written as:

$$C_{irrig,z,t} = W_{z,t} \times P_{water} + Energy_{z,t} \times P_{energy} + Labor_{z,t} \times P_{labor} + C_{mach,z,t} \backslash hfill(4.35)$$

, where:

- W(z,t) - water volume applied;
- Pwater - water price or scarcity-adjusted water cost;
- Energy(z,t) - energy used for pumping or distribution;
- Penergy - energy price;
- Labor(z,t) - labor time;
- Plabor - labor cost;
- Cmach_(z,t) - machinery or irrigation-system cost.

This formulation avoids a common weakness in digital agriculture evaluation: treating every alert as valuable. An alert is economically valuable only if it changes action and if the value of that action exceeds the cost of acting.

Table 4.13 Soil-moisture event types and irrigation decision logic

Soil-moisture condition	EO condition	Weather context	Event type	Recommended action	Economic rationale
Moisture below target	NDVI/EVI normal	No rain expected	Preventive water-stress event	Irrigation scheduling	Prevents future yield loss before visible stress
Moisture below target	NDVI/EVI declining	No rain expected / heat risk	Urgent irrigation event	Immediate irrigation or inspection	Protects yield and service window
Moisture below target	NDVI/EVI declining	Rain expected soon	Conditional irrigation event	Compare irrigation cost vs waiting risk	Avoids unnecessary water use if rainfall is reliable
Moisture adequate	NDVI/EVI declining	Heat or disease-prone weather	Non-water stress event	Field inspection / UAV verification	Prevents wrong irrigation response
Moisture high	NDVI/EVI declining	Rainfall or drainage issue	Waterlogging / disease risk event	Drainage check / diagnostic inspection	Avoids adding water and worsening damage
Moisture high	NDVI/EVI normal	Recent irrigation	Over-irrigation risk note	Delay next irrigation	Saves water and energy

Soil-moisture condition	EO condition	Weather context	Event type	Recommended action	Economic rationale
Sensor missing	EO normal	Weather normal	Data-quality event	Maintain sensor / monitor	Avoids false certainty
Sensor missing	EO declining	Heat or drought risk	Verification event	Field visit or backup sensor check	Prevents missed irrigation window

Source: prepared by the authors.

The practical problem in agrarian monitoring is that no single data source is sufficient. NDVI may detect crop stress but not its cause. Soil moisture may detect water deficit but not disease. UAV imagery may identify local symptoms but may not be available regularly. Weather data may explain risk but cannot prove field condition. Therefore, the decision-support system should combine several indicators into a composite stress score and a confidence score.

A composite agronomic stress score can be written as:

$$CSS_{z,t} = w_{VI} \times VI\_anom_{z,t} + w_{SM} \times SMD_{z,t} + w_{W} \times WeatherStress_{z,t} + w_{UAV} \times UAVD_{z,t} + w_{H} \times HistRisk_{z,t} \backslash hfill(4.36)$$

, where:

- CSS(z,t) - composite stress score;
- VI_anom(z,t) - vegetation-index anomaly;
- SMD(z,t) - soil-moisture deficit;
- WeatherStress(z,t) - weather-derived risk indicator;
- UAVD(z,t) - UAV diagnostic score;
- HistRisk(z,t) - historical risk for the field zone;
- w - weights assigned to each component.

The event confidence score can be calculated separately:

$$CONF_{z,t} = q_1 \times Q_{S2,z,t} + q_2 \times Q_{IoT,z,t} + q_3 \times Q_{UAV,z,t} + q_4 \times Q_{W,z,t} + q_5 \times Q_{GIS,z,t} \backslash hfill(4.37)$$

, where:

- CONF(z,t) - confidence level of the event;
- QS2, QIoT, QUAV, QW, QGIS - data-quality scores for satellite, IoT, UAV, weather, and GIS data;
- q1 ... q5 - reliability weights.

The event severity and event confidence should not be confused. Severity indicates how serious the agronomic problem may be. Confidence indicates how reliable the evidence is. A high-severity but low-confidence event should usually trigger verification, not immediate expensive action. A moderate-severity but high-confidence event may justify a low-cost intervention or targeted inspection. This distinction is essential for economic efficiency because it prevents both overreaction and underreaction.

The event class can be determined as:

$$Class_{z,t} = f\left(CSS_{z,t}, CONF_{z,t}, T_{window,z,t}, C_{action,z,t}, Risk_{z,t}\right) \backslash hfill(4.38)$$

, where:

- Twindow(z,t) - remaining agronomic service-window time;
- Caction(z,t) - expected action cost;
- Risk(z,t) - agronomic, operational, or environmental risk.

Table 4.14 Composite event classes and recommended economic response

Event severity	Event confidence	Time-window pressure	Recommended response	Economic logic
High	High	High	Immediate intervention	Expected avoided loss likely exceeds action cost

Event severity	Event confidence	Time-window pressure	Recommended response	Economic logic
High	Medium	High	Rapid field inspection or UAV verification, then action	Verification cost justified by high risk
High	Low	High	Emergency verification; avoid expensive full-field action without evidence	Prevents large loss while controlling false-positive cost
Medium	High	Medium	Targeted intervention or scheduled inspection	Efficient if affected area is limited
Medium	Medium	Medium	Monitor + verify with lower-cost source	Avoids unnecessary intervention
Medium	Low	Low	Wait for additional data	Expected action value uncertain
Low	High	Low	No action or routine monitoring	Action cost likely exceeds avoided loss
Low	Low	Low	No action; data-quality note	No economic basis for intervention
Any	Low	Any	Data-quality event if source reliability is below threshold	Protects model from misleading outputs

Source: prepared by the authors.

The core of subsection 4.2 is the economic decision rule. A precision intervention should be performed only when the expected net benefit is positive or when it is necessary for compliance, safety, or irreversible loss prevention. In ordinary economic cases, the rule is:

$$ENB_{a,z,t} = B_{avoid,a,z,t} + B_{input,a,z,t} + B_{time,a,z,t} + B_{env,a,z,t} - C_{action,a,z,t} - C_{verify,a,z,t} - C_{risk,a,z,t} \backslash hfill(4.39)$$

, where:

- ENB(a,z,t) - expected net benefit of intervention action a in zone z at time t;
- Bavoid(a,z,t) - avoided yield or damage loss;
- Binput(a,z,t) - saved input cost;
- Btime_a,z,t) - value of saved agronomic time-window;
- Benv(a,z,t) - avoided environmental damage or reduced ecological pressure;
- Caction(a,z,t) - cost of executing the intervention;
- Cverify(a,z,t) - cost of additional verification, such as UAV mission or field inspection;
- Crisk(a,z,t) - residual operational, data, or compliance risk cost.

The decision rule is:

$$Choose\ a^* = arg\ arg\ E\ \ NB_{a,z,t} \quad subject\ to{:}\ ENB_{a^*,z,t} > 0 \quad and\ Feasible_{a^*,z,t} = 1 \backslash hfill(4.40)$$

, where:

- a* - selected intervention;
- Feasible(a*,z,t) - feasibility conditions, including field access, legal restrictions, weather, machinery availability, and service-window constraints.

If all intervention alternatives have negative expected net benefit, the economically preferred decision is no action, monitoring continuation, or low-cost verification. This is important because precision agriculture is not only about doing more precise actions. It is also about avoiding unnecessary actions.

The expected avoided loss can be calculated using risk-adjusted logic:

$$B_{avoid,a,z,t} = \left(P_{0,z,t} \times L_{0,z,t}\right) - \left(P_{a,z,t} \times L_{a,z,t}\right) \backslash hfill(4.41)$$

, where:

- P_0_(z,t) - probability of loss without action;

- L_0_(z,t) - expected loss without action;
- P_a_(z,t) - probability of loss after action a;
- L_a_(z,t) - remaining loss after action a.

The reliability-adjusted expected net benefit is:

ENB_adj_(a,z,t) = ENB_(a,z,t) × CONF_(z,t)

This prevents the system from overestimating economic benefits when evidence is weak. In high-risk cases, the model may still recommend verification, even when confidence is moderate, because the expected loss may be large.

Table 4.15 Economic decision components for precision interventions

Component	Meaning	Example
Avoided yield loss	Value of crop loss prevented by intervention	Irrigation prevents drought stress
Saved input cost	Cost avoided by targeted rather than uniform application	Spraying only affected 12 ha instead of 50 ha
Saved time-window value	Loss avoided by acting before the deadline	Spraying before the disease spreads
Environmental benefit	Reduced water, fertilizer, chemical, runoff, or soil pressure	Reduced over-irrigation
Action cost	Cost of executing the intervention	Irrigation, spraying, fertilization, field work
Verification cost	Cost of additional confirmation	UAV mission or scouting
Residual risk cost	Remaining uncertainty or failure probability	Intervention may not fully solve stress
Reliability adjustment	Confidence correction	Clouded image or partial sensor failure

Source: prepared by the authors.

Expected net benefit is the central economic rule, but in practice farms often face resource constraints. Water, machinery, labor, and time may be limited. Several field zones may require attention simultaneously. Therefore, the system also needs a prioritization mechanism.

MCDA is appropriate when interventions must be ranked by multiple criteria: expected benefit, urgency, cost, environmental impact, confidence, operational feasibility, and risk. This follows the methodological logic developed in subsection 2.2, in which MCDA was used to compare alternatives across economic, temporal, environmental, spatial, risk, and institutional criteria.

The intervention priority score can be written as:

$$IPS_{a,z,t} = w_b \times B'_{avoid,a,z,t} + w_u \times Urgency'_{z,t} + w_q \times CONF'_{z,t} + w_e \times EnvBenefit'_{a,z,t} + w_f \times Feasibility'_{a,z,t} - w_c \times C'_{action,a,z,t} - w_r \times Risk'_{a,z,t} \backslash hfill(4.43)$$

, where:

- IPS_(a,z,t) - intervention priority score;
- B'_avoid - normalized avoided-loss benefit;
- Urgency' - normalized urgency or time-window pressure;
- CONF' - normalized confidence score;
- EnvBenefit' - normalized environmental benefit;
- Feasibility' - normalized feasibility score;
- C'_action - normalized action cost;
- Risk' - normalized operational or data risk;
- w - weights.

The highest priority intervention is:

$$a^* = arg\ arg\ I\ \ PS_{a,z,t} \quad subject\ to:\ ENB_{adj,a,z,t} > 0 \backslash hfill(4.44)$$

, where:

- a* is the optimized, highest-priority tactical intervention chosen for execution;
- ENB{adj},a,z,t} is the reliability-adjusted expected net benefit function serving as the primary economic gatekeeper.

This means that MCDA should rank only economically justifiable interventions unless compliance or emergency conditions override normal calculation.

Table 4.16 MCDA criteria for prioritizing precision interventions

Criterion	Type	Measurement	Interpretation	Example
Expected avoided loss	Benefit	UAH or normalized score	Larger avoided loss increases priority	Preventing drought loss in high-value crop
Action cost	Cost	UAH/ha, UAH/event	Higher cost reduces priority unless benefit is large	UAV mission or whole-field spraying
Urgency	Benefit	Hours/days before service-window closure	More urgent events receive higher priority	Irrigation window closing
Data confidence	Benefit	0–1 score	Higher confidence supports action	EO + IoT + UAV agreement
Environmental benefit	Benefit	Reduced water/fertilizer/chemica l pressure	Higher ecological benefit increases priority	Avoided over-irrigation
Operational feasibility	Benefit	0–1 or binary	Feasible actions are prioritized	Machinery and labor available
Residual risk	Cost	Probability × loss or 0–1	Higher uncertainty reduces priority	Weak diagnosis or poor access
Compliance sensitivity	Constraint / benefit	Binary or score	May override normal ranking	Protected zone or restricted land
Affected area	Context	ha or % field	Helps determine scale and action type	Localized vs whole-field problem
Data latency	Cost	Hours/days	Delayed evidence reduces confidence	Old satellite image

Source: prepared by the authors.

Verification is a special category of precision intervention. It does not directly irrigate, fertilize, or spray. Instead, it improves information quality before a more expensive or irreversible action. UAV missions, field scouting, soil sampling, or sensor maintenance may all be treated as verification actions.

Verification is economically justified when the expected value of the improved information exceeds the verification cost. This can be expressed as:

$$EVI_{info,v,z,t} = E\left[ENB_{after\_verification,z,t}\right] - E\left[ENB_{without\_verification,z,t}\right] \backslash hfill(4.45)$$

, where:

- EVIinfo(v,z,t) - expected value of information from verification action v;
- ENBafterverification - expected net benefit after improved information;
- ENBwithoutverification - expected net benefit without additional verification.

Verification should be performed when:

$$EVI_{info,v,z,t} > C_{verify,v,z,t} \backslash hfill(4.46)$$

, where:

- C{verify},v,z,t is the direct variable cost of executing the specific verification action v (accounting for fuel, labor, drone battery cycles, or third-party data access fees).

For example, if a satellite anomaly suggests a possible disease over 40 hectares but the confidence is moderate, a UAV mission may be justified if it can reduce treatment to 8 hectares, prevent unnecessary agrochemical use, and reduce uncertainty. However, if the affected area is small, crop value is low, and intervention cost is low, field inspection or no verification may be more efficient than UAV deployment.

This is especially important in Ukraine's wartime context, where UAV use may be restricted or unsafe. The previous author's research in agrarian economics notes that, due to security restrictions and regulatory controls, large-scale UAV deployment for agricultural monitoring may not always be feasible; therefore, satellite imagery, ground IoT sensors, and administrative-economic datasets should partly compensate for the limited availability of aerial data. The workshop materials express the same architecture principle: when UAV data are degraded or restricted, the system should rely on EO, IoT, and administrative layers while keeping advisories and audit trails functioning.

Table 4.17 Verification economics for UAV and field inspection

Verification option	Best used when	Main cost	Main benefit	Decision rule
UAV RGB mission	Satellite anomaly is spatially unclear	UAV flight, operator, processing	Localizes affected area	Use if reduced treatment cost exceeds mission cost
UAV multispectral mission	Vegetation anomaly requires high-resolution confirmation	Higher UAV and processing cost	Improves diagnosis and affected-area mapping	Use for high-value crop or high false-positive cost
Field scouting	Moderate anomaly and field access is possible	Labor and travel	Human confirmation of cause	Use when scouting is cheaper than UAV or action error
Soil sampling	Suspected nutrient/salinity/soil problem	Sampling and lab cost	Avoids wrong fertilization decision	Use when input decision is expensive or repeated
Sensor maintenance	Missing or unreliable telemetry	Labor, replacement, calibration	Restores continuous monitoring	Use if data loss creates high decision risk
No verification	High-confidence event or low-cost action	None	Faster action	Use when additional information would not change decision
Delay for next Sentinel-2 image	Low urgency and EO cycle is near	Opportunity cost of waiting	Avoids immediate verification cost	Use if service window permits waiting

Source: prepared by the authors.

Agronomic timing is one of the strongest economic arguments for digital monitoring. A correct action taken too late may have limited value. Conversely, a moderate intervention taken at the right time may prevent a larger loss. Therefore, precision intervention must be evaluated not only by the action taken and where it is taken, but also by when it is taken.

The remaining service-window time can be written as:

$$TW_{remain,a,z,t} = Deadline_{a,z} - t\backslash hfill(4.47)$$

where:

- TWremain(a,z,t) - remaining before the agronomic window closes;
- Deadline(a,z) - latest economically effective time for intervention a;
- t - current time.

The delay-loss function can be expressed as:

$$L_{delay,a,z,t} = A_z \times Y_z \times P_{crop} \times \theta_{a,g} \times \left(0, Delay_{a,z,t} - TW_{tol,a,z}\right) \backslash hfill(4.48)$$

, where:

- Az - affected area;
- Yz - expected yield per hectare;
- Pcrop - crop price;
- θ(a,g) - crop-stage sensitivity coefficient for action a;
- Delay(a,z,t) - delay duration;
- TWtol(a,z) - tolerable delay before losses begin.

The value of timely intervention is:

$$B_{time,a,z,t} = L_{delay\_without\_action,a,z,t} - L_{delay\_with\_action,a,z,t} \backslash hfill(4.49)$$

This equation links monitoring to time-window protection. A monitoring system creates economic value if it detects the event early enough to reduce Ldelay. If the system detects the event after the window has closed, its value is lower. Therefore, detection latency is an economic variable.

Detection latency can be written as:

$$DL_{z,t} = t_{detected} - t_{event\_start} \backslash hfill(4.50)$$

, where:

- DL(z,t) - detection latency;
- tdetected - time when the system detected the event;
- teventstart - estimated start of agronomic stress or problem.

A core efficiency objective is to minimize detection latency while maintaining sufficient data quality.

Table 4.18 Agronomic time-window logic for precision interventions

Intervention	Time-window risk	Monitoring signal	Economic loss if delayed	Decision implication
Irrigation	Water stress becomes yield loss	Soil moisture below threshold, heat risk, early NDVI decline	Reduced yield, lower quality, irreversible stress	High urgency if no rain is expected
Spraying	Pest or disease spreads	Rapid vegetation decline, UAV patch, field observation	Crop damage, higher chemical use	Urgent if spread risk is high
Fertilization	Crop miss's nutrient-response stage	NDVI/EVI anomaly, field history, soil data	Lower nutrient efficiency and yield response	Schedule within growth-stage window
Drainage / waterlogging response	Root damage and disease risk increase	High moisture + low vegetation + rainfall	Localized yield loss and soil damage	Verify quickly before applying other inputs
Field inspection	Diagnosis becomes too late to act	Moderate anomaly with uncertainty	Missed chance to intervene	Prioritize high-severity uncertain events
UAV verification	Detailed diagnosis delayed	EO anomaly with limited confidence	Wider treatment area or delayed action	Use when verification can still change action
No action	Risk may increase unnoticed	Low-severity event	Possible future loss if monitoring is weak	Accept only if monitoring cycle continues

Source: prepared by the authors.

Precision interventions must also be evaluated in an environmental context. The objective is not only to reduce costs, but also to avoid excessive water use, fertilizer runoff, unnecessary agrochemical pressure, soil degradation, and localized ecological damage. This follows the general ecological-economic logic of the author's previous Green Metrics research, in which monitoring systems are designed to calculate natural resource losses, restoration or maintenance costs, land price dynamics, CO_2 emissions, and other ecological-economic variables.

The environmental effect of a precision intervention can be expressed as:

$$B_{env(a,z,t)} = \Delta Water_{a,z,t} * SP_{water} + \Delta Fert(a,z,t) * SP_{runoff} + \Delta Chem_{a,z,t} * SP_{chem} + \Delta Soil(a,z,t) * SP_{soil}(4.51)$$

, where:

- Benv(a,z,t) - environmental benefit of action a;
- ΔWater - reduction in unnecessary water use;
- ΔFert - reduction in fertilizer loss or runoff pressure;
- ΔChem - reduction in agrochemical pressure;
- ΔSoil - reduction in soil degradation or compaction risk;
- SPwater, SPrunoff, SPchem, SPsoil - shadow prices or avoided-damage values.

This environmental value should not be double counted with direct input savings. For example, reduced fertilizer use yields a direct financial benefit by reducing fertilizer purchases. It may also have an environmental benefit because the runoff risk is reduced. Both can be included, but the model must explain that one is a private cost-saving and the other is avoiding external damage.

Table 4.19 Environmental effects of precision interventions

Intervention	Direct economic effect	Environmental effect	Monitoring evidence	Shadow-pricing bridge
Targeted irrigation	Saves water and energy	Reduces over-extraction and waterlogging risk	Soil moisture, weather, flow meter	Water scarcity / avoided damage value
Delayed irrigation	Avoiding unnecessary water application	Reduces runoff and soil saturation	Soil moisture adequate, rain forecast	Avoiding water and environmental pressure
Targeted fertilization	Reduces fertilizer waste	Reduces nutrient runoff and soil imbalance	NDVI/EVI, soil data, affected-area map	Runoff or nutrient-loss shadow price
Targeted spraying	Reduces chemical use	Reduces non-target ecological pressure	UAV patch map, EO anomaly, field log	Agrochemical damage proxy
Field inspection before action	Avoids wrong input application	Prevents unnecessary intervention	Medium-confidence anomaly	Avoided input and environmental cost
Sensor maintenance	Improves monitoring reliability	Prevents wrong or delayed environmental decisions	Missing/abnormal telemetry	Risk-adjusted avoided damage
No action when not justified	Avoids unnecessary input use	Reduces avoidable environmental pressure	Low severity or low expected benefit	Avoided direct and external cost

Source: prepared by the authors.

The methodology developed in this subsection shows that precision intervention is not a simple automatic response to digital data. It is a structured economic decision. Raw monitoring values are first transformed into indicators, then anomalies, then events, then feasible actions, and finally into expected economic outcomes. This prevents the monitoring system from becoming a passive data repository or an uncontrolled alert generator.

The main scientific contribution of subsection 4.2 is the formal connection between monitoring data and economic action. NDVI/EVI anomalies, soil-moisture thresholds, UAV diagnostic outputs, and weather indicators are not interpreted as isolated technical signals. They are interpreted as possible economic events. Each event has severity, confidence, affected area, urgency, feasible interventions, expected benefit, action cost, environmental effect, and audit record.

This logic is especially important for Kyiv agglomeration and similar peri-urban agricultural systems. Under high land pressure, logistical cost volatility, labor competition, and institutional constraints, agricultural decisions must be not only agronomically correct but economically defensible. The authors previously conducted digital agronomy study emphasizes that transport costs, land rents, wage gradients, and land-use pressure directly affect the viability of peri-urban farming, motivating cost-aware digital agronomy. Therefore, precision intervention must be evaluated based on direct costs, expected avoided losses, time-window protection, environmental benefits, and operational feasibility.

The practical conclusion is the following: monitoring creates value only when it changes action. A digital monitoring system becomes economically efficient when it helps farmers and planners apply the right input, in the right place, at the right time, at a justified cost, with measurable reduction of uncertainty and environmental pressure. This prepares the transition to subsection 4.3, where these event and intervention records will be used to quantify reductions in wasted water, fertilizer, and agrochemicals, estimate yield protection, and measure mitigation of localized environmental damage.

Table 4.20 Algorithm for translating monitoring data into economically evaluated precision interventions

Step	Action	Practical explanation	Output
1	Define decision unit	Select parcel, field zone, irrigation block, or management zone	Spatial unit
2	Load monitoring vector	Use IoT, Sentinel-2, UAV, weather, GIS, and field logs	X_(z,t)
3	Calculate indicators	NDVI, EVI, soil-moisture deficit, weather-stress index, affected-area share	Indicator table
4	Check data quality	Compute completeness, latency, confidence, and source reliability	Q_(z,t) / CONF_(z,t)
5	Detect anomaly	Compare indicators with crop-stage baseline or threshold	Candidate anomaly
6	Generate agronomic event	Classify event type, severity, affected area, and urgency	E_(z,t)

Step	Action	Practical explanation	Output
7	Define feasible actions	List irrigation, spraying, fertilization, inspection, verification, no action	A_feasible
8	Estimate intervention cost	Include input, water, energy, labor, machinery, verification, and risk costs	C_action
9	Estimate expected benefit	Calculation avoided loss, saved input, saved time window, and environmental benefit	B_expected
10	Calculating expected net benefit	Apply ENB and reliability-adjusted ENB formulas	ENB_adj
11	Rank alternatives	Use MCDA where several actions compete	Intervention priority score
12	Select action	Choose best feasible action or no action	Recommended intervention
13	Record event	Save event ID, source data, decision logic, and expected values	Audit-ready event record
14	Execute or schedule	Transfer action to farm/task/routing system	Operational task
15	Observe result	Record actual input use, cost, timing, and outcome	Empirical result
16	Feed metrics system	Use event data for input savings, yield protection, and environmental mitigation	Efficiency dataset

Source: prepared by the authors.

4.3. Efficiency Metrics for Monitoring-Based Interventions: Input Savings, Yield Protection, and Localized Environmental Mitigation

Subsections 4.1 and 4.2 established the technical and decision-making foundations of the monitoring case study. Subsection 4.1 described the architecture of a cyber-physical agrarian monitoring system that integrates IoT soil telemetry, Sentinel-2 Earth Observation, UAV diagnostics, weather data, field logs, and economic records. Subsection 4.2 explained how raw monitoring data are transformed into actionable agronomic events and precision interventions. The present subsection completes Case Study II by defining the efficiency metrics needed to prove whether monitoring creates measurable economic and ecological value.

The core methodological question of this subsection is: how can the economic efficiency of IoT telemetry and environmental monitoring be measured after precision interventions are generated and executed? The answer requires a system of indicators that can quantify three groups of effects: first, the reduction of wasted inputs such as water, fertilizer, agrochemicals, energy, labor, and field-inspection time; second, the protection of yield through earlier detection and better timing of interventions; third, the mitigation of localized environmental damage, including water stress, runoff risk, over-application of inputs, soil degradation, and unnecessary ecological pressure.

This subsection follows the broader logic of the monograph, which holds that economic efficiency is not limited to direct savings. The current monograph introduction defines digital environmental management as a multi-layer system in which costs, savings, yields, emissions, input use, water indicators, risk, and time windows must be linked to digital tools and decision-making methods. This is especially important for monitoring systems because their value is often preventive. They create economic value by avoiding unnecessary actions, reducing the scale of interventions, detecting stress earlier, preventing larger losses, and documenting environmental performance.

The previously conducted digital agronomy study by Volodymyr Nazarenko for the Kyiv agglomeration also supports this logic. It states that the proposed decision-support workflow combines UAV/satellite imagery, in-field IoT, climate/crop data, and administrative-economic layers, and that the system converts multisource inputs into stress detection, irrigation timing, and input-allocation recommendations. Therefore, the metrics in this subsection must evaluate not only the presence of monitoring data, but the measurable consequences of using those data for agronomic decisions.

The ecological-economic basis is also consistent with the Green Metrics research, which connects environmental monitoring and management with total system costs, natural resource losses, restoration and maintenance investments, CO_2 emissions, land price dynamics, ecological expenditures, and the cost of environmental degradation. In the present monograph, this ecological-economic logic is transferred from urban to agrarian monitoring: the system must calculate not only farm-level savings but also avoid ecological pressure and reduced damage at the parcel or field zone level.

The efficiency metrics in this subsection are therefore organized into five groups:

1. Input-efficiency metrics - reduction of wasted water, fertilizer, agrochemicals, energy, labor, and field-inspection effort.
2. Yield-protection metrics - avoided yield loss, protected production value, reduction of stress duration, and improved timing of interventions.
3. Environmental-damage mitigation metrics - avoided runoff, reduced over-irrigation, lower chemical pressure, reduced soil stress, and localized damage prevention.
4. Data-to-action performance metrics - detection latency, event confidence, false-positive reduction, affected-area accuracy, and intervention precision.
5. Integrated economic-efficiency metrics - net economic effect, extended benefit-cost ratio, shadow-adjusted benefits, and confidence-adjusted efficiency.

Table 4.21 Main groups of efficiency metrics for IoT telemetry and environmental monitoring

Metric group	Main question answered	Core indicators	Data required	Economic meaning
Input-efficiency metrics	Did monitoring reduce unnecessary input use?	Water saved, fertilizer saved, agrochemicals avoided, energy saved, labor saved	Baseline input use, digital-scenario input use, input prices, intervention records	Direct cost savings and resource-use efficiency
Yield-protection metrics	Did monitoring prevent yield loss?	Avoided yield loss, protected production value, stress-duration reduction, intervention timeliness	Yield estimates, crop price, affected area, stress severity, timing data	Preserved income and reduced agronomic risk
Environmental-damage mitigation metrics	Did monitoring reduce localized ecological pressure?	Avoided runoff, reduced waterlogging, lower chemical pressure, reduced soil-degradation risk	EO/IoT/UAV indicators, field logs, environmental shadow prices	Avoided ecological damage and sustainability value
Data-to-action metrics	Did monitoring produce reliable and timely decisions?	Detection latency, confidence score, false-positive rate, affected-area accuracy, event-to-action conversion	Event records, data-quality scores, UAV/field verification, intervention logs	Measures how well data are converted into useful action
Integrated economic-efficiency metrics	Was the monitoring system economically justified?	Net monitoring benefit, EBCR, shadow-adjusted EBCR, confidence-adjusted benefit	All cost, benefits, environmental, and reliability data	Final economic proof of monitoring efficiency

Source: prepared by the authors.

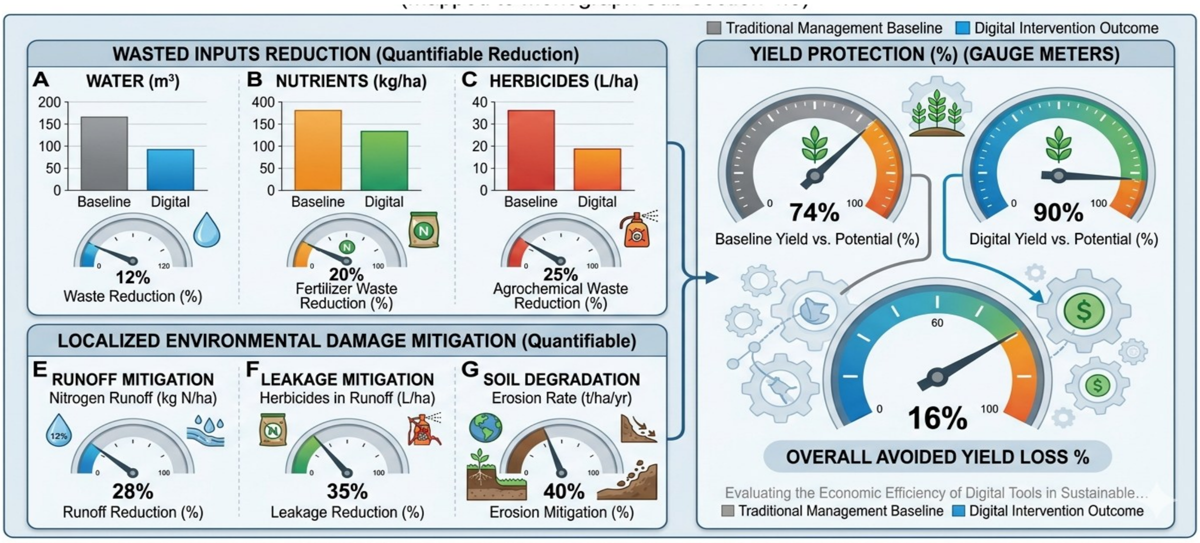


Figure 4.11 Comparative efficiency metrics sample visualization dashboard diagram

The economic efficiency of monitoring must be calculated by comparing costs and benefits. A monitoring system cannot be evaluated solely by counting sensors, images, dashboards, or alerts. It must be evaluated against a baseline. The baseline can represent traditional management, manual field inspection, calendar-based irrigation, uniform fertilizer application, scheduled spraying, or a non-digital decision process.

The digital scenario replicates the same operation, with monitoring data used to support decisions. The difference between the baseline and digital scenario gives the measurable effect of monitoring. This comparison may be made at the field zone, parcel, crop, farm, season, or intervention event level.

The general efficiency effect of monitoring can be written in MS Word-compatible linear equation format as:

$$\Delta_{E_{z,t}} = Result_{digital_{z,t}} - Result_{baseline_{z,t}} \quad (4.52)$$

, where:

- ΔE_(z,t) - efficiency effect for zone z in period t;
- Result_digital_(z,t) - result under monitoring-supported decision-making;
- Result_baseline_(z,t) - result under the baseline decision approach.

For cost indicators, the preferred form is:

$$Saving_{z,t} = Cost_{baseline_{z,t}} - Cost_{digital_{z,t}} \quad (4.53)$$

For undesirable environmental indicators:

$$Reduction_{z,t} = Impact_{baseline_{z,t}} - Impact_{digital_{z,t}} \quad (4.54)$$

For positive performance indicators such as yield protection:

$$Protection_{z,t} = Value_{digital_{z,t}} - Value_{baseline_{z,t}} \quad (4.55)$$

This comparison requires careful definition of the counterfactual. The baseline should not be artificially weak. It should represent realistic current practice. In empirical pilots, three baseline options may be used:

1. Historical baseline - comparison with previous years or previous seasons.
2. Control-zone baseline - comparison with similar field zones not using monitoring-supported intervention.
3. Modeled baseline - calculated scenario based on standard input rates, average yield losses, and typical intervention timing.

Each option has advantages and limitations. Historical baselines are practical but may be affected by weather and market differences. Control zones are stronger scientifically but may be difficult to organize. Modeled baselines are flexible but depend on assumptions. Therefore, the monograph recommends documenting the baseline type for every metric.

Table 4.22 Baseline options for efficiency calculation in Case Study II

Baseline type	Description	Best use	Strength	Limitation
Historical baseline	Uses previous seasons or previous operations before monitoring	Farm-level input and yield comparison	Easy to explain and often available	Weather and market differences may distort comparison
Control-zone baseline	Compare monitored and non-monitored zones in the same season	Field experiment or pilot evaluation	Stronger causal interpretation	Requires comparable control zones
Modeled baseline	Simulates expected input use or yield loss without monitoring	Scenario analysis and unavailable historical data	Flexible and transparent if assumptions are stated	Depends on model assumptions
Standard-practice baseline	Uses regional or farm-standard input rates	Input-use reduction and avoided waste	Useful for operational benchmarking	May not capture local field heterogeneity
Expert baseline	Use agronomist judgment when data are incomplete	Early-stage pilots	Practical under data gaps	Subjective and must be documented
Hybrid baseline	Combines historical, modeled, and expert values	Full monograph evaluation	Balances evidence and feasibility	Requires clear weighting and justification

Source: prepared by the authors.

Water is one of the first and most direct variables through which monitoring creates measurable value. IoT soil-moisture telemetry, weather data, irrigation-flow records, and Sentinel-2 vegetation indicators make it possible to distinguish between necessary irrigation, unnecessary irrigation, delayed irrigation, and over-irrigation risk. The economic effect appears in two forms: direct saving of water and energy and avoiding crop loss from timely irrigation.

Water-saving efficiency can be calculated as:

$$WS_{z,t} = W_{baseline_{z,t}} - W_{digital_{z,t}} (4.56)$$

, where:

- WS(z,t) - water saved in zone z during period t;
- Wbaseline(z,t) - water use under baseline practice;
- Wdigital(z,t) - water use after monitoring-supported irrigation.

The water-use reduction rate is:

$$WUR_{z,t} = \frac{(W_{baseline_{z,t}} - W_{digital_{z,t}})}{W_{baseline_{z,t}}} * 100\% (4.57)$$

The direct monetary saving is:

$$B_{water_{direct_{z,t}}} = WS_{z,t} * P_{water} (4.58)$$

, where:

- Pwater - price or operational cost of water per unit.

If pumping energy is significant:

$$B_{water_{energy_{z,t}}} = WS_{z,t} * P_{water} + ES_{z,t} * P_{energy} (4.59)$$

, where:

- ES(z,t) - energy saved because less water is pumped or distributed;
- Penergy - energy price.

A more complete scarcity-adjusted benefit is:

$$B_{water_{total_{z,t}}} = WS_{z,t} * (P_{water} + P_{energy_{unit}} + SP_{scarcity}) (4.60)$$

, where:

- SPscarcity - shadow price of water scarcity or environmental pressure.

The water metric must be interpreted carefully. A decrease in water use is not always beneficial if it results in yield loss. Therefore, water-saving metrics must be evaluated together with yield-protection metrics. The preferred indicator is water productivity, not only absolute water reduction.

Water productivity can be calculated as:

$$WP_{z,t} = \frac{Y_{z,t}}{W_{z,t}} (4.61)$$

, where:

- WP_(z,t) - water productivity;
- Y_(z,t) - yield or expected yield;
- W_(z,t) - water applied.

The improvement in water productivity is:

$$\Delta_{WP_{z,t}} = WP_{digital_{z,t}} - WP_{baseline_{z,t}} (4.62)$$

If monitoring reduces water use without reducing yield, then the efficiency effect is strong. If monitoring reduces water use while protecting yield, the economic argument becomes even stronger.

Table 4.23 Water-use efficiency metrics for monitoring-supported irrigation

Metric	Equation	Unit	Data required	Interpretation
Water saved	WS = W_baseline - W_digital	m³	Baseline water use, monitored water use	Absolute reduction of water use
Water-use reduction rate	WUR = (W_baseline - W_digital) / W_baseline × 100%	%	Baseline and digital water use	Relative efficiency gain
Direct water saving	B_water_direct = WS × P_water	UAH	Water saved, water price	Direct financial benefit
Energy-adjusted water saving	B_water_energy = WS × P_water + ES × P_energy	UAH	Water saved, energy saved, prices	Captures pumping/distribution savings

Metric	Equation	Unit	Data required	Interpretation
Scarcity-adjusted water benefit	B_water_total = WS × (P_water + P_energy_unit + SP_scarcity)	UAH	Water saved, energy cost, scarcity shadow price	Adds environmental scarcity value
Water productivity	WP = Y / W	t/m³ or UAH/m³	Yield, water use	Shows whether less water maintains or improves output
Water-productivity improvement	ΔWP = WP_digital - WP_baseline	t/m³ or UAH/m³	Baseline and digital WP	Indicates quality of irrigation efficiency
Over-irrigation avoidance	OI = W_unnecessary_baseline - W_unnecessary_digital	m³	Soil moisture, irrigation logs, thresholds	Shows avoided waste rather than simple reduction
Irrigation timing gain	ITG = t_baseline_action - t_digital_action	hours/days	Event logs and irrigation timing	Measures earlier response to stress

Source: prepared by the authors.

Fertilizer efficiency is another central metric because it is both a production input and a potential source of environmental pressure. Uniform application may be operationally simple, but it often ignores field heterogeneity. Monitoring-supported fertilization can reduce wasted input by identifying zones where fertilizer is unnecessary, where response is unlikely, or where additional diagnosis is required before application.

The fertilizer-saving metric is:

$$FS_{z,t} = F_{baseline_{z,t}} - F_{digital_{z,t}} (4.63)$$

, where:

- FS(z,t) - fertilizer saved; Fbaseline(z,t) - fertilizer quantity under baseline practice; Fdigital(z,t) - fertilizer quantity under monitoring-supported practice.

The direct monetary benefit is:

$$B_{fert_{direct_{z,t}}} = FS_{z,t} * P_{fert} (4.64)$$

, where:

- Pfert - price per unit of fertilizer.

If the intervention reduces only the treated area, the fertilizer saving may be calculated as:

$$FS_{z,t} = Rate_{fert} * \left(A_{baseline_{treated_{z,t}}} - A_{digital_{treated_{z,t}}}\right) (4.65)$$

, where:

- Ratefert - fertilizer application rate per hectare;
- Abaselinetreated - area that would have been treated uniformly;
- Adigitaltreated - area treated after monitoring-based targeting.

The fertilizer-efficiency indicator can be expressed as:

$$FE_{z,t} = \frac{Y_{z,t}}{F_{z,t}} (4.66)$$

, where:

- FE(z,t) - fertilizer productivity or fertilizer-use efficiency;
- Y(z,t) - yield;
- F(z,t) - fertilizer applied.

The improvement is:

$$\Delta_{FE_{z,t}} = FE_{digital_{z,t}} - FE_{baseline_{z,t}} (4.67)$$

However, fertilizer reduction should not be interpreted as efficient if it causes nutrient deficiency and yield loss. Therefore, the evaluation should combine fertilizer savings with yield response and environmental pressure indicators. The preferred interpretation is that monitoring is efficient when it reduces fertilizer waste, maintains or improves yield, and reduces runoff or the risk of nutrient loss.

The environmental benefit of reduced fertilizer use can be estimated through a runoff-risk or nutrient-loss proxy:

$$B_{fert_{env_{z,t}}} = \Delta N_{loss_{z,t}} * SP_N (4.68)$$

, where:

- $\Delta Nloss(z,t)$ - avoided nitrogen or nutrient loss;
- SPN - shadow price of nutrient-related environmental damage.

If nutrient-loss data is not available:

$$\Delta_{N_{loss_{z,t}}} = FS_{z,t} * LF_N \quad (4.69)$$

, where:

- LFN - estimated nutrient-loss factor.

This approach follows the ecological-economic logic proposed in the Volodymyr Nazarenko Green Metrics methodology, where the model includes not only direct costs but also natural-resource loss, restoration cost, environmental expenditures, and ecological consequences of development and resource use.

Table 4.24 Fertilizer-use efficiency metrics

Metric	Equation	Unit	Data required	Interpretation
Fertilizer saved	FS = F_baseline - F_digital	kg or t	Baseline and digital fertilizer use	Absolute reduction of fertilizer input
Fertilizer cost saving	B_fert_direct = FS × P_fert	UAH	Fertilizer saved, fertilizer price	Direct financial benefit
Area-based fertilizer saving	FS = Rate_fert × (A_baseline_treated - A_digital_treated)	kg	Application rate and treated area	Measures the benefit of the targeted application
Fertilizer-use reduction rate	FUR = (F_baseline - F_digital) / F_baseline × 100%	%	Baseline and digital fertilizer use	Relative input reduction
Fertilizer productivity	FE = Y / F	t/kg or UAH/kg	Yield, fertilizer quantity	Shows output per fertilizer unit
Fertilizer productivity improvement	ΔFE = FE_digital - FE_baseline	t/kg or UAH/kg	Baseline and digital FE	Captures efficiency rather than simple reduction
Avoided nutrient loss	ΔN_loss = FS × LF_N	kg N or nutrient unit	Fertilizer saved, loss factor	Environmental-pressure proxy
Fertilizer environmental benefit	B_fert_env = ΔN_loss × SP_N	UAH	Avoided nutrient loss, shadow price	Monetized reduction of runoff/nutrient pressure
Fertilizer-response validity	FRV = ΔY / ΔF	t/kg	Yield response, fertilizer change	Tests whether the reduction was agronomically safe

Source: prepared by the authors

Agrochemical use is economically and environmentally sensitive. Crop-protection products may protect yield, but unnecessary or poorly targeted applications increase costs and ecological pressure. Monitoring can improve agrochemical efficiency by identifying affected zones, reducing whole-field treatment, supporting field verification before action, and avoiding treatment when evidence is weak.

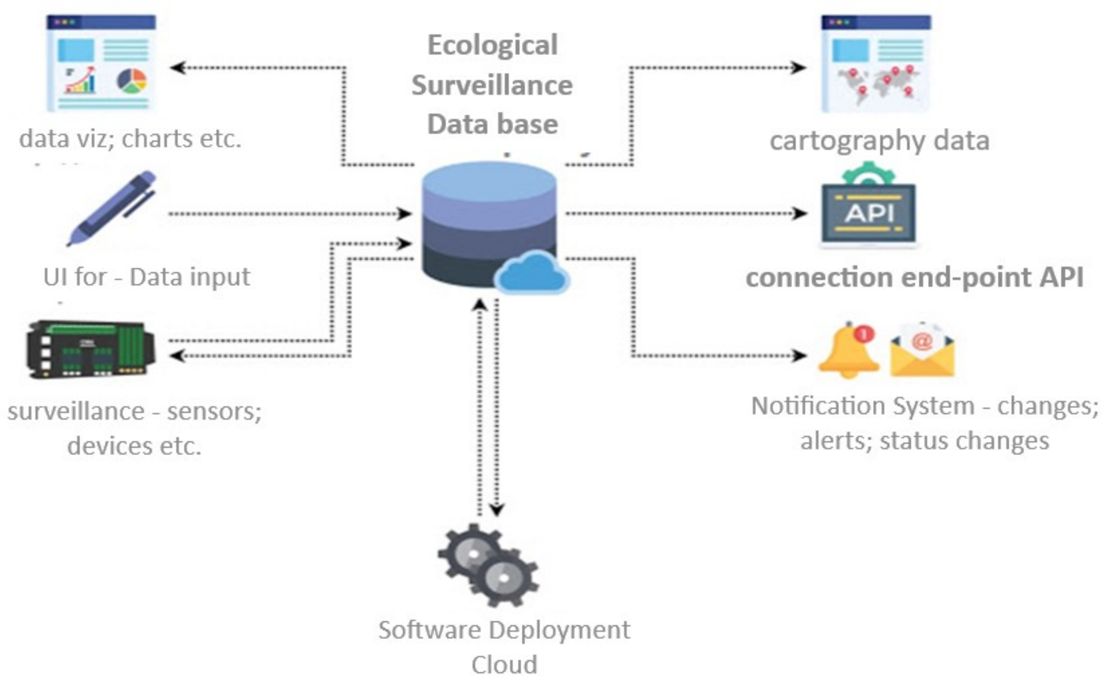


Figure 4.12 Ecological surveillance system diagram

The agrochemical-saving metric is:

$$AS_{z,t} = ACh_{baseline_{z,t}} - ACh_{digital_{z,t}} \quad (4.70)$$

, where:

- $AS(z,t)$ - agrochemical saved;
- $ACh_{baseline(z,t)}$ - agrochemical quantity under baseline practice;
- $ACh_{digital(z,t)}$ - agrochemical quantity after monitoring-supported targeting.

The direct financial benefit is:

$$B_{agrochem_{direct_{z,t}}} = AS_{z,t} * P_{agrochem} \quad (4.71)$$

, where:

- Pagrochem - price per unit of agrochemical.

For targeted spraying:

$$AS_{z,t} = Rate_{agrochem} * \left(A_{baseline_{treated_{z,t}}} - A_{digital_{treated_{z,t}}}\right) \quad (4.72)$$

The agrochemical-use reduction rate is:

$$AUR_{z,t} = \frac{\left(ACh_{baseline_{z,t}} - ACh_{digital_{z,t}}\right)}{ACh_{baseline_{z,t}}} * 100\% \quad (4.73)$$

The environmental benefit can be expressed as:

$$B_{agrochem_{env_{z,t}}} = AS_{z,t} * SP_{chem} \quad (4.74)$$

, where:

- SPchem - shadow price or avoided-damage proxy for agrochemical pressure.

If toxicity classes or ecological-sensitivity zones are included, the environmental metric can be weighted:

$$ChemPressure_{z,t} = \sum_{c=1}^{C} \left[ACh_{c_{z,t}} * ToxicityWeight_c * Sensitivity_z\right] \quad (4.75)$$

, where:

- $AChc(z,t)$ - quantity of agrochemical class c;
- $ToxicityWeight_c$ - relative toxicity or ecological-pressure coefficient;
- $Sensitivity_z$ - ecological sensitivity of zone z.

The reduction is:

$$\Delta_{ChemPressure_{z,t}} = ChemPressure_{baseline_{z,t}} - ChemPressure_{digital_{z,t}} \quad (4.76)$$

This metric is particularly important in peri-urban and environmentally sensitive territories because chemical pressure is not only farm-level cost. It may affect adjacent land, water, green zones, residential areas, biodiversity, and public perception of agricultural activity. This is why localized treatment and verification are economically relevant, especially where agricultural land is embedded in complex urban-rural systems.

Table 4.25 Agrochemical-use efficiency metrics

Metric	Equation	Unit	Data required	Interpretation
Agrochemical saved	AS = ACh_baseline - ACh_digital	L, kg, active ingredient	Baseline and digital agrochemical use	Absolute reduction of chemical input
Agrochemical cost saving	B_agrochem_direct = AS × P_agrochem	UAH	Quantity saved, product price	Direct financial benefit
Area-based agrochemical saving	AS = Rate_agrochem × (A_baseline_treated - A_digital_treated)	L or kg	Application rate, treated area	Benefit of affected-area targeting
Agrochemical-use reduction rate	AUR = (ACh_baseline - ACh_digital) / ACh_baseline × 100%	%	Baseline and digital use	Relative input reduction
Chemical-pressure index	ChemPressure = Σ(ACh_c × ToxicityWeight_c × Sensitivity_z)	index	Product class, toxicity weight, zone sensitivity	Ecological-pressure estimate
Chemical-pressure reduction	ΔChemPressure = ChemPressure_baseline - ChemPressure_digital	index	Baseline and digital pressure index	Environmental mitigation effect
Avoided unnecessary treatment area	AUTA = A_baseline_treated - A_digital_treated	ha	Treated-area records	Shows spatial precision benefit
Verification-adjusted saving	B_verified = B_agrochem_direct - C_verify	UAH	Saving and verification cost	Tests whether UAV/scouting was worth it
Yield-safe chemical reduction	YSCR = 1, if Y_digital ≥ Y_baseline and ACh_digital < ACh_baseline	binary / score	Yield and agrochemical data	Confirms reduction did not damage production

Source: prepared by the authors.

Digital monitoring does not always increase maximum potential yield. Often its value lies in preventing yield loss. Early detection of water stress, nutrient deficiency, disease risk, weed pressure, or waterlogging can reduce the duration and severity of stress. The economic value is the difference between the expected loss under baseline management and the expected loss after a monitoring-supported intervention.

The avoided yield loss can be calculated as:

$$AYLz,t = Yloss_{baseline},z,t - Yloss_{digital},z,t \quad (4.77)$$

, where:

- AYL(z,t) - avoided yield loss;
- Ylossbaseline(z,t) - expected yield loss without monitoring-supported intervention;
- Ylossdigital(z,t) - expected yield loss after intervention.

The monetary value of protected yield is:

$$Byield,z,t = AYLz,t \times Aaffected,z,t \times Pcrop \quad (4.78)$$

, where:

- Aaffected(z,t) - affected area;
- Pcrop - crop price.

If yield is measured directly:

$$Byield,z,t = (Ydigital,z,t - Ybaseline,z,t) \times Az \times Pcrop (4.79)$$

, where:

- Ydigital(z,t) - observed or estimated yield under monitoring-supported management;
- Ybaseline(z,t) - baseline yield.

If only stress duration is known, yield loss can be approximated by a stress-loss function:

$$Yloss,z,t = Ypotential,z,t \times SSIz,t \times DurStressz,t \quad (4.80)$$

, where:

- Ypotential(z,t) - potential or expected yield;
- SSI(z,t) - stress-sensitivity index;
- DurStress(z,t) - duration of stress.

The monitoring system creates value when it reduces stress duration:

$$Byield\_time,z,t = Ypotential,z,t \times SSIz,t \times (DurStressbaseline,z,t - DurStressdigital,z,t) \times Aaffected,z,t \times Pcrop \quad (4.81)$$

This metric connects yield protection to the time-window logic developed in subsection 2.3 and operationalized in subsection 4.2. It is particularly relevant for irrigation and crop-protection events, where detection latency strongly influences yield outcome.

Yield-protection metrics must also be interpreted together with input-use metrics. A digital system may reduce input but also reduce yield, which would not be efficient. Conversely, it may keep input use stable but prevent a larger yield loss, which may still be economically efficient. The strongest case occurs when monitoring both reduces input waste and protects yield.

Table 4.26 Yield-protection efficiency metrics

Metric	Equation	Unit	Data required	Interpretation
Avoided yield loss	AYL = Y_loss_baseline - Y_loss_digital	t/ha	Expected baseline and digital yield loss	Physical yield protected
Monetary value of protected yield	B_yield = AYL × A_affected × P_crop	UAH	Avoided loss, affected area, crop price	Direct economic benefit
Direct yield difference	B_yield = (Y_digital - Y_baseline) × A_z × P_crop	UAH	Observed/estimated yields	Used when measured yield data exist
Stress-duration reduction	SDR = DurStress_baseline - DurStress_digital	hours/days	Event timing and monitoring logs	Measures earlier detection and action
Stress-duration yield benefit	B_yield_time = Y_potential × SSI × SDR × A_affected × P_crop	UAH	Potential yield, sensitivity, stress duration	Monetizes earlier intervention
Yield stability index	YSI = 1 - SD(Y_digital) / Mean(Y_digital)	index	Yield variability across zones/seasons	Shows resilience of production
Yield protection per monitoring cost	YPMC = B_yield / C_monitoring	UAH/UAH	Yield benefit and monitoring cost	Shows monitoring return via yield protection
Yield-safe input reduction	YSIR = 1, if Inputs_digital < Inputs_baseline and Y_digital ≥ Y_baseline	binary / score	Input and yield records	Confirms input reduction did not harm output
Protected output share	POS = B_yield / Total_crop_value × 100%	%	Protected yield value and total crop value	Shows importance of monitoring revenue protection

Source: prepared by the authors.

The third major efficiency block is mitigation of localized environmental damage. Unlike direct input savings, environmental mitigation is often partly external to farm accounting. It may not immediately appear as farm income, but it has economic value for land quality, water resources, public policy, environmental compliance, and long-term sustainability. This is why subsection 2.3 introduced shadow pricing of environmental and temporal variables.

Localized environmental damage in this case study may include:

- over-irrigation and waterlogging;

- nutrient runoff;
- agrochemical over-application;
- soil compaction caused by unnecessary field passes;
- degradation of sensitive field edges or nearby green zones;
- pollution risk near water bodies;
- ecological pressure in restricted or environmentally sensitive areas.

The general environmental-damage mitigation value can be expressed as:

$$Benv,z,t = m = 1\sum M[(Dbaseline,m,z,t - Ddigital,m,z,t) \times SPm] \quad (4.82)$$

, where:

- Benv_(z,t) - shadow-priced environmental benefit;
- Dbaseline,m_(z,t) - environmental damage indicator of type m under baseline;
- Ddigital,m_(z,t) - environmental damage indicator under monitoring-supported intervention;
- SPm - shadow price or avoided-damage value for damage type m;
- M - number of environmental damage categories.

For localized damage area:

$$LDMz,t = Adamage\_baseline,z,t - Adamage\_digital,z,t \quad (4.83)$$

, where:

- LDM_(z,t) - localized damage mitigated;
- Adamage_baseline_(z,t) - expected affected area under baseline;
- Adamage_digital_(z,t) - affected area under monitoring-supported scenario.

The monetary value is:

$$BLDM,z,t = LDMz,t \times Crestore\_ha \quad (4.84)$$

, where:

- Crestore_ha - restoration or damage-mitigation cost per hectare.

For runoff or nutrient-loss pressure:

$$Brunoff,z,t = (RunoffRiskbaseline,z,t - RunoffRiskdigital,z,t) \times SPrunoff \quad (4.85)$$

For soil compaction:

$$Bcompaction,z,t = (Passesbaseline,z,t - Passesdigital,z,t) \times Apass,z,t \times Ccompaction\_ha \quad (4.86)$$

, where:

- Passes_baseline and Passes_digital - number of machinery passes;
- Apass - area affected per pass;
- Ccompactionha - estimated economic cost of compaction per hectare.

These indicators are not substitutes for detailed ecological assessment, but they provide a practical economic bridge between monitoring and sustainability. They allow the monograph to show that precision observation can reduce environmental pressure at the operational level, especially when targeted interventions replace whole-field or delayed interventions.

The final step is to convert metrics into a decision-support and reporting format. A monitoring system creates more value when farmers, planners, researchers, and policymakers can interpret the results. Therefore, the subsection recommends an efficiency dashboard that separates direct financial metrics, agronomic metrics, environmental metrics, data-quality metrics, and integrated indicators.

The dashboard should support three levels of reporting:

1. Operational level - daily or weekly event metrics for farm managers and agronomists.
2. Seasonal level - crop and parcel efficiency metrics for farm planning and investment decisions.
3. Policy/audit level - environmental mitigation, input reduction, and sustainability indicators for local authorities, subsidy programs, and sustainability reporting.

The proposed Green Metrics methodology emphasizes the importance of e-service platforms for calculating net costs, natural resource losses, replenishment costs, and ecological-economic effects per unit area and per unit time. The same reporting logic is applicable here. The monitoring dashboard should allow the calculation of efficiency per hectare, per event, per crop, per season, and per environmental-damage category.

Table 4.27 Recommended dashboard structure for monitoring efficiency metrics

Dashboard section	Main indicators	User group	Decision supported
Input-efficiency panel	Water saved, fertilizer saved, agrochemicals saved, labor saved	Farm manager, agronomist	Resource-use optimization
Yield-protection panel	Avoided yield loss, protected crop value, stress-duration reduction	Farm manager, investor	Production-risk management
Environmental panel	Avoided runoff, chemical-pressure reduction, water stress reduction, soil-risk mitigation	Local authority, sustainability officer	Environmental compliance and policy reporting
Event-performance panel	Detection latency, action latency, event-to-action conversion, false-positive rate	Agronomist, system operator	Monitoring-system improvement
Data-quality panel	Sensor uptime, EO usability, UAV availability, confidence score, provenance completeness	Researcher, system administrator	Reliability and auditability
Economic panel	NMB, NPV, EBCR, benefit per hectare, cost per hectare	Farm owner, cooperative, policymaker	Investment justification
Spatial panel	MEI map, affected zones, intervention maps, environmental-risk layers	Planner, GIS specialist	Spatial prioritization
Audit panel	Event records, data sources, model version, intervention logs	Certifier, public institution	Sustainability verification

Source: prepared by the authors.

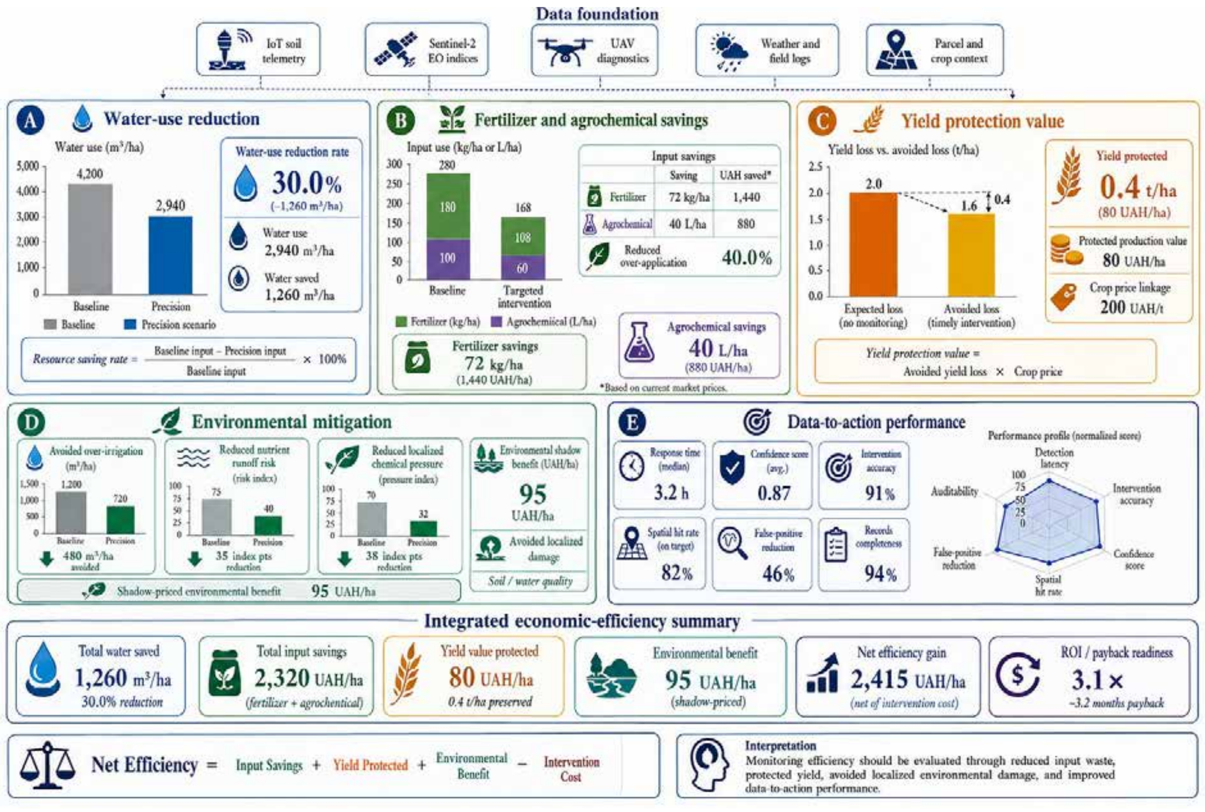


Figure 4.13 Economic efficiency outcomes of monitoring-based precision interventions of the digital agtrictech dashboard diagram

The efficiency metrics developed in this subsection complete the economic logic of Case Study II. Architecture in 4.1 defines how monitoring data is collected, harmonized, validated, stored, and transformed into field-zone indicators. The decision model in 4.2 defines how these indicators become agronomic events and precision interventions. Subsection 4.3 defines how the results of these interventions are measured economically and environmentally.

The main conclusion is that the efficiency of IoT telemetry and environmental monitoring should be measured by combining direct input savings, yield protection, environmental mitigation, time-window performance, and data reliability. Monitoring creates economic value by reducing unnecessary water, fertilizer, and agrochemical use; protecting yield through earlier, better-targeted interventions; reducing localized ecological damage; and providing auditable data for future decisions. Monitoring does not create value simply by producing data. It creates value when data changes decisions, and those decisions produce measurable results.

For the Kyiv agglomeration and similar peri-urban agricultural systems, such metrics are especially important. The conducted study shows that agrarian viability in the Kyiv agglomeration is shaped by land-use pressure, wage differences, logistics costs, and competition for urban land, while digital agronomy is proposed as a policy- and cost-aware decision-support workflow. Under such conditions, every wasted input, delayed intervention, unnecessary treatment, and unverified ecological impact reduces the economic resilience of agriculture. Therefore, monitoring efficiency must be evaluated not only by technical accuracy but by its contribution to cost reduction, yield stability, environmental protection, and institutional auditability.

The practical output of this subsection is a complete metric system that can be used in empirical pilots, farm-level dashboards, public-sector sustainability reporting, and policy mechanisms. It provides the quantitative link between monitoring data and economic proof. This prepares the transition to Section 5, where the outputs of the land-management and monitoring cases are integrated into spatio-temporal routing and operational optimization.

Figure 4.14 System components architecture

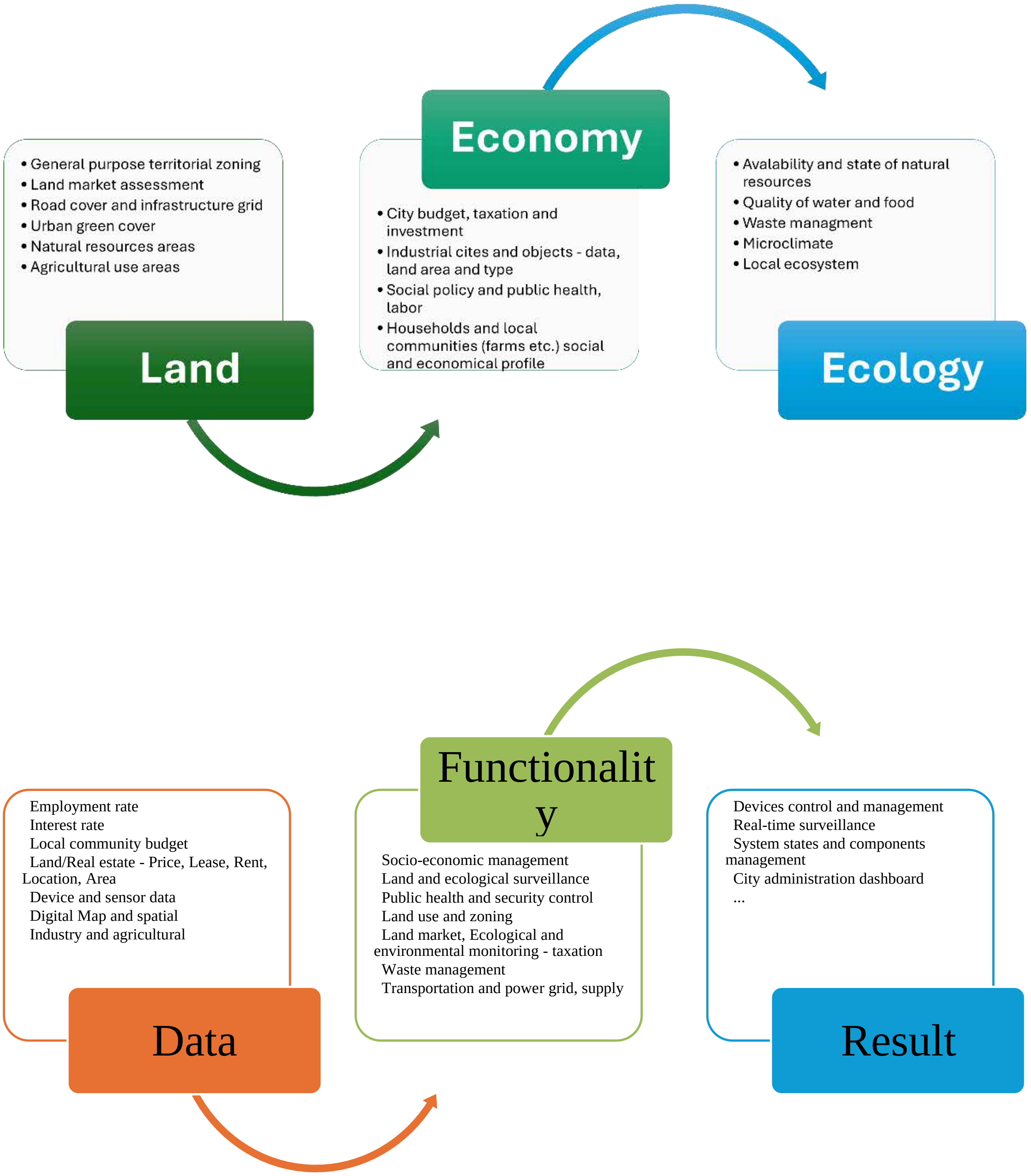


Figure 4.15 System data and services flow architecture

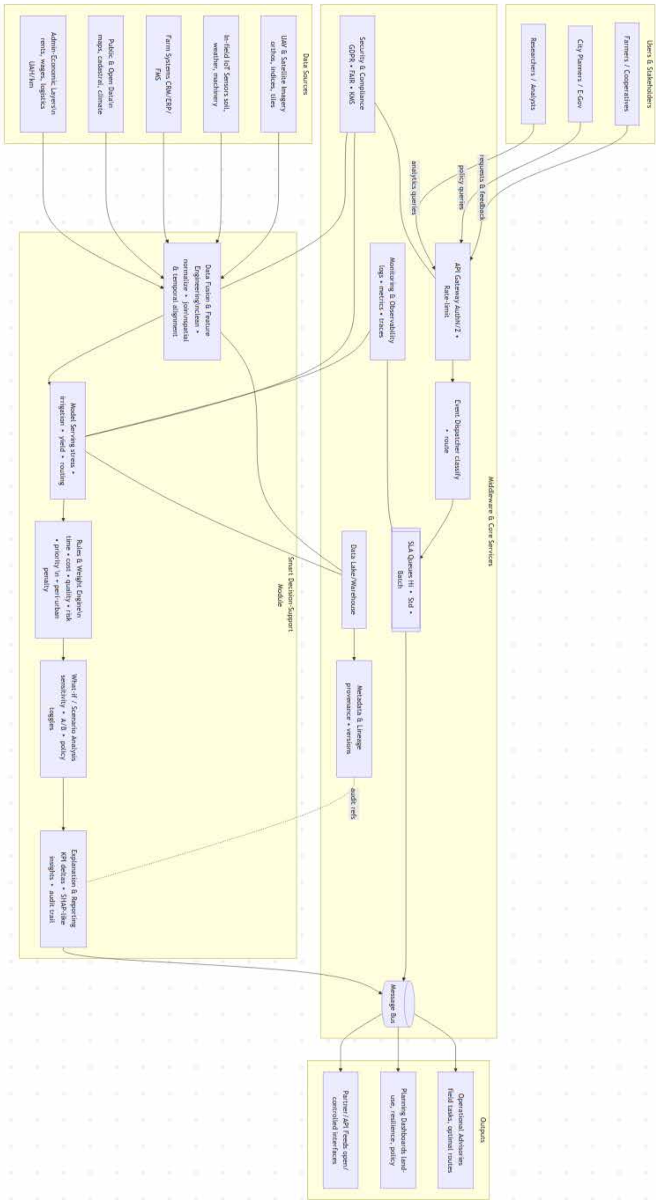
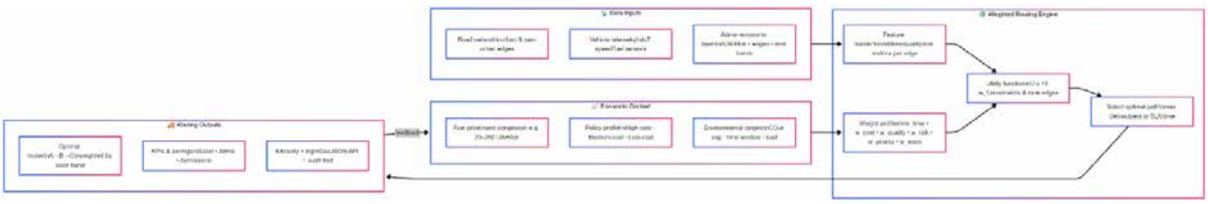


Figure 4.16 Middleware routing system architecture



For each candidate serviceable to process event e, the middleware computes a weighted utility:

$$U(s) = \sum_k w_k \cdot f_k(s)$$

with w_k from policy and f_k the normalized criteria (larger is better). We invert cost and risk as $f_{cost} = 1 - x_{cost}$, $f_{risk} = 1 - x_{risk}$.

$$U(e) = w_{\text{time}} f_{\text{time}}(e) + w_{\text{cost}} f_{\text{cost}}(e) + w_{\text{quality}} f_{\text{quality}}(e) + w_{\text{risk}} f_{\text{risk}}(e) + w_{\text{priority}} f_{\text{priority}}(e) + w_{\text{econ}} f_{\text{econ}}(e)$$

$$\text{Optimal route} = \arg\max_{p \in P} \frac{1}{|p|} \sum_{e \in p} U(e)$$

where each $f_k(e) \in [0, 1]$ is a normalized metric (lower cost/time → higher score).

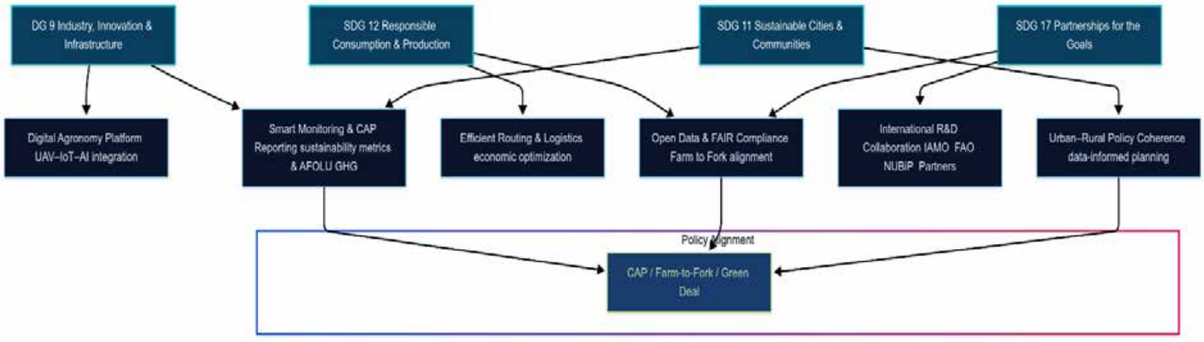


Figure 4.17 Weighted Utility and Queue Class

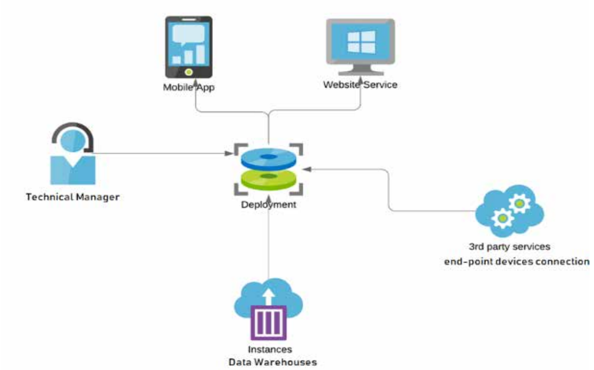


Figure 4.18 IoT system deployment architecture

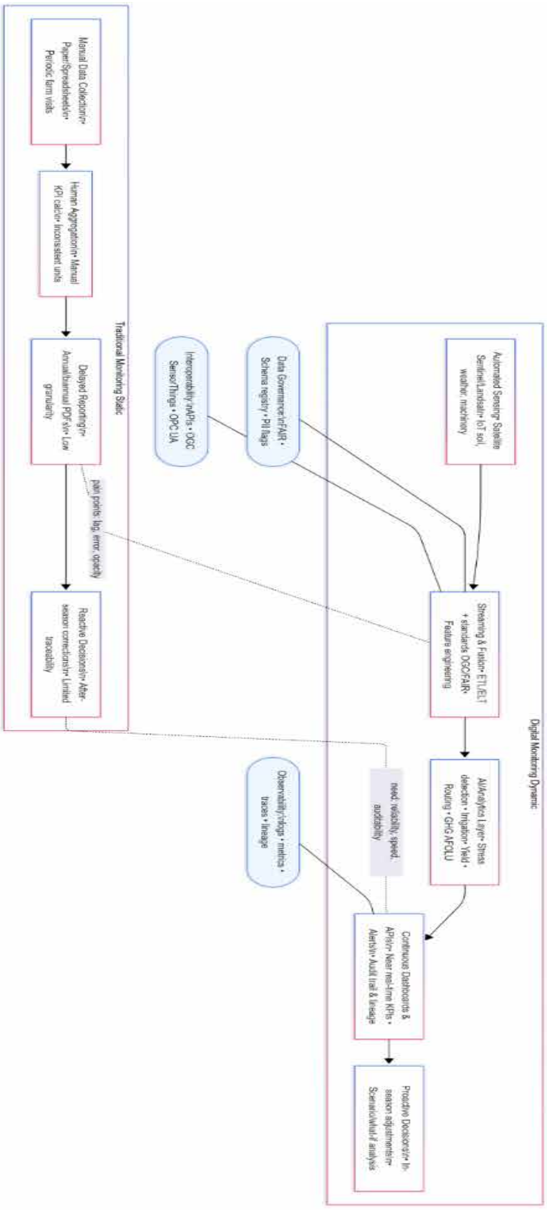


Figure 4.19 Weighted Utility and Queue Class

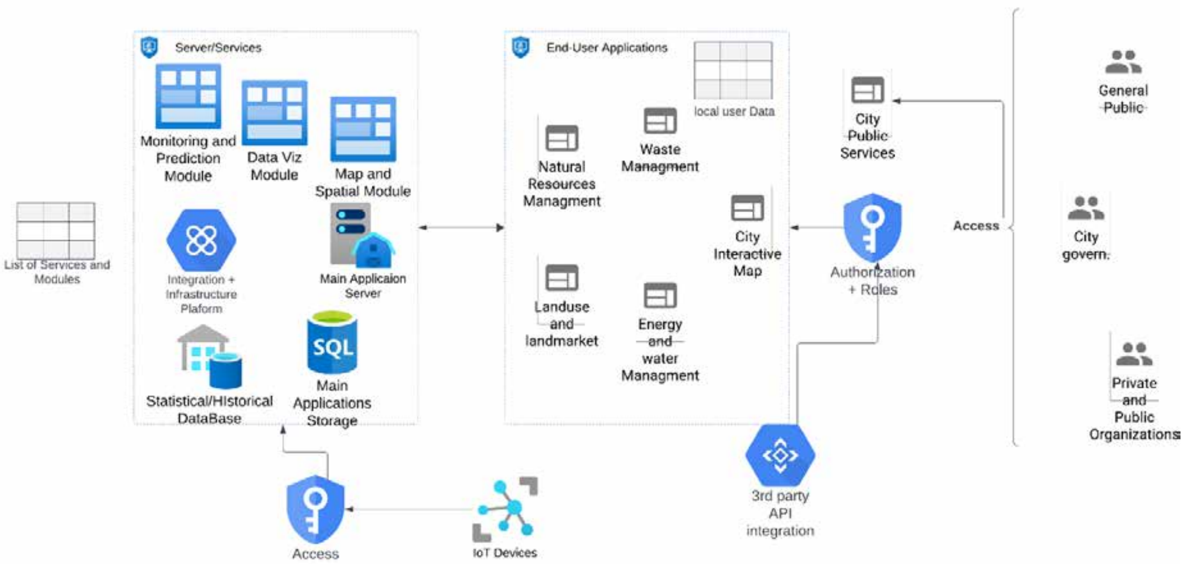


Figure 4.20 IoT system architecture

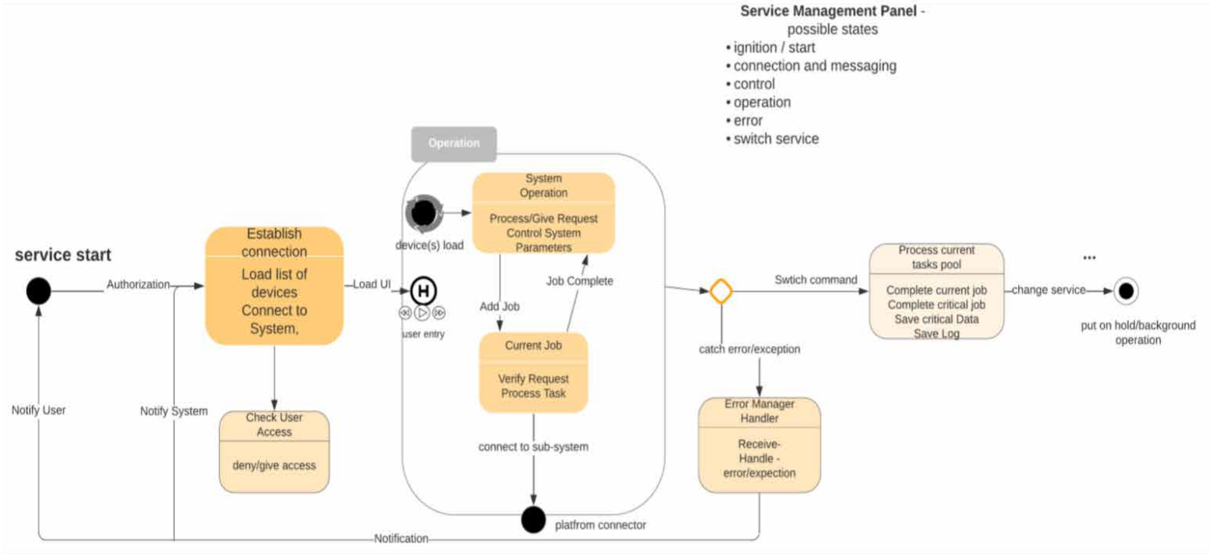


Figure 4.21 Routing services system architecture

CHAPTER 5

Case Study III - Economic Efficiency of Spatio-Temporal Optimization and Routing

5.1. Spatio-Temporal Routing Middleware: Integrating Land Constraints, Monitoring Events, Fleet Data, and Economic Parameters

The fifth section of the monograph presents the third empirical case study and functions as the capstone application of the methodological framework developed in Section 2. The first empirical case study created the spatial and institutional basis for economic evaluation through digital land management, cadastral data, FAIR/OGC-aligned spatial services, hard masks, and soft penalties. The second empirical case study created environmental and agronomic observation basis through IoT soil telemetry, Sentinel-2 imagery, UAV diagnostics, event detection, and precision-intervention records. The present case study integrates both previous blocks into a live spatio-temporal routing framework.

In the logic of the monograph, spatio-temporal routing is not treated as a narrow transport problem. It is treated as an operational economic mechanism that converts land constraints and monitoring events into time-sensitive agricultural decisions. The current monograph structure explicitly defines Case Study III as the block where the data and results of the first two case studies are integrated into a live logistical decision-support framework, because agricultural operations depend on machinery, transport, labor, fuel, field accessibility, road conditions, processing capacity, and agronomic service windows. In peri-urban territories, routing cannot be reduced to the shortest path; it must be justified economically, environmentally, spatially, and temporally.

The Kyiv agglomeration is particularly appropriate for this case study because it combines several pressures within a single territorial system: rapid land-use transformation, fragmented agricultural operations, urban and peri-urban congestion, volatile logistics costs, wartime mobility restrictions, limited UAV availability, and changing operational access to fields. The conducted routing study defines the same problem context: Ukraine's agricultural sector faces peri-urban land-use transformation, disrupted logistics, volatile fuel costs, and restricted mobility, while the Kyiv agglomeration increasingly requires rapid replanning under changing constraints.

The routing framework developed in this subsection, therefore, integrates three types of information. The first type is spatial-institutional information from Case Study I: parcel boundaries, land-use categories, access rights, protected zones, military or safety restrictions, hard masks, and soft penalties. The second type is environmental-monitoring information from Case Study II: NDVI/EVI anomalies, soil-moisture thresholds, UAV diagnostic polygons, weather context, precision-intervention events, affected areas, event severity, and event confidence. The third type is operational-economic information: road graph, congestion, vehicle type, fleet availability, fuel price, cost band, service time, labor cost, route risk, CO_2e factor, and task priority.

The economic meaning of the framework is simple but important: a route becomes efficient only when it allows the farm, cooperative, service provider, or local authority to complete the right task, in the right place, at the right time, through an allowed route, at a justified cost, without violating land-use restrictions, and with measurable environmental consequences.

Table 5.1 Role of the spatio-temporal routing framework in the empirical logic of the research work

Research logical block	Main output	Purpose	Economic role in routing
Case Study I: Digital land management	Parcel boundaries, land-use categories, protected areas, restrictions, hard masks, soft penalties, and cadastral reliability	Converts the physical and legal territory into a feasible routing graph	Prevents prohibited movement, reduces legal/ecological risk, improves compliance
Case Study II: IoT telemetry and environmental monitoring	Monitoring events, soil-moisture thresholds, NDVI/EVI anomalies, UAV diagnostic areas, event severity, affected area, data confidence	Convert environmental and agronomic signals into routeable tasks	Creates irrigation, spraying, inspection, verification, and maintenance jobs

Research logical block	Main output	Purpose	Economic role in routing
Section 2 methodology: MCDA	Weighted criteria: time, direct cost, CO_2e, risk, feasibility, data quality	Defines the route-cost function and scenario weights	Enables comparison of route alternatives under different priorities
Section 2 methodology: shadow pricing	Monetary value of CO_2e, delay, avoided damage, and compliance	Extends route evaluation beyond direct fuel cost	Internalizes environmental and temporal effects
Section 2 methodology: simulation	Baseline, stress, sustainability-adjusted scenarios; sensitivity testing	Tests on whether routing remains efficient under volatile fuel prices, restrictions, and data gaps	Proves resilience and robustness
Case Study III: Routing	Route plan, task schedule, vehicle assignment, cost, time, CO_2e, risk, feasibility, audit trail	Final operational decision-support output	Demonstrates the economic efficiency of integrated digital environmental management

Source: prepared by the authors.

The spatio-temporal routing framework is a middleware-based decision-support system that transforms spatial constraints, monitoring events, operational tasks, and economic parameters into route and schedule recommendations. It differs from a traditional routing model in three ways.

First, it is spatially constrained. The framework does not route machinery only across a road network. It routes machinery through a spatial system that includes parcels, land-use regimes, protected areas, restricted edges, field entrances, access roads, and safety constraints. This makes the routing framework an extension of digital land administration, rather than merely a transport calculator.

Second, it is temporally constrained. Agricultural work has service windows. Irrigation, spraying, field inspection, harvesting, transport to processing, and machinery maintenance are time sensitive. A cheap route is not efficient if it misses an agronomic window. A fast route is not acceptable if it crosses a restricted area. A low-emission route is not enough if field operations are delayed agronomically.

Third, it is economically weighted. Each route segment is evaluated according to time, direct cost, CO_2e, and operational risk. The conducted routing study presents this as a weights-based real-time routing platform that allows users to tune explicit weights over time for direct cost, CO_2e, and operational risk, while enforcing restrictions via hard masks and soft penalty layers.

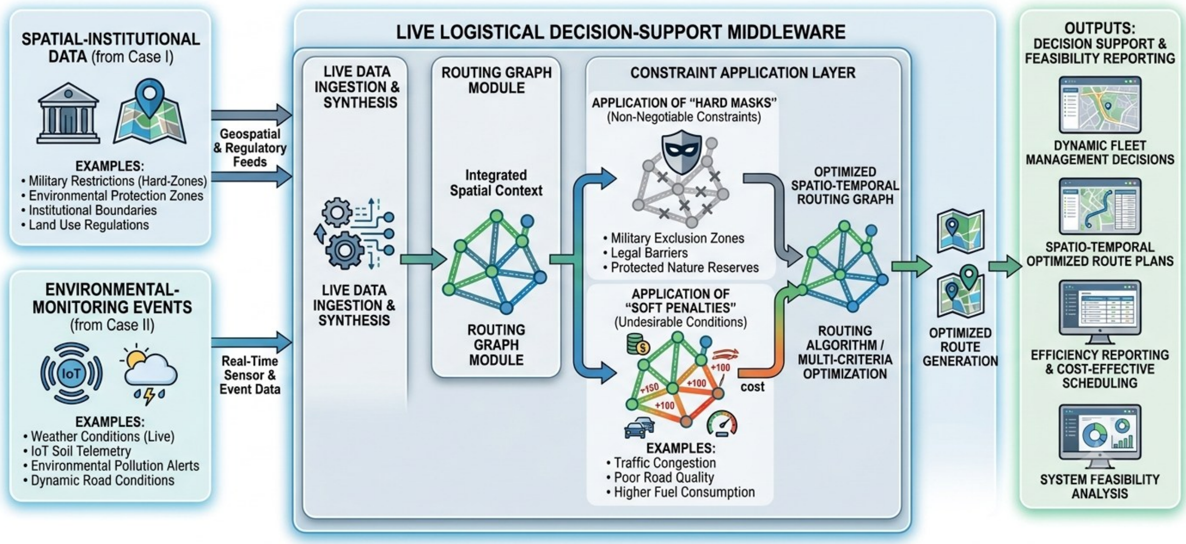


Figure 5.1 Spatio-temporal routing middleware architecture

For the purposes of this monograph, the routing framework may be represented as a dynamic routing state:

$$RTt = \{Gt, Kt, Mt, Jt, Vt, Et, Wt, Pt, Qt\} \quad (5.1)$$

, where:

- RT_t - routing state at time t;
- G_t - routing graph, including road network, access roads, field entrances, and edge attributes;

- K_t - spatial constraints from Case Study I, including hard masks and soft penalties;
- M_t - monitoring state from Case Study II, including IoT, EO, UAV, and weather indicators;
- J_t - set of agricultural jobs or intervention tasks; V_t - fleet state, including vehicle type, availability, capacity, fuel use, and emission factors;
- E_t - economic parameters, including fuel price, UAH/km bands, labor cost, and input cost;
- W_t - time-window structure for agricultural tasks;
- P_t - policy, safety, environmental, and land-use rules;
- Q_t - data quality and reliability state.

The routing framework receives input from the land-management and monitoring layers, transforms them into feasible tasks and routeable constraints, and produces route advisories. These advisories are not only operational outputs; they are also economic records. Each route contains cost, time, emissions, risk, feasibility, and provenance.

The routing output for one planning cycle can be expressed as:

$$ROt = \{RoutePlant, VehicleAssignmentt, TaskSchedulet, KPIt, AuditTrailt\} \quad (5.2)$$

, where:

- RoutePlan_t - selected route or route set;
- VehicleAssignment_t - assignment of vehicles or machinery to tasks;
- TaskSchedule_t - temporal order of operations;
- KPI_t - cost, time, CO_2e, risk, feasibility, and violation indicators;
- AuditTrail_t - record of data sources, weights, assumptions, and constraints used.

Table 5.2 Core routing-state components

Component	Symbol	Origin	Description	Economic function
Routing graph	G_t	Road network, field access, local mobility data	Nodes, edges, travel times, distances, road classes, access paths	Defines possible movement space
Spatial constraints	K_t	Case Study I	Hard masks, soft penalties, land-use restrictions, protected zones	Prevents illegal or ecologically risky movement
Monitoring state	M_t	Case Study II	NDVI/EVI, soil moisture, UAV diagnostics, weather indicators	Generates task urgency and intervention location
Jobs/tasks	J_t	Case Study II + farm operations	Irrigation, spraying, field inspection, UAV verification, transport	Defines what must be routed and scheduled
Fleet state	V_t	Farm/fleet records	Vehicles, tractors, machinery, capacity, speed, fuel use	Determines operational feasibility and cost
Economic parameters	E_t	Market feeds, accounting, price records	Fuel price, UAH/km, labor cost, maintenance, input cost	Converts route into monetary cost
Time windows	W_t	Agronomic calendar and intervention records	Earliest/latest task times, service duration, deadlines	Determines temporal feasibility
Policy and risk rules	P_t	Land administration, safety notices, environmental rules	Military restrictions, protected areas, compliance rules	Controls legal and institutional acceptability
Data quality	Q_t	Middleware metadata	Reliability, latency, completeness, provenance	Adjust confidence in route advisories

Source: prepared by the authors.

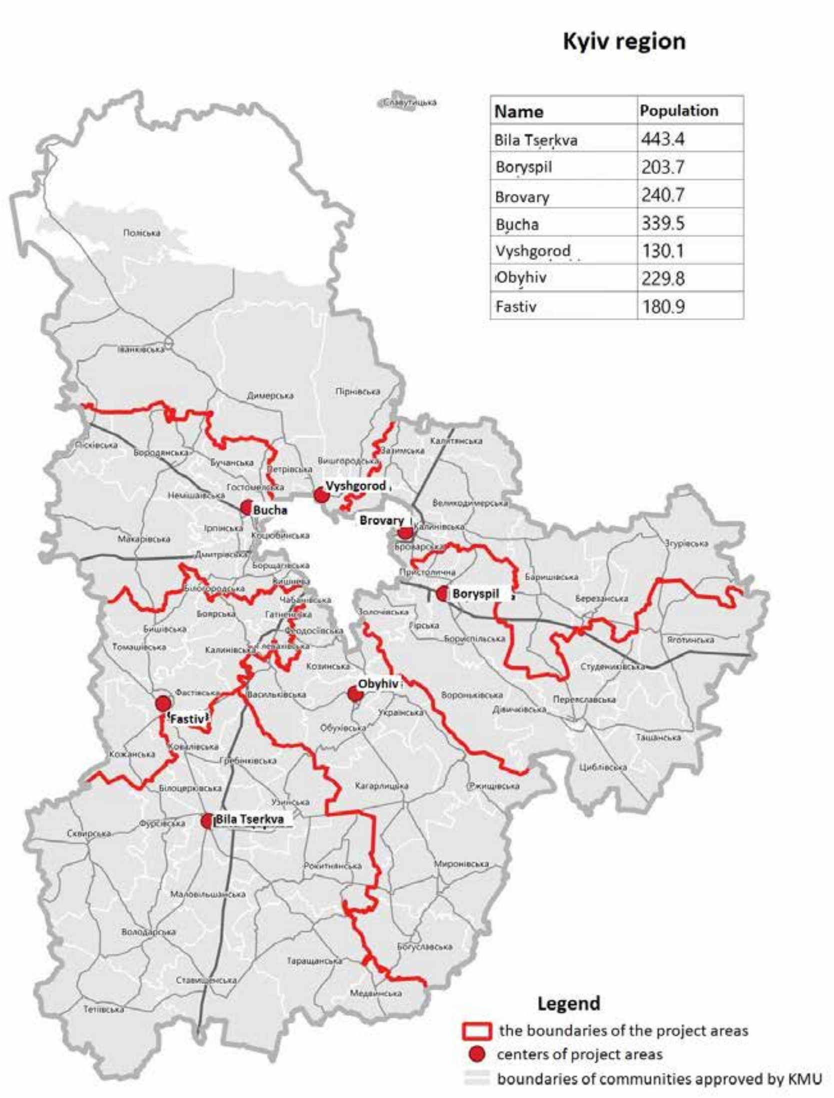


Figure 5.2 Kyiv agglomeration study data

The routing framework requires a middleware architecture to integrate heterogeneous data streams that differ in format, scale, update frequency, reliability, and institutional origin. Satellite imagery is raster-based and periodic. UAV imagery is high-resolution and event based. IoT telemetry is point-based and continuous. Cadastral and land-use data are vector-based and institutionally controlled. Road networks are graph-based. Fuel and cost feeds are scalar or tabular. Safety restrictions may be polygons, lines, event notices, or temporary instructions.

The author's previous smart-city and digital agronomy work already uses a three-layer architecture: application layer, middleware layer, and core services layer. In the digital agronomy article, the middleware layer includes API gateways, event routing, weighted decision parameters, data management, and decision-support services, while the agricultural use case connects satellite imagery, orthomosaics, NDVI, policies, route/logistics optimization, yield forecasting, irrigation scheduling, and scenario "what-if" analysis. The same architecture is adapted here for spatio-temporal agricultural routing.

In this subsection, the middleware performs seven main functions. First, it ingests data from multiple sources: WFS/WMS/WCS services, IoT endpoints, field logs, farm management systems, road networks, price feeds, and safety notices. Second, it harmonizes spatial and temporal references. Third, it compiles constraints into hard masks and soft penalties. Fourth, it converts monitoring events into tasks. Fifth, it updates economic and risk parameters. Sixth, it runs the routing and scheduling engine. Seventh, it exports advisories and provenance records.

The general middleware dataflow may be written as: D_raw,t -> Ingest -> Harmonize -> Validate -> CompileConstraints -> GenerateTasks -> OptimizeRoutes -> PublishAdvisory

This architecture aligns with the conducted routing study, which states that the proposed middleware consolidates satellite EO, UAV imagery (when permitted), IoT telemetry, road and congestion layers, and administrative-economic registers into a FAIR/OGC-aligned platform. The same study emphasizes that route advisories are exported as reproducible CSV/GeoJSON files with provenance.

Table 5.3 Middleware services for the spatio-temporal routing framework

Middleware service	Main function	Input data	Output	Economic role
Data ingestion service	Receives EO, UAV, IoT, road, cadastral, price, and safety data	WFS/WMS/WCS, SensorThings, CSV, GeoJSON, APIs	Raw data packages	Makes multi-source data available for routing
Harmonization service	Aligns coordinate systems, timestamps, units, identifiers	Raster, vector, point, tabular data	Common spatial-temporal dataset	Prevents incorrect route decisions caused by mismatched data
Data-quality service	Checks completeness, latency, reliability, provenance	Metadata, timestamps, source logs	Q_t reliability indicators	Prevents overconfidence in weak data
Constraint compiler	Converts land-use and safety rules into hard masks and soft penalties	Cadastral data, restrictions, protected zones	Feasible graph and penalty layers	Prevents legal/ecological violations
Event-to-task service	Converts monitoring events into routeable agricultural tasks	Soil moisture events, NDVI/EVI anomalies, UAV diagnostics	Job list J_t	Links monitoring value to operational action
Cost-band service	Updates UAH/km, fuel, labor, and machinery cost assumptions	Fuel prices, fleet data, cost registers	Edge and vehicle cost parameters	Converts route alternatives into monetary indicators
Emission service	Calculates route-level CO_2e estimates	Distance, fuel intensity, emission factor	CO_2e per edge/route/task	Enables environmental comparison
Routing engine	Solves weighted route and schedule problem	Graph, jobs, fleet, weights, constraints	Route plan and vehicle assignment	Produces cost/time/risk/CO_2e optimized plan
Scenario engine	Applies baseline, stress, and sustainability-adjusted weight templates	Scenario parameters	Scenario-specific routing outputs	Supports comparative economic evaluation
Advisory exporter	Publishes recommendations and records	Route plan, KPIs, provenance	Dashboard, CSV, GeoJSON, reports	Creates auditable decision-support output
Feedback service	Updates weights and parameters after new data	Actual travel time, cost, task success, restrictions	Improved next-cycle model	Supports learning and resilience

Source: prepared by the authors.

The empirical relevance of the spatio-temporal routing framework is determined by the specific spatial and economic structure of the Kyiv agglomeration. The available baseline data shows that the analyzed territorial system covers approximately 82.64 thousand hectares and is characterized by a highly uneven distribution of land-use categories. Green zones dominate the spatial structure, occupying 54.48% of the total area, or approximately 45.03 thousand hectares. This confirms the strong ecological and recreational components of the agglomeration and explains why routing decisions cannot be treated only as a technical shortest-path problem. Agricultural and farming land, in contrast, represents only 0.21% of the total area, or approximately 0.18 thousand hectares. Such a critically limited share of agricultural land indicates that agrarian activities in the Kyiv agglomeration operate under intense spatial pressure and must compete with residential, infrastructural, industrial, ecological, and urban-development functions.

Other land-use categories further demonstrate the complexity of peri-urban routing conditions. Industrial and production areas account for 7.99% of the territory, transport and infrastructure for 7.45%, water bodies for 7.33%, private buildings for 4.75%, and residential buildings for 1.56% of the total region, according to the baseline table. This spatial composition means that agricultural mobility occurs not in an open rural landscape but in a fragmented peri-urban environment where field access, protected areas, road infrastructure, water zones, residential development, and industrial logistics intersect. Therefore, the routing middleware proposed in this case study must integrate land-use categories as operational constraints. Green zones, water areas, protected territories, infrastructure corridors, and built-up areas may become hard masks, soft penalties, or risk-weighted route segments depending on their legal and environmental status.

The socio-economic indicators reinforce the need for a live logistical decision-support system. The same baseline dataset indicates that agricultural land accounts for only 0.21% of the total area, while green zones account for approximately 54%. At the same time, prime-zone land rents reach up to 25 million UAH per hectare per year, creating strong pressure to convert land to higher-rent uses, such as urban, commercial, residential, or infrastructure uses. This land-rent pressure directly affects the economic viability of peri-urban agriculture because agricultural activity must operate in a territory where land is increasingly influenced by metropolitan development dynamics.

Labor-market conditions also demonstrate the structural imbalance between primary agriculture and related urban-industrial sectors. The average monthly wage in food processing is approximately 16,500 UAH, while in agriculture it is approximately 14,000 UAH. This wage differential makes food processing and urban-linked activities more attractive for labor than primary agricultural production, thereby increasing the importance of logistics, automation, and digital decision-support tools. If agricultural producers face difficulties retaining labor, then optimizing machinery movement, field-service scheduling, inspection routes, and input-delivery logistics becomes an important compensatory mechanism to maintain productivity.

Transport costs are another critical driver of the routing framework. The baseline data indicates that logistics costs vary from 20 to 250 UAH per kilometer. Such a wide range reflects the heterogeneity of the peri-urban transport environment: some routes may rely on relatively efficient corridors, while others may involve congestion, poor access roads, detours, restricted segments, or high-friction delivery conditions. In this context, route optimization cannot be reduced to minimizing distance. A route may be geographically shorter but economically inefficient if it passes through high-cost, risky, congested, or restricted segments. Conversely, a slightly longer route may be economically preferable if it preserves agronomic service windows, avoids restricted areas, reduces delay risk, and stabilizes operational costs.

These data justify the integration logic of Section 5.1. The spatio-temporal routing middleware must combine three groups of information: land-use and cadastral constraints, environmental and monitoring events, and operational and economic parameters. Land-use data define where agricultural mobility is possible, restricted, penalized, or environmentally sensitive. Monitoring data from Case Study II defines where and when agronomic actions are required. Economic variables, including fuel prices, transport cost bands, labor costs, and service-window urgency, define how alternative routes should be evaluated. The result is a decision-support architecture that jointly processes spatial constraints and economic pressures before generating route advisories.

Therefore, the Kyiv agglomeration should be interpreted as a high-pressure empirical testbed for evaluating the economic efficiency of spatio-temporal routing. The very small share of agricultural land, the dominance of green zones, the high value of prime urban land, the wage gap between agriculture and food processing, and the broad range of transport costs all indicate that agricultural logistics in this territory require dynamic, data-driven coordination. The routing framework proposed in this monograph addresses this need by transforming land-use structures, environmental constraints, monitoring signals, and economic cost parameters into auditable route plans, vehicle assignments, service-window schedules, and performance indicators.

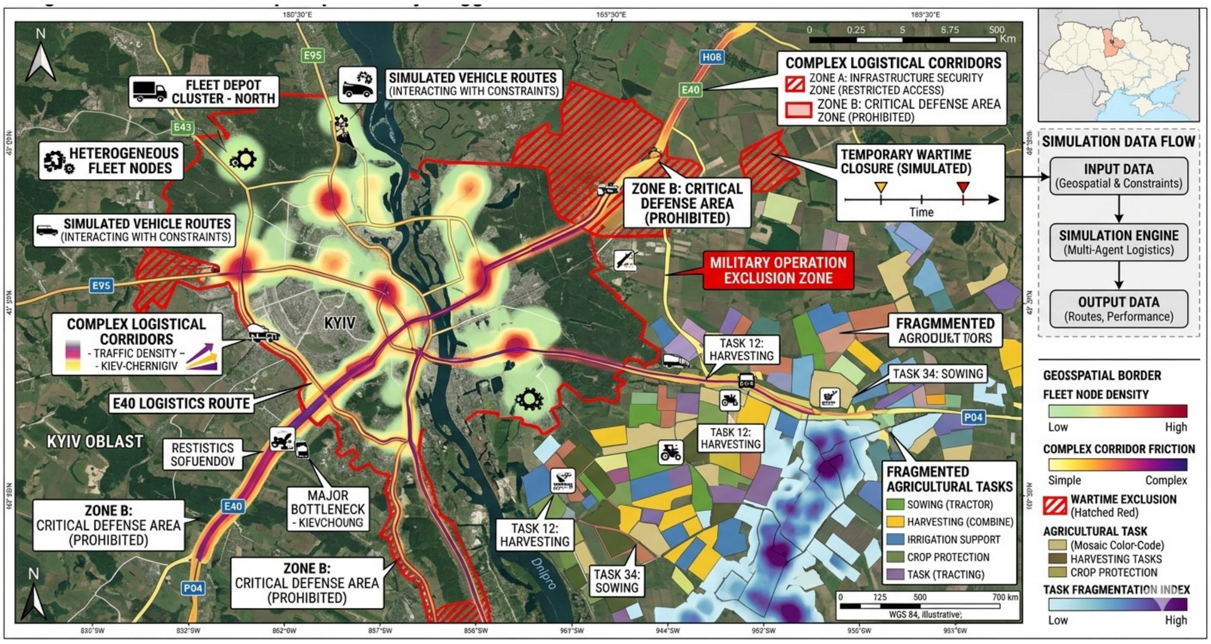


Figure 5.3 Sample simulation map visualization of Kyiv agglomeration under various conditions

The first empirical case study provides the spatial and institutional basis for routing. In the monograph structure, digital land management is selected as the first empirical block because reliable land data, zoning rules, ownership information, restrictions, environmental protection areas, and spatial interoperability are necessary for monitoring and routing to produce reliable decisions.

In the routing framework, land-management data are transformed into two types of constraints: hard masks and soft penalties. Hard masks represent non-negotiable restrictions. They remove parts of the spatial graph from the feasible route set. These may include protected environmental zones, military restrictions, unsafe areas, closed roads, private parcels without access rights, contaminated areas, or legally prohibited routes.

Soft penalties represent undesirable but not absolutely prohibited conditions. They do not remove the route segment, but they increase the generalized route cost. Examples include poor road quality, slow rural corridors, congestion, high risk, high environmental sensitivity, uncertain data quality, or difficulty with field access.

This structure corresponds directly to the routing article, where certain areas are designated as strictly prohibited, such as protected environmental strips, military zones, or private parcels, while other routes are assigned economic penalties, such as slow-travel rural corridors.

The economic importance of hard masks is that they prevent unacceptable decisions before optimization begins. This is necessary because a route cannot be selected merely because it is cheaper if it crosses a prohibited zone. The economic importance of soft penalties is that they make risk and inconvenience visible without automatically eliminating all imperfect options. In peri-urban agriculture, this distinction is essential because field access is often imperfect, roads may be degraded, and restrictions may change quickly.

Table 5.4 Transformation of Case Study I outputs into routing constraints

Case Study I output	Routing representation	Type	Example	Economic meaning
Parcel boundary	Polygon joined to the route graph	Spatial reference	Field access and task location	Assigns tasks and costs to land units
Land-use category	Attribute layer	Constraint/criterion	Agricultural, residential, industrial, green zone	Determines permitted movement and operation
Protected environmental zone	Forbidden polygon or buffer	Hard mask	Water protection strip, conservation zone	Avoids ecological/legal violation
Military or safety restriction	Forbidden polygon/line	Hard mask	Restricted corridor, temporary exclusion zone	Prevents unsafe or illegal routing
Private parcel without access	Forbidden parcel or access restriction	Hard mask	No permitted entry	Avoids land-use conflict
Poor rural road	Edge penalty	Soft penalty	Low-quality field road	Increases time/risk/cost but remains possible
Congested road	Dynamic edge penalty	Soft penalty	Urban/peri-urban bottleneck	Increases travel time and fuel cost
Environmentally sensitive edge	Ecological penalty	Soft penalty	Road near a green or water-sensitive zone	Internalizes environmental risk
Uncertain cadastral status	Data-quality penalty	Soft penalty/verification flag	Incomplete boundary or unclear access	Reduces confidence and may trigger verification
Field entrance	Node/access point	Routing node	Gate, service entrance, loading point	Defines a practical route endpoint

Source: prepared by the authors.

The second empirical case study provides the environmental and agronomic event layer. In the monograph structure, this block transforms raw environmental and agronomic data into actionable decisions. Sentinel-2 imagery supports NDVI/EVI monitoring, IoT sensors provide continuous field-level telemetry, and UAV imagery adds high-resolution diagnostics where available. However, the economic value of monitoring becomes evident only when data are translated into concrete interventions, such as irrigation, fertilization, crop protection, risk alerts, or field inspections.

In the routing framework, monitoring events become routeable tasks. A soil-moisture deficit event may require irrigation. A vegetation index anomaly may become an inspection or a UAV verification task. A localized disease or weed patch may become a targeted spraying task. A data-quality event may become a sensor maintenance task. A compliance-sensitive anomaly may become a planner notification or restricted-action task.

Table 5.5 Transformation of monitoring events into routeable tasks

Monitoring event	Main source	Routeable task	Required vehicle/resource	Time-window logic	Economic role
Soil-moisture deficit	IoT telemetry, weather, Sentinel-2	Irrigation task or irrigation inspection	Irrigation vehicle, pump, tractor, labor	Before water stress becomes yield loss	Protects yield and avoids over/under-irrigation
Over-irrigation risk	IoT, irrigation flow, weather	Delay/cancel irrigation; optional inspection	No vehicle or inspection vehicle	Before next scheduled irrigation	Saves water, energy, and reduces waterlogging risk
NDVI/EVI anomaly	Sentinel-2, UAV, field history	Field inspection or UAV verification	Light vehicle, UAV team, agronomist	Before stress spreads or service window closes	Reduces false interventions and protects yield
Localized weed/disease patch	UAV or EO anomaly plus field confirmation	Targeted spraying	Sprayer, tractor, chemical input	Within crop-protection window	Reduces agrochemical waste and avoids crop loss
Nutrient stress event	EO, field log, soil data	Targeted fertilization or sampling	Fertilizer applicator, sampling team	Within nutrient-response stage	Reduces fertilizer waste and protects yield response
Sensor failure	IoT telemetry status	Sensor maintenance task	Technician, replacement parts	Before next high-risk decision cycle	Restores data continuity
Weather-risk alert	Weather data, crop model	Pre-emptive inspection or schedule adjustment	Vehicle/machinery depending on task	Before rain/heat/frost impact	Avoids missed agronomic windows
Compliance-sensitive anomaly	Monitoring event intersecting restricted layer	Planner review or restricted intervention	Manager/planner, GIS validation	Before field operation	Avoids legal/ecological risk
Harvest readiness event	EO, crop stage, field report	Harvest or transport task	Harvester, truck, tractor	Within crop-quality window	Protects product quality and market value
Processing/transport demand	Farm record, processing schedule	Delivery route	Truck/tractor-trailer	Before processing or storage deadline	Reduces logistics cost and spoilage risk

Source: prepared by the authors.

The core of the spatio-temporal routing framework is the dynamic route-cost function. It converts time, direct cost, CO_2e, and risk into a comparable route score. This follows the MCDA logic developed in Section 2.2, in which heterogeneous indicators are normalized and weighted to enable transparent comparison of alternatives.

The conducted routing study states that the middleware's core is a dynamic cost function for each route edge, calculated as a normalized weighted sum of transit time, direct fuel cost, carbon-equivalent emissions, and operational risk. It also notes that scenario weights differ across baseline, stress, and sustainability-adjusted routing logic.

The generalized route cost for edge e, vehicle v, and time t may be written as:

$$GCe,v,t = wT \times Te,v,t' + wC \times Ce,v,t' + wCO2 \times CO2ee,v,t' + wR \times Re,t' + Pe,t' \quad (5.3)$$

, where:

- GC_{e,v,t} - generalized cost of edge e for vehicle v at time t;
- T'_{e,v,t} - normalized travel-time value;
- C'_{e,v,t} - normalized direct-cost value;
- CO2e'_{e,v,t} - normalized emission value;
- R'_{e,t} - normalized operational-risk value;
- P'_{e,t} - normalized soft penalty;
- w_T, w_C, w_CO2, w_R - weights for time, cost, emissions, and risk.

The weight condition is:

$$wT + wC + wCO2 + wR = 1 \quad (5.4)$$

The direct cost of an edge may be calculated as:

$$Ce,v,t = de \times kv,t \quad (5.5)$$

, where:

- d_e - edge length;
- k_{v,t} - vehicle-specific cost per kilometer at time t.

A more detailed direct-cost formula is:

$$Ce,v,t = de \times (100FCv) \times Pfuel,t + de \times Cmaint,v + Te,v,t \times Clabor,t \quad (5.6)$$

, where:

- FC_v - fuel consumption of vehicle v, liters per 100 km;
- P_fuel,t - fuel price at time t;
- C_maint,v - maintenance and depreciation cost per kilometer;
- C_labor,t - labor cost per unit.

Travel time may be calculated as:

$$Te,v,t = de/Se,v,t + Delaye,t \quad (5.7)$$

, where:

- S_{e,v,t} - effective speed of vehicle v on edge e;
- Delay_{e,t} - congestion, waiting, safety, or access delay.

The CO_2e value may be calculated as:

$$CO2ee,v,t = de \times (FCv/100) \times EFv \quad (5.8)$$

, where:

- EF_v - emission factor per liter of fuel for vehicle v.

Operational risk may be represented as:

$$Re,t = rsafety,e,t + rroad,e,t + raccess,e,t + rdata,e,t + rweather,e,t \quad (5.9)$$

, where:

- r_safety,e,t - safety or wartime risk;
- r_road,e,t - road or terrain risk;
- r_access,e,t - land-access or field-entry risk;
- r_data,e,t - data uncertainty;
- r_weather,e,t - weather-related operational risk.

The optimized route for a task or task sequence is:

$$Route *= argmine \in Route \sum GCe,v,t \quad (5.10)$$

subject to:

- e ∈ E_feasible(t)
- Arrival_i ≤ b_i
- VehicleCapacity_v ≥ Demand_i
- RestrictedViolations = 0

This formulation makes routing compatible with the monograph’s economic-efficiency framework. It includes direct financial cost, time, environmental impact, risk, and compliance.

Table 5.6 Variables of the dynamic weighted route-cost function

Variable	Symbol	Unit	Source	Economic interpretation
Edge distance	d_e	km	Road graph, GIS	Base distance for cost, time, and emissions

Variable	Symbol	Unit	Source	Economic interpretation
Travel time	T_{e,v,t}	minutes/hours	Road speed, congestion, vehicle class	Determines labor cost and service-window feasibility
Direct cost	C_{e,v,t}	UAH	Fuel price, vehicle cost, labor cost	Main private logistics cost
Fuel consumption	FC_v	L/100 km	Fleet data	Determines fuel-driven cost and emissions
Fuel price	P_fuel,t	UAH/L	Market feed	Drives cost-band scenario
Cost per km	k_{v,t}	UAH/km	Fleet/economic model	Simplified operational cost parameter
CO_2e	CO2e_{e,v,t}	kg CO_2e	Fuel use, emission factor	Environmental performance metric
Operational risk	R_{e,t}	index	Safety notices, road data, weather, data reliability	Penalizes risky or uncertain segments
Soft penalty	P_{e,t}	index / UAH proxy	Case I constraints, congestion, road quality	Internalizes non-prohibitive disadvantages
Hard-mask status	H_e(t)	0/1	Restricted zones, land-use rules	Excludes prohibited edges
Time weight	w_T	0–1	Scenario configuration	Priority of time minimization
Cost weight	w_C	0–1	Scenario configuration	Priority of direct cost minimization
CO_2e weight	w_CO2	0–1	Scenario configuration	Priority of sustainability
Risk weight	w_R	0–1	Scenario configuration	Priority of safety and reliability

Source: prepared by the authors.

In real agricultural operations, the routing framework must continue to function even when some data are incomplete or delayed. UAV imagery may be unavailable due to wartime restrictions, safety notices, weather, or operational limitations. Network connectivity may fail. IoT telemetry may be delayed. Satellite imagery may be affected by cloud cover. Cadastral or road data may be incomplete. Therefore, the middleware must include fallback logic.

The conducted routing study explicitly reports that the middleware maintained continuous advisory generation under intermittent UAV availability and short-lived network outages by using store-and-forward edge buffers, asynchronous refresh, and lineage capture. It also states that exported route advisories were reproducible as CSV/GeoJSON with full provenance.

The routing framework must produce auditable outputs. This requirement is important for three reasons. First, the economic analysis in subsections 5.3 and 5.4 requires reliable records of route cost, time, CO_2e, feasibility, and violations. Second, farms and cooperatives need to understand why a route was recommended. Third, public or policy-oriented use of the system requires transparency, especially when routing decisions interact with land-use restrictions, protected zones, or sustainability indicators.

The routing framework can be operationalized as a repeatable algorithm. The algorithm is designed for daily and weekly agricultural planning in peri-urban territories. It supports both normal operation and re-planning under disruptions.

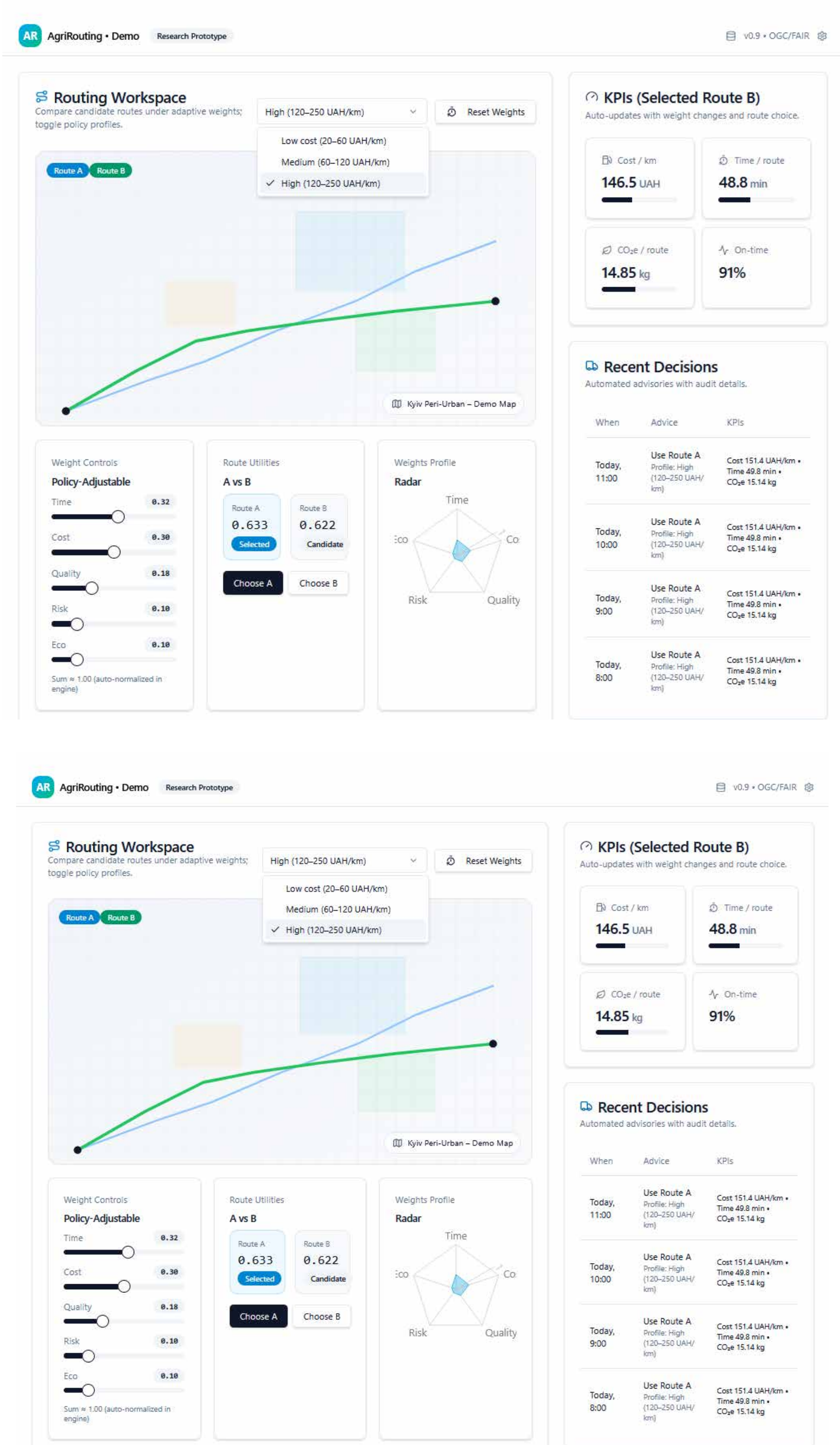


Figure 5.4 Software service UI panels and dashboard

The conducted routing study presents a similar operational sequence: collect and harmonize satellite, IoT, administrative-economic, and UAV data; create masks and penalties; form daily tasks and time windows; update transportation cost and CO_2e; apply user weights; generate potential routes; check capacity and restrictions; compare route options; publish the plan; and store the full decision history for later recalculation if missing data become available.

Table 5.7 Algorithm for the spatio-temporal routing framework

Step	Action	Practical explanation	Output
1	Define planning cycle	Select daily, weekly, or emergency re-planning cycle	Planning horizon
2	Load land-management layers	Parcels, land-use categories, restrictions, protected zones, access rights	Spatial governance dataset
3	Load monitoring outputs	IoT, Sentinel-2, UAV diagnostics, weather events, field logs	Monitoring event dataset
4	Load economic parameters	Fuel price, UAH/km bands, labor cost, machinery cost, input cost	Economic parameter table
5	Load road and access graph	Road network, field entrances, service roads, congestion, closures	Routing graph G_t
6	Load fleet state	Vehicle types, availability, speeds, capacities, fuel consumption, emission factors	Fleet dataset V_t
7	Harmonize data	Align coordinates, time stamps, parcel IDs, field-zone IDs, units	Common routing dataset
8	Compile hard masks	Remove prohibited zones, closed roads, restricted parcels	Feasible graph G_feasible(t)
9	Compile soft penalties	Add congestion, road quality, safety, environmental and uncertainty penalties	Penalty layer P_e(t)
10	Generate tasks	Convert monitoring events and farm operations into routeable jobs	Task set J_t
11	Assign service windows	Define earliest/latest service times and service durations	Time-window table W_t
12	Select scenario weights	Baseline, Stress, Sustainability-adjusted, or custom profile	Weight vector
13	Calculate edge costs	Time, direct cost, CO_2e, risk, penalties	Edge-cost table
14	Optimize route and schedule	Apply weighted route-cost function with time windows and fleet constraints	Route plan
15	Validate route	Check capacity, feasibility, restricted violations, data quality	Validated advisory
16	Publish route advisory	Export dashboard, CSV, GeoJSON, and operational task schedule	Decision-support output
17	Store provenance	Record data sources, weights, model version, and assumptions	Audit trail
18	Monitor feedback	Update actual travel time, costs, completed tasks, and new restrictions	Feedback dataset
19	Recalculate if needed	Trigger re-routing when fuel, weather, restrictions, or task status changes	Updated route advisory
20	Feed economic evaluation	Send route KPIs to 5.3 and 5.4 calculations	Economic-efficiency dataset

Source: prepared by the authors.

The proposed framework creates economic value through several channels. First, it reduces direct logistics cost by converting fuel price, vehicle class, distance, congestion, and labor time into an explicit route-cost function. This is especially important under volatile fuel prices and high UAH/km cost bands.

Second, it protects agronomic service windows. A routing system that completes irrigation, spraying, inspection, or transport within the correct time window protects yield and reduces delay-related losses.

Third, it reduces legal and ecological risk by enforcing hard masks before optimization. The routing study reports that restricted-edge violations remained zero because prohibited edges were removed through hard spatial masks before optimization.

Fourth, it supports environmental accounting by calculating CO_2e per route, per job, or per week. In the current pilot configuration, CO_2e values remained stable across scenarios because distance and emission factors were unchanged, but the framework is designed to become more sensitive when differentiated fleet classes or low-carbon corridors are included.

Fifth, it improves institutional auditability. By storing weights, data sources, route geometry, restrictions, and KPI outputs, the system creates evidence that can support farm management, public reporting, sustainability certification, eco-subsidy design, and post-war recovery planning.

The framework, therefore, transforms routing from a technical service into an economic and institutional instrument. It allows digital land management and environmental monitoring to produce operational results that can be measured, compared, audited, and improved.

Table 5.8 Economic value channels of the spatio-temporal routing framework

Value channel	Mechanism	Indicators
Direct logistics cost reduction	Weighted route-cost optimization using fuel price, cost bands, distance, labor, and vehicle type	Direct logistics cost, UAH/km, weekly cost
Time-window protection	Routing under agronomic service-window constraints	Feasibility rate, jobs within windows, delay
Fuel and energy efficiency	Reduced unnecessary travel and better vehicle assignment	Fuel use, cost per km, cost per job
Environmental accounting	Route-level CO_2e calculation and sustainability-adjusted weights	kg CO_2e per route/job/week
Risk reduction	Hard masks and risk penalties	Restricted-edge violations, risk score
Compliance protection	Cadastral and land-use restrictions integrated into route graph	Zero prohibited-edge use, avoided violation
Data resilience	Fallback routing under missing UAV/IoT/EO data	Data availability, confidence score
Auditability	CSV/GeoJSON/provenance export	Reproducible advisory record
Policy relevance	Standardized KPIs linked to sustainability and land governance	Policy-ready route metrics

Source: prepared by the authors.

Subsection 5.1 defines the architecture and logic of the spatio-temporal routing framework. The framework integrates the spatial-institutional outputs of Case Study I and the environmental-monitoring outputs of Case Study II into a live logistical decision-support middleware. This is the operational bridge of the monograph: land management defines where agricultural operations are allowed; monitoring defines what needs to be done and when; routing determines how to perform those operations efficiently, legally, and sustainably.

The main methodological position is that agricultural routing in peri-urban territories must be treated as a multi-criteria, spatially constrained, temporally sensitive, and economically auditable process. The route is not simply the shortest path. It is the selected path and schedule that best balances direct cost, time, CO_2e, and operational risk while respecting service windows, land-use restrictions, environmental constraints, data reliability, and fleet limitations.

The Kyiv agglomeration case confirms the need for such a framework. The conducted routing study shows that a standards-based middleware platform, combined with weight-based routing, can integrate spatial constraints, cost dynamics, and sustainability indicators into a single operational workflow. It also demonstrates the importance of continuous advisory generation, fallback logic under UAV/network disruptions, CSV/GeoJSON provenance, hard-mask enforcement, and scenario-based weight profiles.

This subsection prepares the transition to 5.2, where the routing framework will be operationalized through simulation setup: heterogeneous fleet modeling, road-network construction, task generation, wartime and logistical constraints, and scenario preparation for the peri-urban belt of the Kyiv agglomeration.

5.2 Simulation Design for the Kyiv Peri-Urban Belt: Heterogeneous Fleet Modeling under Wartime and Logistical Constraints.

Subsection 5.1 defined the spatio-temporal routing framework as the operational integration layer of the monograph. It explained how cadastral and land-use constraints from Case Study I and environmental-monitoring outputs from Case

Study II are transformed into routeable agricultural tasks, weighted route costs, service-window schedules, and auditable route advisories. The present subsection develops the simulation setup required to test that framework under controlled, yet realistic, peri-urban conditions.

The purpose of the simulation is not to build a purely theoretical vehicle-routing model. Its purpose is to reproduce the operational problem faced by agricultural producers, service providers, cooperatives, and planners in the Kyiv agglomeration: how to route a mixed fleet of agricultural and transport vehicles across fragmented peri-urban space when fuel prices are volatile, field access is uneven, UAV availability is restricted, road conditions change, and agricultural operations must still be completed within strict service windows.

The routing research attached to the monograph defines the empirical context in exactly this way. It states that Ukraine's agriculture faces peri-urban land-use transformation, disrupted logistics, volatile fuel costs, and restricted mobility in wartime conditions, while the Kyiv agglomeration increasingly depends on rapid re-planning under changing constraints. It also states that the tested platform integrates satellite EO, UAV imagery when permitted, IoT telemetry, road and congestion layers, and administrative-economic registers into a FAIR/OGC-aligned middleware architecture.

Figure 5.5 Simulation technological components conceptual visualization

The simulation setup, therefore, has five methodological tasks:

1. Define the peri-urban spatial testbed.
2. Define the heterogeneous fleet.
3. Define agricultural jobs and service windows.
4. Define wartime, logistical, environmental, and data-availability constraints.
5. Define scenario inputs and performance outputs for later evaluation in 5.3 and 5.4.

This subsection prepares empirical ground for the scenario-based economic evaluation. The results themselves are interpreted later. Here, the emphasis is on how the simulation is constructed, what assumptions are used, which variables enter the model, and how the model remains consistent with the economic-efficiency methodology of the monograph.

Table 5.9 Simulation setup logic for Case Study III

Simulation block	Main modeling question	Main data required	Output
Spatial testbed	Where does routing take place?	Kyiv peri-urban belt, road graph, parcel boundaries, hromada boundaries, field entrances	Feasible routing territory
Heterogeneous fleet	Which vehicles can perform the tasks?	Trucks, tractors, speeds, fuel consumption, capacity, terrain suitability, emission factor	Vehicle state table
Agricultural jobs	What must be done?	Irrigation tasks, spraying tasks, inspection tasks, transport tasks, maintenance tasks	Job set with time windows
Service windows	When must tasks be completed?	Agronomic calendar, monitoring events, field conditions, weather, crop stage	Time-window constraints
Wartime constraints	Which routes or data sources are restricted?	NOTAMs, safety notices, local restrictions, military or protected zones	Hard masks and risk penalties
Logistical constraints	What operational friction affects routes?	Road class, congestion, bridge/road closures, unpaved access, distance, fuel price	Edge costs and travel-time modifiers
Data constraints	Which data is missing or delayed?	UAV restrictions, EO cloud cover, IoT gaps, network outages	Confidence scores and fallback rules
Scenario templates	How are priorities varied?	Baseline, Stress, Sustainability-adjusted weights and fuel bands	Scenario-specific input sets
Performance metrics	How is efficiency measured?	Cost, time, CO_2e, feasibility, violations, data reliability	KPI table for economic evaluation

Source: prepared by the authors.

The empirical focus of the simulation is the peri-urban belt of the Kyiv agglomeration. This territory is appropriate because it combines agricultural land-use pressure, fragmented parcels, mixed road conditions, proximity to the urban core, logistics intensity, and high sensitivity to restrictions. The attached routing study defines the empirical focus as the outer districts of Kyiv City and adjacent hromadas, characterized by rapid land-use turnover, mixed farm sizes, and frequent mobility constraints.

For modeling purposes, the testbed is represented as a spatial graph:

$$G = (N, E) \quad (5.11)$$

, where:

- G - road and field-access graph;
- N - nodes, including road intersections, field entrances, depots, loading points, irrigation points, and service locations;
- E - edges, including paved roads, unpaved roads, field access tracks, service corridors, and permissible local routes.

Each edge is assigned attributes:

$$e = \{ide, nfrom, nto, de, roadtypee, surfacee, speede, accesse, riske, restrictione, coste, co2ee\} (5.12)$$

, where:

- id_e - edge identifier;
- n_from, n_to - starting and ending nodes;
- d_e - length of edge;
- roadtype_e - road classification;
- surface_e - paved, unpaved, degraded, field track, or restricted-access surface;

- `speed_e` - effective speed;
- `access_e` - access permission status;
- `risk_e` - operational or safety risk score;
- `restriction_e` - hard-mask or restriction status;
- `cost_e` - direct logistics cost;
- `co2e_e` - edge-level emission estimate.

The spatial testbed must also contain task locations. A task location is not necessarily the geometric center of a parcel. In practical agricultural routes, the vehicle must reach an **access node**: a field gate, service entrance, irrigation point, loading point, machinery stop, or safe turn-around point. For this reason, the simulation assigns each parcel or field zone to one or more feasible access nodes.

The field-access mapping can be written as:

`Access(z_i) = {n_1, n_2, ..., n_k}`

, where:

- `z_i` - field zone or parcel;
- `Access(z_i)` - set of feasible access nodes for zone `i`;
- `n_k` - access node.

The selected access node is:

`n_i^* = argmin_{n∈Access(z_i)} GC(n, z_i)`

, where:

- `GC(n, z_i)` - generalized access cost from node `n` to the operational location of zone `z_i`.

This distinction is important. If a simulation routes machinery only to parcel centroids, it may underestimate access cost and ignore real constraints such as field entrances, roads, turning space, and safety restrictions. In a peri-urban environment, access-node modeling is necessary because agricultural plots are often interrupted by urban roads, private parcels, green zones, industrial infrastructure, and temporary restrictions.

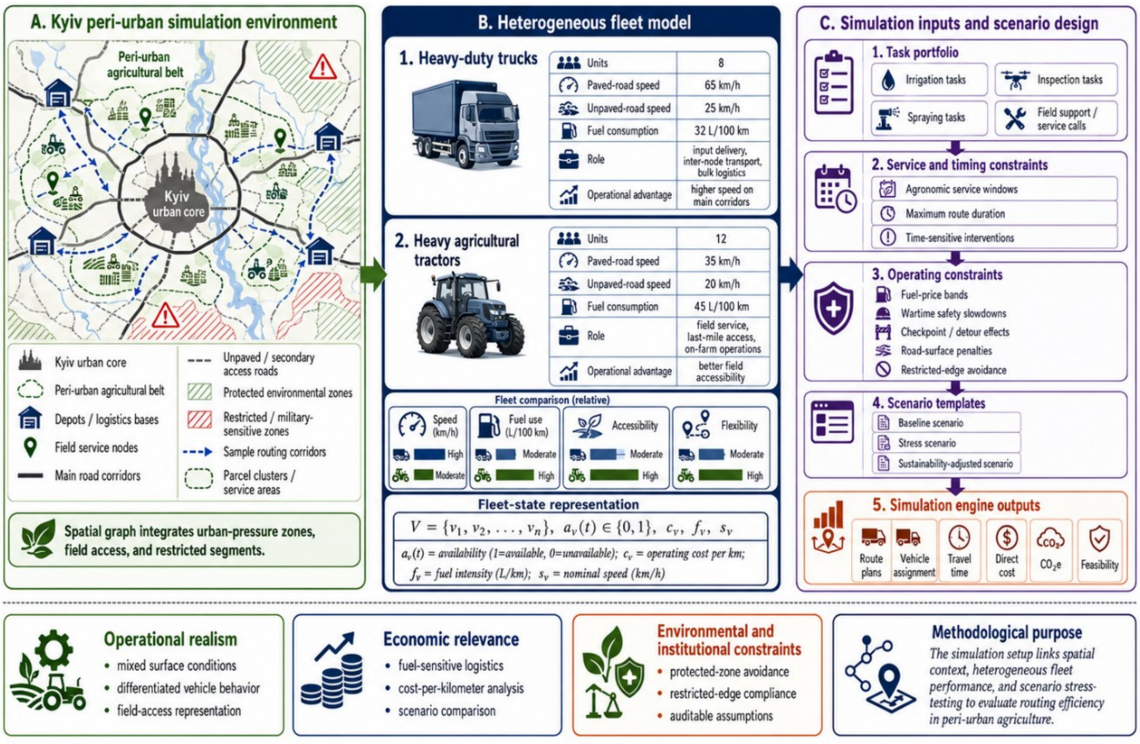


Figure 5.6 Heterogeneous fleet and Kyiv peri-urban simulation setup

5.10 Spatial components of the Kyiv peri-urban routing test set-up

Spatial component	Representation in simulation	Example	Economic role
Kyiv peri-urban belt	Area of interest/boundary polygon	Outer Kyiv districts and adjacent hromadas	Defines modeling territory
Road network	Graph edges and nodes	Paved roads, rural roads, field tracks	Determines distance, speed, and cost
Field parcels	Polygon layer	Agricultural fields, leased plots, field zones	Defines task destinations
Field entrances	Graph nodes	Gates, service points, safe access points	Determines the real route endpoint
Depots/bases	Graph nodes	Machinery yard, cooperative base, storage point	Defines route origin and return points
Processing/delivery points	Graph nodes	storage, processor, warehouse, loading station	Supports harvest or delivery tasks
Protected zones	Polygon hard masks	water-protection strips, green areas	Prevents prohibited routing
Military/safety zones	Polygon or line hard masks	temporary restricted areas, unsafe segments	Prevents wartime-related violations
Slow rural corridors	Soft-penalty edges	unpaved or degraded access roads	Increases cost/time/risk
Congested corridors	Dynamic edge penalties	peri-urban bottlenecks	Modifies travel time and fuel cost
Environmental sensitivity zones	Soft penalty or hard mask	zones near water, green infrastructure	Internalizes ecological risk

Source: prepared by the authors.

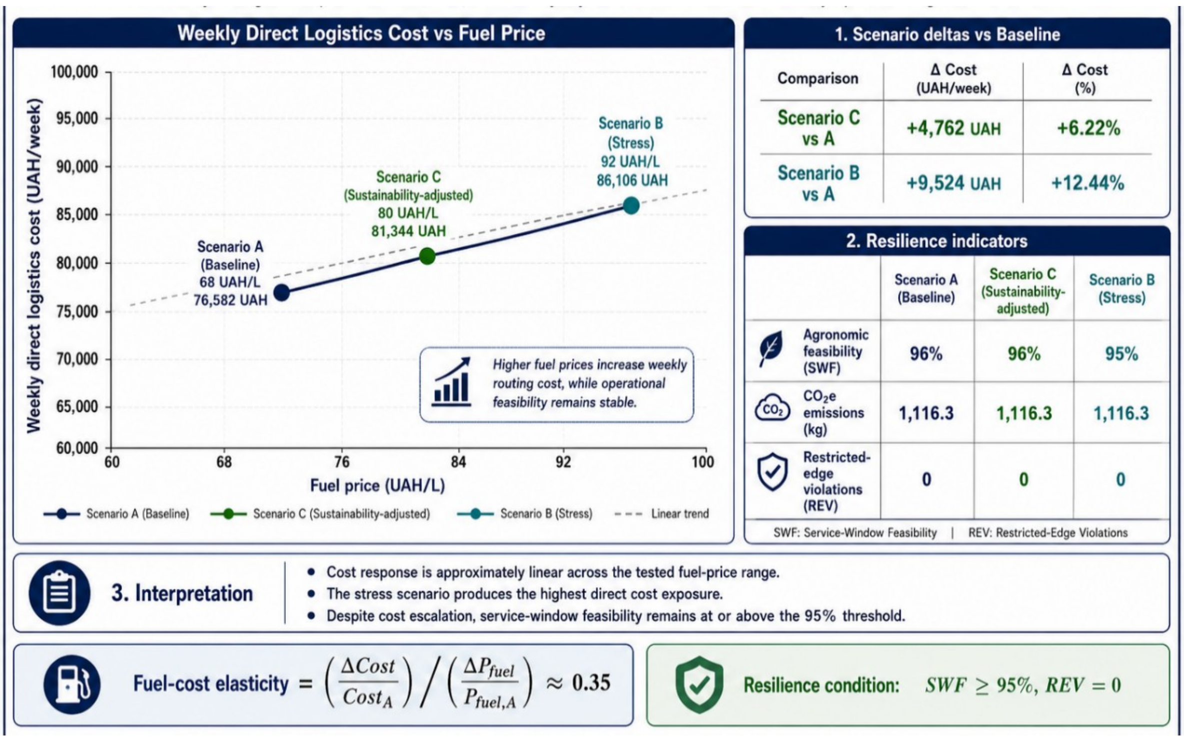


Figure 5.7 Fuel price diagram for spatio-temporal routing in the Kyiv agglomeration

The simulation can be implemented as a repeatable workflow. It should be possible to rerun the experiment when fuel prices, road restrictions, fleet parameters, data availability, or task sets change. The simulation uses the same data-integration logic developed in 5.1. The difference is that 5.2 formalizes those inputs as simulation variables. The routing study combines EO and UAV streams, IoT telemetry, administrative and economic layers, road network and congestion data, market signals, and safety notices. It specifies that Sentinel-2 MSI is used for NDVI/EVI and field-level stress masks; UAV orthomosaics and vegetation indices are task-driven; IoT sensors provide soil moisture and micro-meteorological information at 15–60 minute intervals; cadastral and land-use data provide parcel polygons and legal constraints; road data provide travel-time costs and detours; market signals define UAH/l and UAH/km cost bands; and safety/restriction notices define no-fly and slow-down zones.

In the simulation, each data layer has a specific role. EO and UAV data do not directly calculate a route. They generate task priorities and affected zones. IoT data refines timing. Cadastral data eliminates prohibited areas. Road and congestion data define possible movement and travel time. Fuel and cost feeds convert route geometry into monetary cost. Safety notices modify both the feasible graph and risk penalties.

The general simulation input vector is:

$$D_{(sim,t)} = D_{(EO,t)}, D_{(UAV,t)}, D_{(IoT,t)}, D_{(CAD,t)}, D_{(ROAD,t)}, D_{(ECON,t)}, D_{(SAFE,t)}, D_{(WEATHER,t)} (5.13)$$

, where:

- D_EO,t - satellite Earth Observation data;
- D_UAV,t - UAV imagery and diagnostic outputs;
- D_IoT,t - telemetry from field sensors and machinery logs;
- D_CAD,t - cadastral, land-use, and administrative constraints;
- D_ROAD,t - road network, congestion, closures, surface classes;
- D_ECON,t - fuel price, UAH/km bands, labor cost, machinery cost;
- D_SAFE,t - safety notices, NOTAMs, local restrictions;
- D_WEATHER,t - weather and agroclimatic data.

The simulation requires harmonization:

$$D_{(harm,t)} = H\left(D_{(sim,t)}\right) (5.14)$$

, where:

- H - harmonization function aligning coordinate systems, timestamps, identifiers, and units.

The most important output of harmonization is a common routing table:

$$RTablet = EdgeTablet, NodeTablet, TaskTablet, FleetTablet, ConstraintTablet, ScenarioTablet (5.15)$$

, where each table is updated before each planning cycle.

Table 5.11 Data inputs for the routing simulation

Data layer	Source/standard	Spatial-temporal resolution	Simulation role	Main variables
Sentinel-2 MSI	EO hub; OGC WMS/WCS	10–20 m; approx. 5-day cycle	Field stress masks and fallback priority classification	NDVI, EVI, crop vigor, stress proxy
UAV orthomosaics and VIs	Mission logs, GeoTIFF, STAC	2–10 cm; task-driven	Micro-windows for spraying, spot irrigation, obstacle detection	affected area, vegetation anomaly, obstacle
IoT sensors	OGC SensorThings API	Point grids; 15–60 min	Trigger irrigation/frost alerts and refine time windows	soil moisture, micro-met, field activity
Cadastral and land-use data	GeoJSON/WFS; registers	Parcel polygons; annual or event-updated	Legal constraints, crop/ownership, feasibility masks	parcel ID, land-use category, restriction
Road network and congestion	OSM and local feeds	Edges; 5–15 min where available	Travel-time cost, restricted segments, detours	distance, speed, closure, congestion
Market signals	Weekly price feeds	Scalar; weekly	UAH/l and UAH/km band priors; scenario stressors	fuel price, input price, transport band
Safety/restriction notices	NOTAMs, civil advisories, local notices	Polygons/lines; event-based	No-fly/slow-down zones and risk penalties	restricted area, validity period, risk score
Weather data	forecast and local/weather-grid sources	hourly/daily	Task timing, service-window risk, access risk	precipitation, heat, wind, field workability

Data layer	Source/standard	Spatial-temporal resolution	Simulation role	Main variables
Field logs	farm/task records	event-based	Actual tasks, prior interventions, service durations	job type, duration, status
Fleet data	farm/cooperative records	vehicle-level; updated by planning cycle	Vehicle assignment and route cost	vehicle type, speed, fuel use, capacity

Source: prepared by the authors based on the routing study's core dataset structure

The simulation uses a heterogeneous fleet because peri-urban agricultural logistics cannot be accurately modeled with a single generic vehicle type. Heavy-duty transport trucks and heavy agricultural tractors differ in speed, terrain suitability, fuel consumption, capacity, operational purpose, and road restrictions.

The routing dataset attached to the monograph explicitly contrasts heavy-duty transport trucks and heavy agricultural tractors. It defines 8 heavy-duty transport trucks with a speed of 65 km/h on paved roads, 25 km/h on unpaved roads, fuel consumption of 32 L/100 km, and emission factor of 2.68 kg CO_2e/L. It also defines 12 heavy agricultural tractors with a speed of 35 km/h on paved roads, 20 km/h on unpaved roads, fuel consumption of 45 L/100 km, and the same emission factor of 2.68 kg CO_2e/L.

This structure reflects the operational trade-off. Trucks are faster on paved roads and appropriate for transport, delivery, and logistics routes. Tractors are slower and more fuel-intensive, but they are necessary for access to unpaved fields, spraying, fertilization, towing, and field-level operations. In the Kyiv peri-urban setting, both vehicle types are needed because the road system combines urban/peri-urban paved corridors with unpaved field access routes.

This fleet model allows the simulation to show why route selection depends on vehicle type. A route that is cheap and fast for a truck may be infeasible for a tractor-drawn implement. A field route suitable for a tractor may be inefficient or impossible for a truck. Therefore, the routing algorithm must assign both the route and the vehicle.

Table 5.12 Baseline heterogeneous fleet parameters

Vehicle class	Fleet size	Speed on a paved road	Speed on an unpaved road	Fuel consumption	Emission factor	Main use in simulation
Heavy-duty transport trucks	8 units	65 km/h	25 km/h	32 L/100 km	2.68 kg CO_2e/L	Transport, delivery, logistics routes, long paved corridors
Heavy agricultural tractors	12 units	35 km/h	20 km/h	45 L/100 km	2.68 kg CO_2e/L	Field access, spraying, fertilization, irrigation support, unpaved routes

Source: prepared by the authors based on the fleet parameters in the routing dataset

The simulation requires a defined set of agricultural tasks. In this monograph, tasks are generated from two sources. The first source is the monitoring event layer from Case Study II: soil-moisture deficit, NDVI/EVI anomaly, UAV diagnostic event, sensor failure, localized stress, or compliance-sensitive anomaly. The second source is the farm-operational calendar: irrigation, spraying, inspection, transport, field service, and delivery.

The routing study's scenario template uses irrigation tasks on Tuesday and Thursday, and spraying tasks on Wednesday and Friday, under both baseline and sustainability-adjusted scenarios. Under the stress scenario, the same baseline days are retained, but safety slowdowns and more restricted segments are introduced.

The economic logic is that routing must preserve task feasibility. It is not enough to minimize cost if critical irrigation or spraying tasks are completed too late. The routing study reports that operational reliability remained high, with at least 95% of scheduled agricultural tasks completed within required agronomic timeframes.

The simulation must represent the fact that wartime and logistical constraints are not secondary background conditions. They directly change route feasibility, travel time, cost, risk, and data availability.

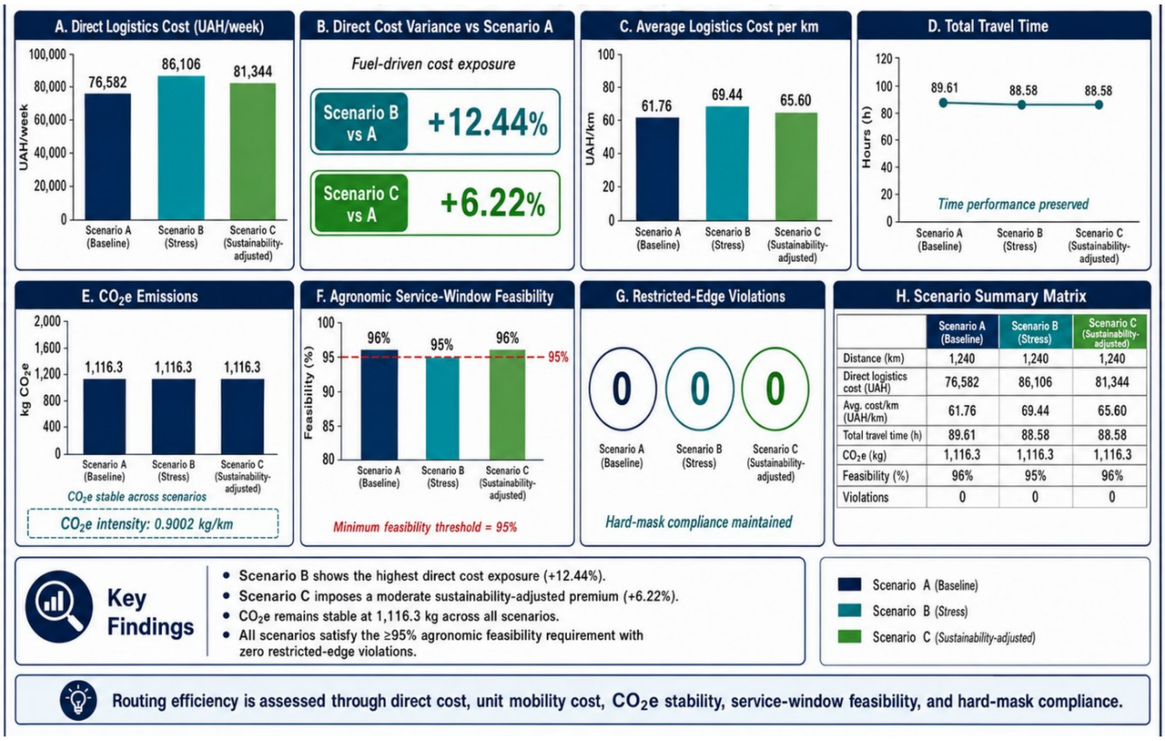


Figure 5.8 Routing scenario results dashboard visualization

The routing study identifies several relevant constraints: restricted mobility in wartime, intermittent UAV availability, short-lived network outages, NOTAMs or local restrictions preventing flights, safety slow-downs, restricted segments, volatile fuel prices, and partially degraded data environments. These constraints are incorporated into the simulation in three ways.

This increases travel time, labor cost, and possibly missed-window risk. The simulation should also model data disruption. When UAV data is missing, the system continues. It falls back to satellite and ground-sensor data. The routing study states that when NOTAMs or local restrictions prevented flights, the system switched to satellite data and in-field IoT telemetry, using store-and-forward edge buffers and asynchronous refresh to preserve event integrity and backfill high-resolution layers later.

The simulation uses three weekly scenario templates: Baseline, Stress, and Sustainability-adjusted. These scenarios use the same job set and spatial masks, but different fuel prices, cost bands, and routing weights. This design is important because it isolates the effect of weighing and cost conditions while keeping the operational demand comparable.

The routing study defines the three templates as follows: Baseline uses fuel price 68 UAH/L, medium cost band 60–120 UAH/km, and weights 0.35/0.35/0.20/0.10 for time, cost, CO_2e, and risk; Stress uses fuel price 92 UAH/L, high cost band 120–250 UAH/km, and weights 0.25/0.45/0.20/0.10; Sustainability-adjusted uses fuel price 80 UAH/L, medium cost band 60–120 UAH/km, and weights 0.25/0.30/0.35/0.10.

The scenario set is:

$$S = A, B, C \quad (5.16)$$

, where:

- A - Baseline scenario;
- B - Stress scenario;
- C - Sustainability-adjusted scenario.

Each scenario is defined as:

$$S_s = P_{(fuel,s)}, Band_s, W_s, K_s, J_{(week)} \quad (5.17)$$

, where:

- P_fuel,s - fuel price in scenario s;
- Band_s - UAH/km cost band;
- W_s - weight vector for time, cost, CO_2e, and risk;
- K_s - scenario-specific restrictions and slow-downs;

- J_week - common weekly task set.

The weight vector is:

$$W_s = w_{(T,s)}, w_{(C,s)}, w_{(CO2,s)}, w_{(R,s)} \quad (5.18)$$

with:

$$w_{(T,s)} + w_{(C,s)} + w_{(CO2,s)} + w_{(R,s)} = 1 \quad (5.19)$$

Scenario A uses balanced time and cost weighting:

$$W_A = 0.35, 0.35, 0.20, 0.10\} \quad (5.20)$$

Scenario B increases cost weight under high fuel and transport-risk conditions:

$$W_B = 0.25, 0.45, 0.20, 0.10 \quad (5.21)$$

Scenario C increases CO_2e weight:

$$W_C = 0.25, 0.30, 0.35, 0.10 \quad (5.22)$$

This scenario design allows the monograph to compare the effect of economic stress and sustainability preferences without changing the full agricultural demand structure.

Table 5.13 Simulation scenario templates

Scenario	Fuel price	UAH/km cost band	Weights: time/cost / CO_2e / risk	Weekly task pattern	Main interpretation
Baseline A	68 UAH/L	60–120 UAH/km	0.35 / 0.35 / 0.20 / 0.10	Irrigation Tue/Thu; spraying Wed/Fri	Reference operating week
Stress B	92 UAH/L	120–250 UAH/km	0.25 / 0.45 / 0.20 / 0.10	Same as baseline, with safety slow-downs	High fuel price and higher transport risk
Sustainability-adjusted C	80 UAH/L	60–120 UAH/km	0.25 / 0.30 / 0.35 / 0.10	Irrigation Tue/Thu; spraying Wed/Fri	Preference for low-CO_2 routing logic

Source: adapted for the research from the routing study's scenario templates.

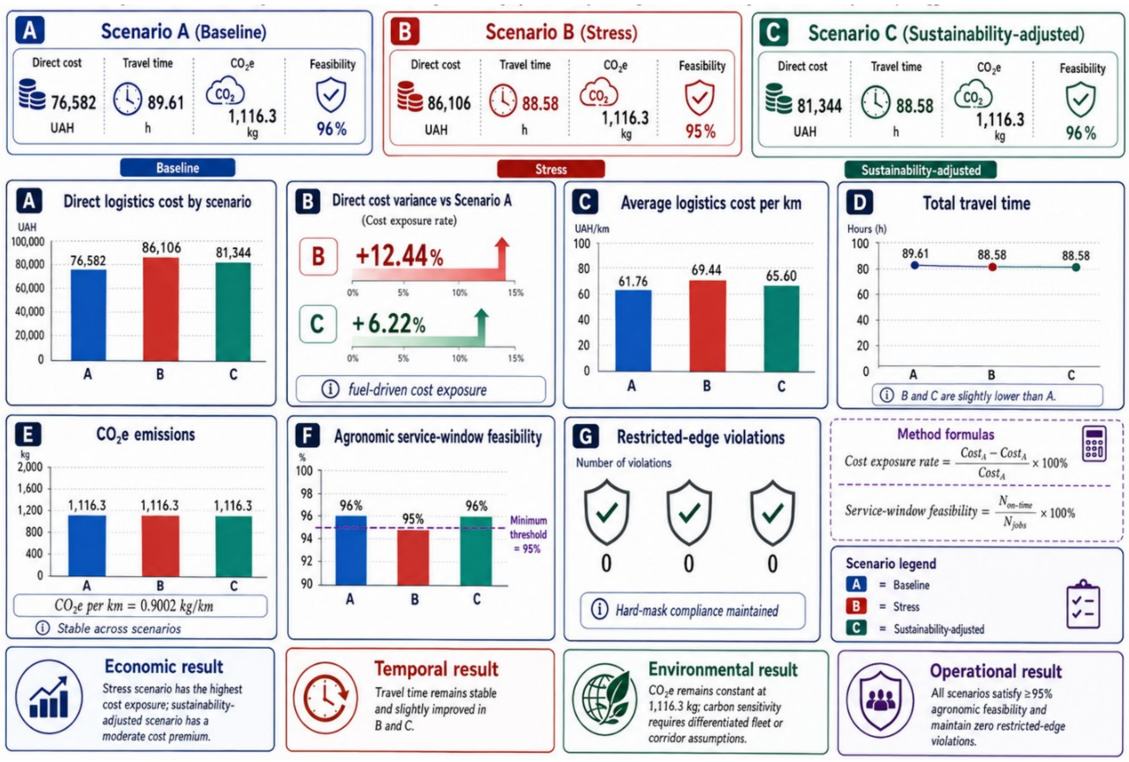


Figure 5.9 Fuel scenarios efficiency visualization charts

The simulation combines a route-cost model with vehicle assignment. This is necessary because not every vehicle can perform every task. A truck may be suitable for delivery and long paved transport but may not be suitable for some field operations. A tractor may be slower and more fuel-intensive, but it is required for spraying, field access, and unpaved terrain.

The simulation uses a two-level routing procedure. At the daily task level, the problem is treated as a shortest-path problem with time windows. At the weekly planning level, the model constructs daily subproblems and applies an iterative greedy-plus-repair heuristic seeded by shortest-path solutions. This is consistent with the routing study, which formulates the method as a multi-objective shortest-path/VRP hybrid with service-time windows; for small fleets and daily tours, it uses a label-setting shortest-path with time windows on a pruned graph, while weekly plans are constructed as daily subproblems with a greedy-plus-repair heuristic seeded by SP-TW solutions.

The simulation must produce economic and environmental indicators that can be compared across scenarios. The basic outputs are distance, direct logistics cost, average cost per kilometer, total travel time, CO_2e, service-window feasibility, and restricted-edge violations.

The simulation must include reliability logic, as the routing system is expected to operate under partial data loss. This is not a marginal issue for Ukraine’s wartime and peri-urban context. The routing research reports that the middleware maintained continuous advisory generation under intermittent UAV availability and short-lived network outages by using store-and-forward edge buffers, asynchronous refresh, and lineage capture. The Grail of Science article similarly reports that middleware-based coaching and asynchronous queues enabled high data uptime under partial data loss or UAV flight restrictions.

Table 5.14 Practical algorithm for running the heterogeneous-fleet routing simulation

Step	Action	Practical explanation	Output
1	Define the simulation boundary	Select the Kyiv peri-urban belt and pilot corridors	area of interest
2	Build road/access graph	Load paved roads, unpaved roads, field tracks, depots, and field entrances	base graph G
3	Load cadastral and restriction layers	Parcels, protected zones, military/safety zones, access restrictions	constraint layers
4	Apply hard masks	Remove prohibited edges and areas	feasible graph G_allowed
5	Add soft penalties	Congestion, road quality, terrain risk, safety slow-downs, and environmental sensitivity	penalty table
6	Load monitoring events	Soil-moisture deficits, NDVI/EVI anomalies, UAV diagnostics, sensor events	event layer
7	Generate task set	Convert monitoring and farm operations into routeable jobs	J_week
8	Assign service windows	Define earliest/latest service times and service durations	time-window table
9	Load a heterogeneous fleet	Trucks, tractors, speeds, fuel consumption, emission factors, and availability	fleet table
10	Check compatibility	Match tasks with possible vehicles	compatibility matrix
11	Select scenario	Baseline, Stress, Sustainability-adjusted	scenario parameter set
12	Calculating edge costs	Time, direct cost, CO_2e, risk, penalties	weighted edge-cost table
13	Run daily SP-TW	Solve daily task routing on a pruned graph	daily route candidates
14	Build a weekly plan	Apply greedy construction and repair heuristic	weekly route schedule
15	Validate feasibility	Check time windows, capacity, restrictions, and data confidence	validated solution
16	Calculate KPIs	Distance, cost, time, fuel, CO_2e, feasibility, violations	KPI dataset

Step	Action	Practical explanation	Output
17	Export outputs	CSV/GeoJSON/dashboard and provenance log	auditable route advisory
18	Run sensitivity tests	vary weights and fuel values	robustness profile
19	Prepare comparison tables	compute deltas relative to baseline	input for 5.3
20	Interpret setup limitations	document-controlled nature and assumptions	methodological transparency

Source: prepared by the authors.

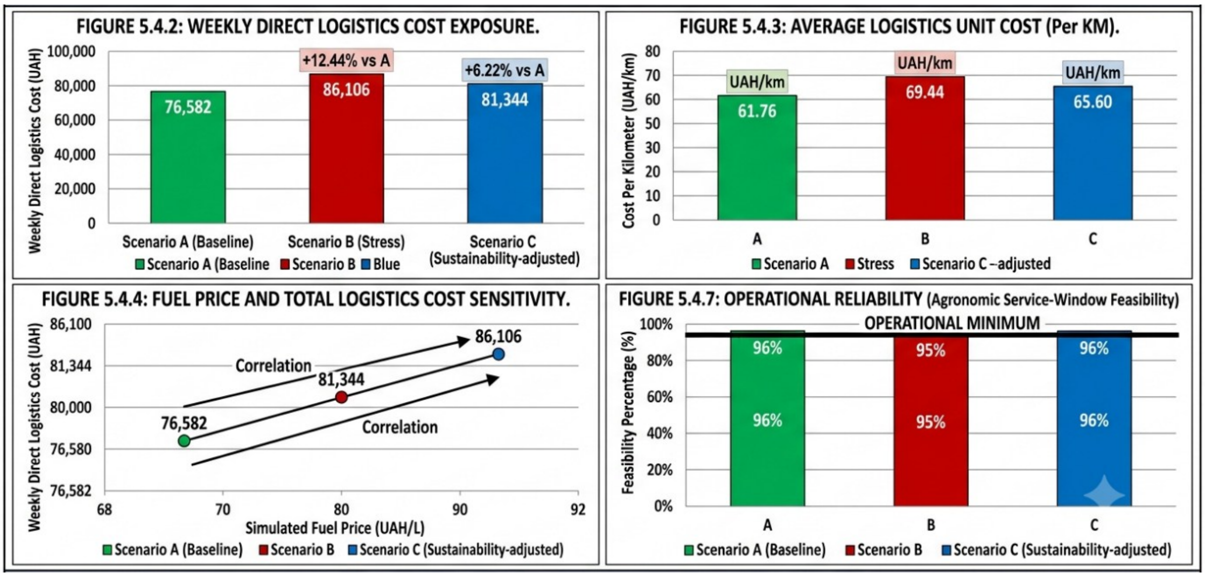


Figure 5.10 Digital logistics evaluation dashboard for Kyiv agglomeration simulation

The simulation setup is intentionally controlled. This provides methodological clarity, but it also imposes limitations that must be stated before interpreting the results.

First, the simulation uses a simplified heterogeneous fleet. It includes heavy-duty trucks and heavy agricultural tractors, which are appropriate for demonstrating the main trade-offs between paved transport and field access. However, future extensions should include sprayers, tankers, harvesters, light service vehicles, electric vehicles, low-emission vehicles, and contractor machinery.

Second, the CO_2e calculation uses a uniform emission factor in the current pilot configuration. The routing study notes that CO_2e totals remained stable across scenarios when uniform emission factors and unchanged weekly distance were used, which highlights the need for differentiated low-carbon corridors or fleet classes in future pilots.

Third, the scenario design is not a full seasonal stochastic simulation. It is a controlled scenario-comparative demonstration. It compares baseline, stress, and sustainability-adjusted logic under fixed inputs. This is appropriate for establishing the model's structure, but future work should include seasonal crop calendars, weather shocks, labor shortages, equipment failures, variable field conditions, and repeated Monte Carlo runs.

Fourth, UAV data is treated as intermittent, not permanently available. This is correct for wartime conditions, but it means that some high-resolution field diagnostics are replaced by Sentinel-2 and IoT fallback logic. This protects operational continuity but may reduce precision in the affected area.

Fifth, the model is designed to preserve hard-mask compliance. This is necessary for land-use governance, but it also means that the system may select longer or more expensive routes when spatial restrictions are strict. Such outcomes are not model failures; they reflect the real economic cost of compliance.

Subsection 5.2 defined the simulation setup for testing the spatio-temporal routing framework developed in 5.1. The simulation is built around the peri-urban belt of the Kyiv agglomeration, where agricultural routing must operate under land-use fragmentation, volatile fuel costs, degraded or restricted infrastructure, intermittent UAV availability, and strict agronomic service windows.

The simulation uses a heterogeneous fleet consisting of heavy-duty transport trucks and heavy agricultural tractors. This distinction is methodologically necessary because trucks and tractors perform different economic and operational roles. Trucks are faster and more efficient on paved transport corridors, while tractors are slower and more fuel-intensive but essential for field access and agricultural operations. The fleet structure therefore captures the main physical and economic trade-offs of peri-urban agricultural routing.

The simulation integrates multi-source data: Sentinel-2 imagery and optional EO layers, UAV orthomosaics (where available), IoT telemetry, cadastral and land-use layers, road and congestion data, fuel and market feeds, safety notices, weather data, field logs, and fleet records. These data are harmonized into a routing graph, a task table, a fleet table, a constraint table, a scenario table, and a KPI dataset.

The scenario design includes Baseline, Stress, and Sustainability-adjusted templates. These scenarios use different fuel prices, cost bands, and weights for time, direct cost, CO_2e, and risk, while preserving a comparable weekly job set. This allows later subsections to evaluate how economic stress and sustainability priorities change routing outcomes.

The methodological contribution of this subsection is to translate the conceptual routing framework into a reproducible simulation protocol. It defines what is modeled, how the fleet is represented, how tasks and service windows are generated, how wartime and logistical constraints are incorporated, how data disruption is handled, and how simulation outputs are prepared for economic evaluation.

5.3. Scenario-Based Economic Evaluation of Routing Alternatives: Baseline, Stress, and Sustainability-Adjusted Results

Subsections 5.1 and 5.2 established the architectural and simulation basis of the routing case study. Subsection 5.1 defined the spatio-temporal routing framework as a live middleware that integrates land-management constraints, monitoring events, road-network data, fleet parameters, fuel prices, time windows, and route advisories. Subsection 5.2 defined the simulation setup for a heterogeneous fleet operating across the peri-urban belt of the Kyiv agglomeration under wartime, logistical, and data-availability constraints. The present subsection moves from setup to economic interpretation.

The purpose of this subsection is to compare routing scenarios not as abstract algorithmic variants, but as different economic decision regimes. In agricultural logistics, a route may be selected to minimize direct financial costs, protect time-sensitive agronomic windows, reduce emissions, avoid risk, or balance all of these criteria. The economic task is therefore not only to identify which route is “shortest,” but to understand which scenario remains efficient under a specific operational priority.

The routing manuscript attached to the monograph provides the empirical basis for this subsection. It evaluates a weights-based routing platform in the Kyiv peri-urban belt through three controlled weekly templates: Baseline A, Stress B, and Sustainability-adjusted C. These scenarios use the same job set and spatial masks but differ in fuel price, UAH/km cost band, and the weights assigned to time, direct cost, CO_2e, and operational risk. The manuscript reports that Stress B increased direct logistics costs by 12.44% relative to Baseline A, while Sustainability-adjusted C increased them by 6.22%; total travel time decreased by approximately 1.15% in B and C, feasibility remained at or above 95%, restricted-edge violations remained zero, and CO_2e totals remained stable under uniform emission factors.

Following established scientific paradigms and methodologies, the three scenarios are interpreted as follows:

- Time-optimized / baseline-balanced scenario A: a reference scenario where time and direct cost have equal importance, and the system protects normal operational performance.
- Cost-optimized / stress scenario B: a scenario where direct cost receives the highest weight because fuel prices and transport risks are elevated.
- Sustainability-adjusted scenario C: a scenario where CO_2e receives the highest weight and the routing logic becomes more environmentally oriented.

This interpretation requires one methodological clarification. Scenario B is called cost-optimized, not because its total monetary cost is lower than the baseline. Its absolute cost is higher because fuel and UAH/km bands are higher. It is cost-optimized in a stress environment, meaning that the routing algorithm gives direct cost the highest decision weight to control cost growth under adverse fuel-price conditions. This distinction is essential for correct economic interpretation.

Table 5.15 Economic interpretation of the three routing scenarios

Scenario	Analytical label in this subsection	Core decision priority	Main economic question	Expected interpretation
Scenario A: Baseline	Time-optimized / balanced reference	Equal emphasis on time and direct cost, moderate CO_2e, and risk	What is the reference to weekly logistics performance under ordinary operating assumptions?	Baseline for comparison
Scenario B: Stress	Cost-optimized under fuel-price stress	The highest weight is assigned to direct cost under high fuel and high UAH/km conditions	How much does the cost increase under stress, and can routing still protect time and feasibility?	Cost-resilience test
Scenario C: Sustainability-adjusted	Sustainability-adjusted routing	The highest weight is assigned to CO_2e while preserving cost and time constraints.	What is the additional cost of sustainability-oriented routing under the pilot assumptions?	Sustainability trade-off test

Source: prepared by the authori based on the scenario structure of the Kyiv routing simulation.

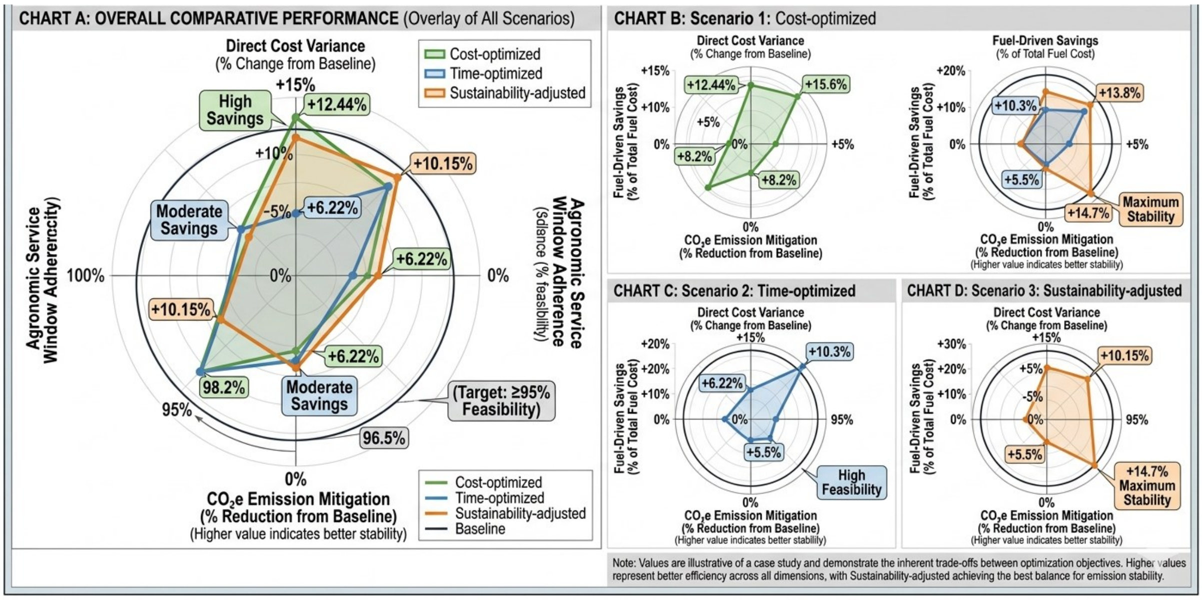


Figure 5.11 Scenario comparison charts for routing optimization

Scenario-based evaluation is useful only if the scenarios are comparable. In this case, comparability is achieved by using the same weekly job set and the same spatial masks across the main scenario comparison. This means that the differences in performance are not caused by a different number of agricultural tasks or by a different basic routing territory. They are caused primarily by fuel-price assumptions, cost bands, and route-priority weights.

Table 5.17 Scenario parameterization for economic evaluation

Scenario	Fuel price	UAH/km cost band	Time weight	Direct cost weight	CO_2e weight	Risk weight	Scenario logic
A: Baseline / time-balanced reference	68 UAH/L	60–120 UAH/km	0.35	0.35	0.20	0.10	Balanced operational reference
B: Cost-optimized under stress	92 UAH/L	120–250 UAH/km	0.25	0.45	0.20	0.10	Direct-cost control under high fuel and risk
C: Sustainability-adjusted	80 UAH/L	60–120 UAH/km	0.25	0.30	0.35	0.10	Higher priority for CO_2e and sustainability

Source: adapted for the research work from the Kyiv routing scenario dataset (Nazarenko, Введіть тут рівняння.*2025, 2026).*

The controlled weekly simulation produced the following KPI values: identical weekly distance of 1,240 km in all scenarios; direct logistics costs of 76,582 UAH in A, 86,106 UAH in B, and 81,344 UAH in C; average cost per kilometer of 61.76 UAH/km in A, 69.44 UAH/km in B, and 65.60 UAH/km in C; total travel time of 89.61 h in A and 88.58 h in both B and C; CO_2e of 1,116.3 kg in all scenarios; feasibility of 96% in A, 95% in B, and 96% in C; and zero restricted-edge violations in all scenarios.

The weekly output vector for scenario s may be written as:

$$KPI_s = Dist_s, Cost_s, AvgCostKm_s, Time_s, CO2e_s, Feasibility_s, REV_s \quad (5.23)$$

, where:

- Dist_s - weekly distance;
- Cost_s - direct weekly logistics cost;
- AvgCostKm_s - average cost per kilometer;
- Time_s - total travel time;
- CO2e_s - weekly carbon-equivalent emissions;
- Feasibility_s - share of jobs completed within service windows;
- REV_s - restricted-edge violations.

The fact that distance remains constant across all three scenarios is methodologically important. This means that differences in weekly distance do not explain differences in cost. The main driver of direct cost variation is the fuel-driven cost band and the economic scenario assumptions. Similarly, CO_2e remains constant because the pilot uses the same modeled weekly distance and uniform emission factors. Therefore, sustainability adjustments affect the priority logic but do not yet yield differentiated emissions outcomes under the pilot fleet configuration.

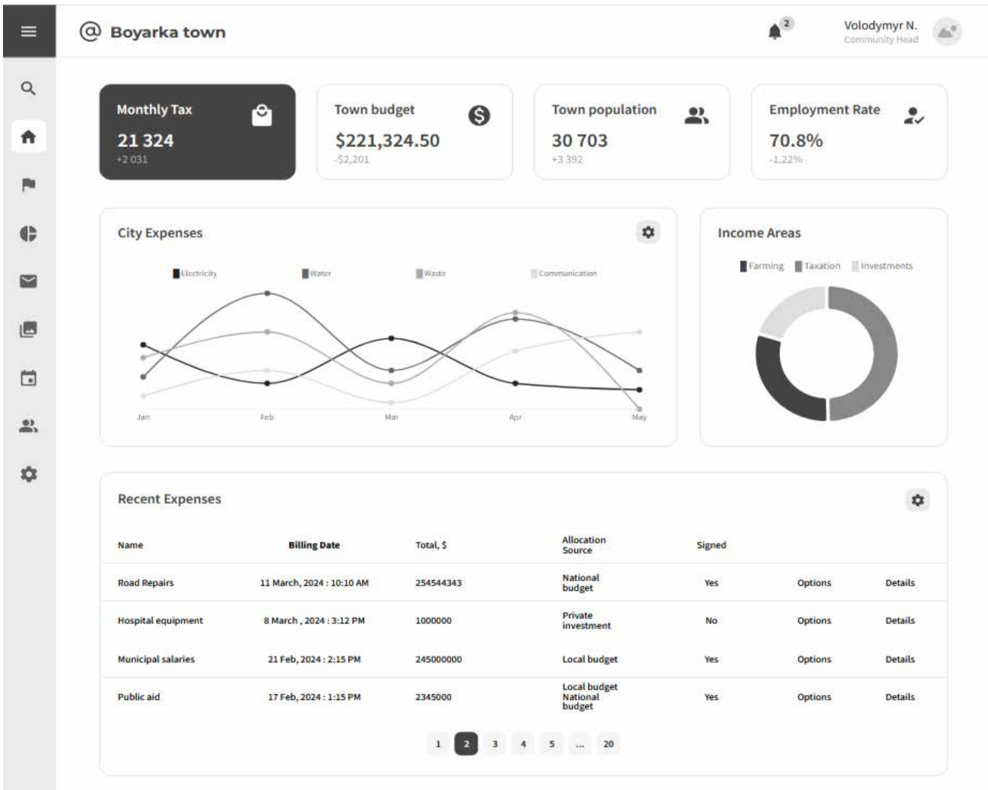


Figure 5.12 Monitoring service UI dashboard

Table 5.18 Weekly scenario outputs for the routing simulation

KPI	Scenario A: Baseline / time-balanced	Scenario B: Cost-optimized under stress	Scenario C: Sustainability-adjusted
Distance, km	1,240	1,240	1,240
Direct logistics cost, UAH	76,582	86,106	81,344
Average cost per km, UAH/km	61.76	69.44	65.60
Total travel time, h	89.61	88.58	88.58
CO_2e, kg	1,116.3	1,116.3	1,116.3

KPI	Scenario A: Baseline / time-balanced	Scenario B: Cost-optimized under stress	Scenario C: Sustainability-adjusted
Feasibility, % jobs within windows	96%	95%	96%
Restricted-edge violations, count	0	0	0

Source: adapted from the controlled weekly routing simulation results.

The sustainability-adjusted scenario increases the CO_2e weight from 0.20 in A and B to 0.35 in C. Under the current pilot configuration, however, total CO_2e remains identical across the three scenarios: 1,116.3 kg. The routing manuscript explains that CO_2e was calculated from modeled weekly transportation distance, a baseline fuel-use intensity, and a fixed emission factor; because these inputs remained unchanged, the total CO_2e remained unchanged.

The CO_2e calculation can be written as:

$$CO2e_s = \sum_{(v \in V)} \sum_{(r \in Routes_{(v,s)})} Fuel_{(r,v,s)} \times EF_v (5.24)$$

, where:

- CO2e_s - total emissions in scenario s;
- Fuel_(r,v,s) - fuel used by vehicle v on route r under scenario s;
- EF_v - emission factor.

If fuel use is calculated from distance and fuel intensity:

$$Fuel_{(r,v,s)} = \left(Dist_{(r,v,s)} \times FC_v\right)/100 (5.25)$$

Therefore:

$$CO2e_s = \sum_{(v \in V)} \sum_{(r \in Routes_{(v,s)})} \left[\left(Dist_{(r,v,s)} \times FC_v\right)/100 \times EF_v\right] (5.26)$$

The CO_2e variance relative to A is:

$$\Delta CO2e_{(s,A)} = (CO2e_s - CO2e_A)/CO2e_A \times 100$$

For B and C:

$$\Delta CO2e_{(B,A)} = 0.00$$

$$\Delta CO2e_{(C,A)} = 0.00$$

This result should not be interpreted as a failure of the sustainability scenario. It identifies a limitation of the pilot configuration. If all scenarios use the same weekly distance, the same vehicle mix, and the same emission factors, then a higher CO_2e weight cannot produce a lower CO_2e total unless the graph contains alternative route segments, vehicle classes, or corridors with different emission intensities. Therefore, the sustainability scenario is methodologically valid as a weighting template, but the pilot assets are not yet sufficiently differentiated for CO_2e to serve as a strong live discriminator.

For future test studies, CO_2e can become dynamic if the model includes:

- different vehicle fuel types;
- electric or low-emission vehicles;
- differentiated road-speed fuel-intensity curves;
- low-emission corridors;
- load-dependent fuel consumption;
- congestion-dependent fuel consumption;
- field versus paved-road fuel intensity;
- route-specific stop-and-go penalties.

The shadow-priced carbon value can be added as:

$$B_C O2_{(s,A)} = (CO2e_A - CO2e_s) \times SCP (5.30)$$

, where:

- SCP - social or policy carbon price.

In the current pilot:

$$B_C O2_{(B,A)} = 0 (5.31)$$

$$B_C O2_{(C,A)} = 0 (5.32)$$

because:

$$CO2e_A = CO2e_B = CO2e_C (5.33)$$

Section 5.4 presents CO_2e stability as a measured result and future differentiation as a development requirement.

Table 5.19 CO_2e performance and sustainability interpretation

Indicator	Scenario A	Scenario B	Scenario C
CO_2e weight	0.20	0.20	0.35
Weekly CO_2e, kg	1,116.3	1,116.3	1,116.3
CO_2e change vs A	-	0.00%	0.00%
Carbon shadow benefit vs A	-	0	0
Interpretation	Reference emissions	Stable emissions under stress	Sustainability priorities are reflected in weights, but not yet in emissions, because fleet/distance/emission factors remain unchanged.

Source: calculated and interpreted by the authors based on the controlled simulation results.

The scenario comparison demonstrates three different types of routing efficiency. The time-optimized / balanced reference logic of Scenario A is appropriate when the objective is stable weekly execution under ordinary assumptions. It preserves high feasibility, balanced cost and time priorities, and a reference cost of 76,582 UAH. It should serve as a benchmark for comparing other conditions.

The cost-optimized stress logic of Scenario B is appropriate when fuel prices and transport risk increase. In this scenario, direct cost receives the highest weight, but absolute cost still increases because the fuel and UAH/km environment is worse. The economic value of Scenario B is not lower nominal cost; it is the ability to preserve time and compliance under stress. With only a −1 percentage-point change in feasibility and zero restricted-edge violations, the model shows that cost stress does not collapse operational reliability.

The sustainability-adjusted logic of Scenario C is appropriate when the planner wants to increase the weight of CO_2e without abandoning cost and time constraints. Its direct cost increase is moderate compared with Scenario B: +6.22% instead of +12.44%. This indicates that the additional financial burden of sustainability weighting is smaller than the burden of the high-fuel stress scenario. However, because CO_2e remained stable in the pilot, the sustainability result should be interpreted as a scenario-design test rather than proof of achieved emission reduction.

One of the most useful interpretations for policy and farm management is the incremental cost of sustainability adjustment. Scenario C increases the CO_2e weight from 0.20 to 0.35 and increases direct cost by 4,762 UAH relative to A. In the pilot, this cost does not yet buy a measurable CO_2e reduction because emissions remain constant. However, it defines the financial space within which future sustainability improvements must be justified.

The incremental cost of sustainability adjustment is:

- IC_Sust = Cost_C - Cost_A
- IC_Sust = 81,344 - 76,582 = 4,762 UAH

The incremental cost rate is:

- ICR_Sust = (Cost_C - Cost_A) / Cost_A × 100%
- ICR_Sust = 6.22%

If future pilots reduce CO_2e, the cost per avoided kg CO_2e will be:

- CostPerKgCO2eAvoided = (Cost_C - Cost_A) / (CO2e_A - CO2e_C)

In the current pilot:

- CO2e_A - CO2e_C = 0

Therefore:

- CostPerKgCO2eAvoided is not computable under the present assumptions.

This is a scientifically important result. It prevents overstating sustainability outcomes. The current pilot shows that the middleware can implement sustainability-adjusted routing logic, but real emissions benefits require differentiated emission pathways. In future pilots, this could be achieved through low-emission vehicles, route segments with varying fuel intensities, load-sensitive fuel models, or avoided-congestion-based emission factors.

Table 5.20 Incremental cost of sustainability adjustment

Indicator	Value
Scenario A direct logistics cost	76,582 UAH
Scenario C direct logistics cost	81,344 UAH
Incremental sustainability cost	4,762 UAH
Incremental sustainability cost rate	6.22%
Scenario A CO_2e	1,116.3 kg
Scenario C CO_2e	1,116.3 kg
CO_2e reduction	0.0 kg
Cost per kg CO_2e avoided	Not computable in current pilot
Interpretation	Sustainability weighting is operationally implemented, but emission reduction requires differentiated fleet, corridors, or fuel-intensity assumptions

Source: calculated by the authors based on controlled simulation outputs.

Scenario B provides the most direct stress-test result. It shows what happens when the fuel price increases from 68 UAH/L to 92 UAH/L, the cost band shifts from 60–120 UAH/km to 120–250 UAH/km, and the direct cost weight increases from 0.35 to 0.45.

The cost exposure ratio can be written as:

- CER_B = Cost_B / Cost_A
- CER_B = 86,106 / 76,582 = 1.1244

This means that the weekly direct cost under stress is 1.1244 times the baseline cost.

The resilience interpretation should include not only cost increase, but preservation of key operational constraints:

- Resilience_B = {CostIncrease_B, TimeProtection_B, Feasibility_B, REV_B}

where:

- CostIncrease_B = 12.44%
- TimeProtection_B = -1.15%
- Feasibility_B = 95%
- REV_B = 0

A simple stress-resilience condition may be written as:

- StressResilient_B = 1, if Feasibility_B ≥ 95% and REV_B = 0

In the pilot:

- StressResilient_B = 1

This does not mean that stress is economically harmless. It means that the routing system remains operationally viable under stress: it absorbs a cost shock while maintaining service-window feasibility and spatial compliance. This is exactly the kind of result that scenario-based evaluation is designed to identify.

The controlled scenario results should be interpreted as demonstration results, not as final statistical averages. The routing manuscript explicitly notes that the values are from a single controlled test run for each scenario under fixed input parameters and should be interpreted as scenario-comparative demonstration results rather than statistically averaged estimates over independent launches.

Therefore, the scenario comparison should be followed by sensitivity analysis. The routing manuscript states that delta-KPIs are tracked and that sensitivity can vary weights by ±0.1 and fuel by ±10 UAH/L to assess robustness.

The final interpretation should not select one scenario as universally best. Each scenario is best under a different decision context. Scenario A is the most economically attractive under ordinary assumptions because it has the lowest direct cost and the highest feasibility. It should be treated as the reference scenario for normal weeks.

Scenario B is operationally important because it tests stress. It has the highest cost, but it preserves time, feasibility, and spatial compliance. This makes it useful for resilience planning.

Scenario C is strategically important because it introduces a sustainability priority at a moderate additional cost. In the current pilot, it does not reduce CO_2e because the simulation uses identical distance and uniform emission factors, but it demonstrates how a sustainability-weighted route policy can be operationalized.

A decision rule for scenario selection can be written as:

- Select A, if FuelPrice is normal and SustainabilityPriority is moderate
- Select B, if FuelPrice is high and CostControlPriority is dominant
- Select C, if SustainabilityPriority is high and additional cost ≤ AcceptableCostPremium

The acceptable cost premium can be defined as:

- AcceptableCostPremium = MaxExtraCost / Cost_A × 100%

For example, if the decision-maker accepts up to a 7% additional cost for sustainability-oriented routing, then Scenario C is acceptable because:

6.22% ≤ 7%

If the decision-maker accepts only up to 5%, then Scenario C is not acceptable under the current assumptions. This rule makes the scenario comparison policy relevant. It allows farms, cooperatives, and public authorities to define their own tolerance for cost increases, sustainability priorities, and operational risk.

Table 5.21 Scenario selection logic for practical decision-making

Decision condition	Preferred scenario	Rationale
Normal fuel price, ordinary week, no special sustainability requirement	Scenario A	Lowest direct cost and high feasibility
High fuel price, high UAH/km band, increased transport risk	Scenario B	Direct cost receives the highest weight; the system preserves time and compliance
Sustainability reporting priority, moderate fuel price, acceptable cost premium	Scenario C	CO_2e weight increased; additional direct cost is moderate
Strict ecological policy, but no differentiated fleet/corridors	Scenario C with caution	Weighting is active, but emission reduction may not yet materialize
Need for minimum budget exposure	Scenario A	Lowest cost under the current simulation
Need for stress-resilience proof	Scenario B	Test the system under a high-cost environment
Need for future low-carbon planning	Scenario C plus fleet/corridor differentiation	Requires emission-sensitive assets to produce CO_2e reduction

Source: prepared by the authors.

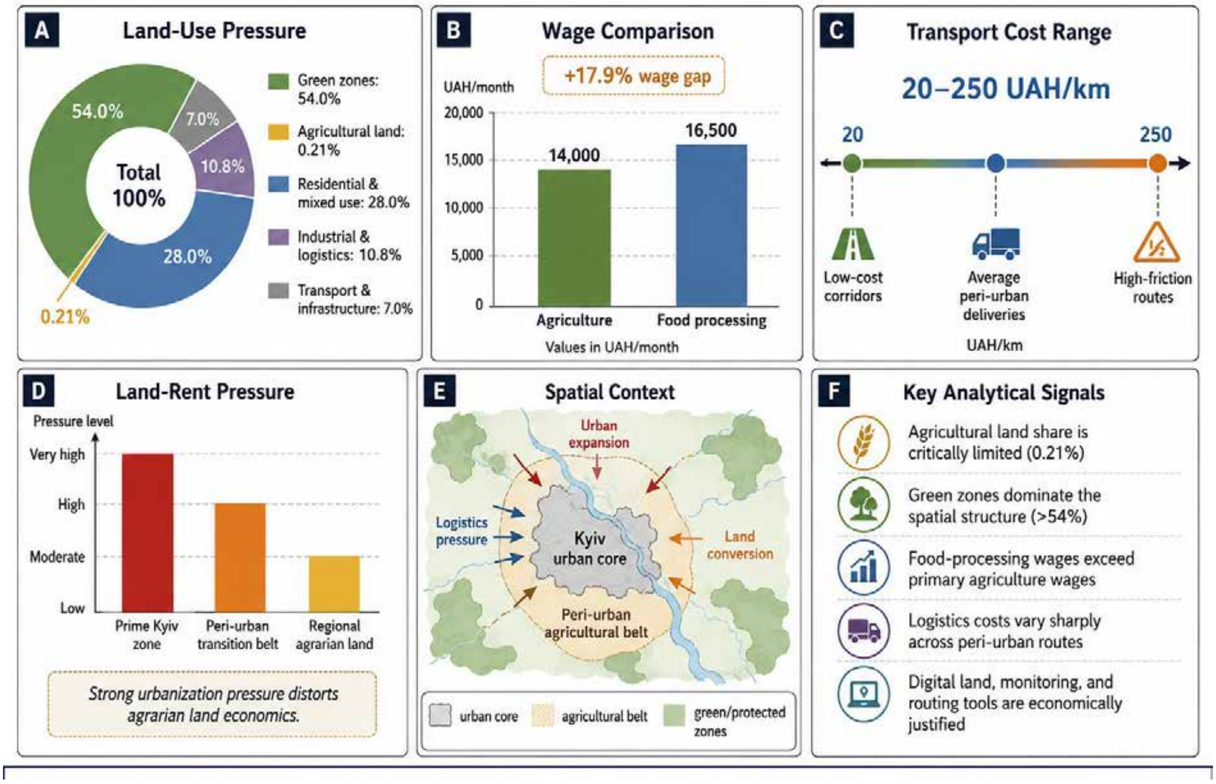


Figure 5.13 Kyiv agglomeration system final simulation visualization

The scenario evaluation is useful, but it must be interpreted within its methodological limits.

First, the results are from controlled scenario testing, not from a large statistical sample of independent runs. The routing manuscript explicitly warns that the values should be interpreted as results of a scenario-comparative demonstration. Second, the same weekly distance across scenarios simplifies the comparison but limits the ability to observe distance-driven changes in emissions. This is why CO_2e remains stable. Third, the sustainability-adjusted scenario increases CO_2e weight but does not yet include differentiated low-emission vehicle classes, electric vehicles, or route segments with different emission intensities. Therefore, it tests the routing policy logic rather than proven emission reduction. Fourth, feasibility remains high, but the difference between 95% and 96% should not be overinterpreted without repeated seasonal simulations. Fifth, direct cost variance is strongly fuel-driven. The model should be extended with sensitivity analyses for vehicle maintenance, labor costs, congestion, weather delays, equipment breakdowns, and field access deterioration. Sixth, hard masks keep violations at zero by design. This is desirable for compliance, but future work should evaluate the economic cost of hard-mask enforcement: how much extra distance, time, or cost is created by avoiding restricted areas.

Subsection 5.3 provides the scenario-based economic evaluation of the spatio-temporal routing case study. The analysis compares three controlled weekly routing scenarios: Baseline A, a time-balanced reference; Stress B, a cost-optimized scenario under high fuel prices; and Sustainability-adjusted C, a routing strategy with increased CO_2e priority.

The main economic result is the strong sensitivity of direct logistics costs to fuel-driven cost bands. Scenario B increases weekly direct logistics cost by 12.44%, or 9,524 UAH, relative to Scenario A. Scenario C increases direct cost by 6.22%, or 4,762 UAH, relative to Scenario A. These results quantify the budget exposure of agricultural logistics under stress and the moderate cost premium of sustainability-adjusted routing in the current pilot.

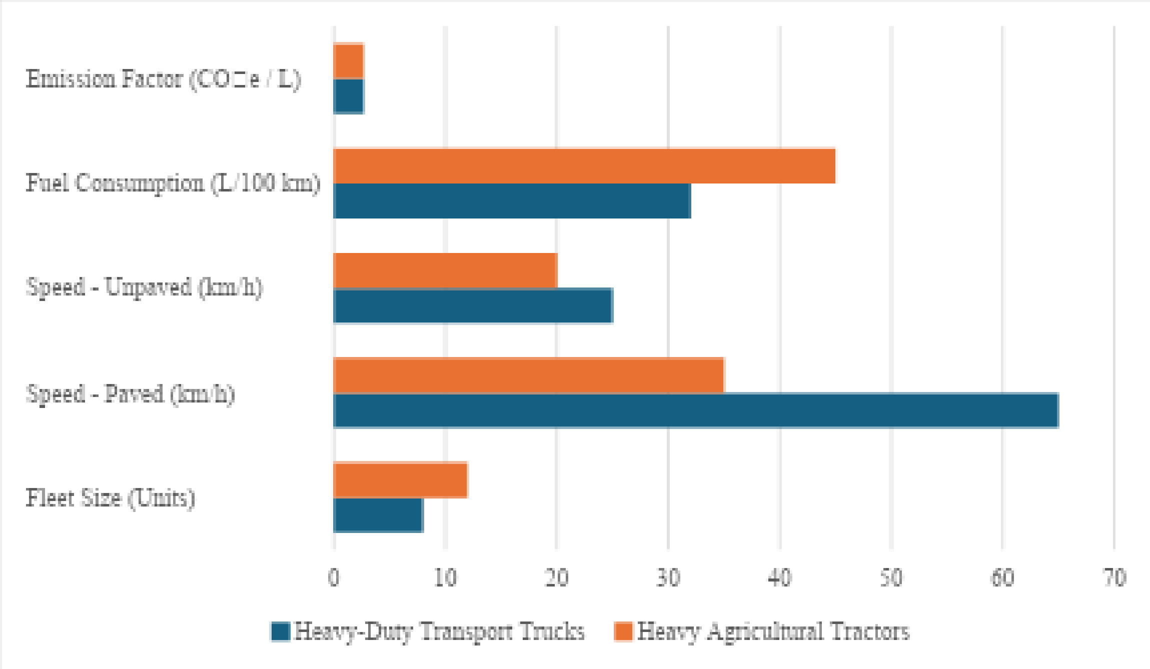


Figure 5.14 Baseline Simulation Fleet and Operational Parameters

The second result is that route re-weighting does not damage time performance in this controlled simulation. Total travel time is approximately 1.15% lower in Scenarios B and C than in Scenario A. This means that cost-stress and sustainability-adjusted routing can preserve and, in this pilot, slightly improve time performance while keeping the same job set and spatial masks.

The third result is that CO_2e remains stable across scenarios. This is not because sustainability is irrelevant, but because the current pilot uses identical weekly distances and uniform emission factors. The sustainability-adjusted scenario therefore demonstrates the operational feasibility of applying a higher CO_2e weighting, but future pilots must add differentiated fleet classes, low-emission corridors, load-sensitive fuel models, or electric assets to convert the sustainability weighting into measurable carbon reductions.

The fourth result is that operational reliability is preserved. Feasibility remains at or above the 95% threshold, and restricted-edge violations remain zero because hard masks remove prohibited edges before optimization. This is critical for the Kyiv agglomeration, where routing must operate under land-use restrictions, safety limitations, environmental constraints, and fragmented peri-urban mobility.

The methodological conclusion is that scenario-based routing evaluation should not focus on a single KPI. Direct cost, time, CO_2e, feasibility, and compliance must be interpreted together. A route is economically efficient only when it is financially acceptable, temporally feasible, spatially compliant, environmentally interpretable, and operationally reliable. The subsection therefore prepares the transition to 5.4, where these results are consolidated into final efficiency metrics: fuel-driven cost savings and exposure, CO_2e emissions stability, and adherence to agronomic service windows with at least 95% feasibility.

5.4. Routing Efficiency Metrics: Fuel-Driven Cost Exposure, CO_2e Stability, Service-Window Feasibility, and Compliance

Subsections 5.1–5.3 developed the routing case study from architecture through simulation to a scenario-based economic evaluation. Subsection 5.1 explained how land-management constraints and monitoring events are integrated into a live routing middleware. Subsection 5.2 defined the simulation setup for a heterogeneous fleet operating across the peri-urban belt of the Kyiv agglomeration. Subsection 5.3 compared the Baseline, Stress, and Sustainability-adjusted scenarios and calculated the key direct cost variances: +12.44% for the Stress scenario and +6.22% for the Sustainability-adjusted scenario relative to the Baseline scenario. The present subsection consolidates these results into a final metric system for evaluating the economic efficiency of spatio-temporal routing.

The purpose of this subsection is to define how routing efficiency should be measured after route optimization has been performed. In this monograph, routing efficiency is not interpreted only as route shortening. A route is efficient if it reduces or controls fuel-driven costs, preserves service-window feasibility, avoids prohibited spatial segments, produces auditable sustainability indicators, and maintains decision continuity under uncertainty. This interpretation corresponds to the routing manuscript, where the platform is described as a FAIR/OGC-aligned middleware service that integrates satellite EO, UAV imagery, where permitted, IoT telemetry, road and congestion layers, and administrative-economic registers while allowing the user to tune weights for time, direct cost, CO_2e, and operational risk.

The empirical basis of this subsection is the controlled weekly scenario comparison from the routing study. The same job set and spatial masks were used across three scenarios: Baseline A, Stress B, and Sustainability-adjusted C. Weekly distance remained constant at 1,240 km; direct logistics costs were 76,582 UAH, 86,106 UAH, and 81,344 UAH, respectively; CO_2e remained stable at 1,116.3 kg; feasibility remained high at 96%, 95%, and 96%; and restricted-edge violations remained zero due to hard-mask enforcement.

The central methodological position of this subsection is that the economic efficiency of spatio-temporal routing should be measured through four connected metric groups:

1. Fuel-driven cost metrics - direct cost, cost per kilometer, fuel exposure, fuel-cost sensitivity, and avoided excess cost.
2. CO_2e stability and carbon-readiness metrics - emissions per kilometer, scenario-level CO_2e stability, carbon shadow value, and readiness for differentiated low-carbon routing.
3. Agronomic service-window metrics - feasibility rate, on-time task completion, delay exposure, and service-window resilience.
4. Compliance and auditability metrics - restricted-edge violations, hard-mask compliance, provenance completeness, and policy-ready reporting.

Table 5.22 Final efficiency-metric groups for Case Study III

Metric group	Main question answered	Core indicators	Required data	Economic interpretation
Fuel-driven cost efficiency	How strongly do fuel prices and route costs affect weekly logistics expenditure?	Direct cost, UAH/km, fuel-cost variance, fuel-cost elasticity, additional weekly cost	route distance, fuel price, UAH/km band, fleet parameters	Shows budget exposure and cost-control performance
CO_2e stability and carbon-readiness	Do emissions change across scenarios, and is the system ready for low-carbon routing?	CO_2e total, kg/km, CO_2e delta, CO_2e stability index, carbon shadow value	route distance, fuel consumption, emission factor, carbon price	Shows environmental-accounting performance
Agronomic service-window performance	Are agricultural jobs completed within required time windows?	feasibility %, on-time jobs, delay, missed-window risk	task list, start/completion times, service windows	Shows operational and agronomic reliability
Spatial compliance	Does the route avoid prohibited or restricted areas?	restricted-edge violations, hard-mask compliance score	routing graph, restricted edges, protected zones, land-use masks	Shows legal, ecological, and safety compliance
Integrated routing efficiency	Is the routing system economically and operationally justified as a whole?	routing efficiency index, resilience score, audit-ready KPI table	all scenario KPIs and data-quality records	Supports decision-making, reporting, and policy scaling

Source: prepared by the authors.

For farm managers and cooperatives, the most important indicators are direct logistics cost, average cost per kilometer, fuel exposure, feasibility, and missed-window exposure. These indicators determine whether weekly operations can be completed within budget and within agronomic deadlines.

For local authorities and land-management institutions, the most important indicators are restricted-edge violations, hard-mask compliance, route provenance, and spatial auditability. These indicators show whether agricultural mobility respects protected zones, safety restrictions, and land-use rules.

For environmental and sustainability reporting, the most important indicators are CO_2e total, CO_2e per kilometer, CO_2e stability, carbon shadow value, and carbon-readiness. In the current pilot, CO_2e is stable rather than reduced, so sustainability reporting should be careful and transparent.

Table 5.23 User-specific interpretation of routing efficiency metrics

User group	Most important metrics	Decision supported
Farm manager	direct cost, UAH/km, fuel exposure, feasibility	weekly operational planning and budget control
Cooperative	cost per task, route efficiency, vehicle utilization, feasibility	shared machinery and service coordination
Agronomist	service-window feasibility, missed-window exposure, delay risk	irrigation, spraying, and inspection timing
Local authority	restricted-edge violations, hard-mask compliance, route provenance	land-use governance and safety compliance
Environmental planner	CO_2e total, kg/km, environmental penalties, carbon-readiness	sustainability monitoring
Policymaker	cost exposure, feasibility threshold, compliance, auditability	eco-subsidy and digital modernization policy
Researcher	scenario deltas, elasticity, CO_2e stability, reliability	reproducible empirical evaluation
Technology provider	dashboard KPIs, data reliability, export records	platform validation and scaling

Source: prepared by the authors.

The final metrics should be interpreted within the current test simulation limitations. First, the pilot evaluates controlled weekly scenarios rather than a full seasonal stochastic model. Therefore, the values show scenario-comparative performance, not long-term statistical averages. The routing manuscript also states that the scenario values should be interpreted as controlled demonstration results rather than statistically averaged estimates over many independent launches.

Second, CO_2e remains stable because distance, fuel-use intensity, and emission factors remain unchanged across scenarios. The sustainability-adjusted scenario, therefore, tests routing priority logic, not measured emission reduction. Third, service-window feasibility is reported at the aggregate level. Future pilots should record job-level delays, affected areas, crop prices, and crop-stage sensitivity to more precisely monetize the value of protected windows. Fourth, hard-mask compliance is structurally enforced by removing prohibited edges before optimization. This is good for compliance, but future analysis should calculate the compliance cost, including the additional distance, time, and costs incurred by avoiding restricted zones.

Fifth, direct cost is strongly fuel-driven in this pilot. Future models should also include labor availability, machinery depreciation, maintenance, downtime, field-workability constraints, refueling logistics, and weather-related delays.

Subsection 5.4 completes the third empirical case study of the monograph. It consolidates the routing framework, simulation setup, and scenario-based evaluation into a final system of efficiency metrics. The routing case demonstrates that spatio-temporal optimization should be evaluated based on direct financial cost, unit mobility cost, CO_2e stability, service-window feasibility, compliance with restricted edges, and auditability.

The first major result is fuel-driven cost sensitivity. Scenario B increases direct logistics cost by 9,524 UAH, or 12.44%, compared to the Baseline scenario. Scenario C increases costs by 4,762 UAH, or 6.22%, compared to Baseline. This confirms that direct logistics cost is highly sensitive to fuel-driven cost bands and that sustainability-adjusted routing has a moderate but measurable cost premium in the current pilot.

The second major result is CO_2e stability. CO_2e remains at 1,116.3 kg across all scenarios, with an emissions intensity of approximately 0.9002 kg/km. This shows that the current routing platform can account for CO_2e, but real carbon reduction requires differentiated fleet classes, low-carbon corridors, dynamic fuel-consumption models, or electric assets. The sustainability-adjusted scenario therefore proves carbon-priority capability, not carbon reduction under the present assumptions.

The third major result is operational reliability. Service-window feasibility remains at 96% in Scenario A, 95% in Scenario B, and 96% in Scenario C. All three scenarios therefore satisfy the monograph's minimum operational threshold of ≥95% feasibility. This confirms that route optimization can preserve agronomic timing even under fuel-price stress and sustainability-adjusted weighting.

The fourth major result is spatial compliance. Restricted-edge violations remain zero in all scenarios because hard masks remove prohibited edges before optimization. This demonstrates that the routing system can enforce land-use, environmental, and safety restrictions while still producing feasible agricultural plans.

The general conclusion is that the spatio-temporal routing platform functions as an economic and institutional decision-support tool rather than merely a route calculator. It translates fuel prices, field tasks, time windows, CO_2e accounting, hard masks, and operational risk into auditable routing recommendations. In the broader structure of the monograph, this completes the empirical chain: digital land management provides spatial constraints; IoT and environmental monitoring generate time-sensitive tasks; spatio-temporal routing converts those tasks into costed, compliant, and operationally feasible plans.

The transition to Section 6 should therefore focus on scaling: how to institutionalize these routing, monitoring, and land-management metrics through interoperability standards, data governance, eco-subsidies, tax incentives, cooperative service models, and auditable sustainability reporting.

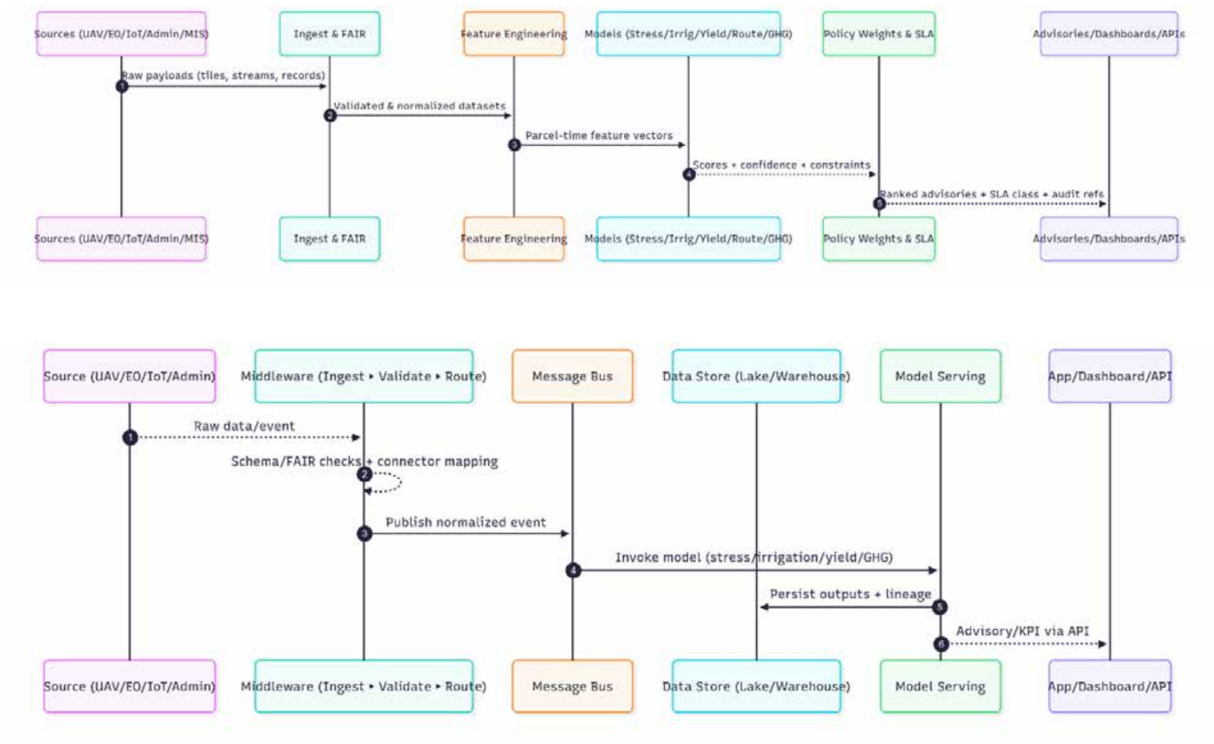


Figure 5.15 Routing services data and functions flow

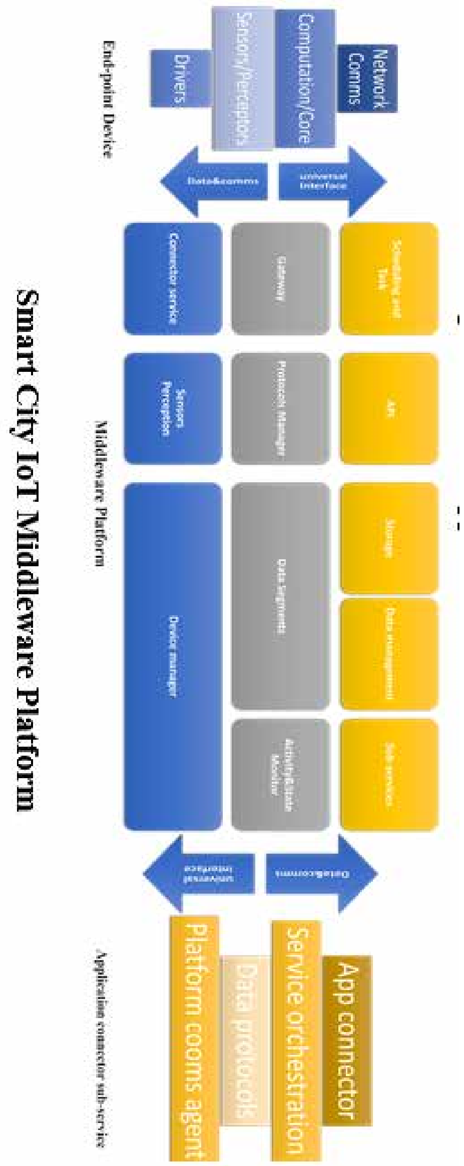


Figure 5.16 Smart City Platform design

Figure 5.17 Digital Twin Simulation concept

Figure 5.18 Digital Twin Simulation concept

CHAPTER 6

Strategic Roadmaps for Scaling Digital Environmental Management

6.1. Overcoming Implementation Barriers: Interoperability, data sovereignty, and the cost of capital for digital upgrades.

The previous chapters established the theoretical, methodological, and empirical basis for evaluating the economic efficiency of digital tools in sustainable environmental management. The first chapter clarified why economic efficiency in environmental management cannot be reduced to direct financial return, since environmental externalities, data value, institutional credibility, and temporal effects are integral to the real economic result. The second chapter proposed an integrated methodological framework based on extended cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario simulation. The third, fourth, and fifth chapters then demonstrated how this framework can be applied to three interconnected domains: digital land management and cadastral systems; IoT telemetry and environmental monitoring; and spatio-temporal optimization and routing.

Chapter 6 moves from methodological and empirical evaluation to strategic scaling. Its purpose is not simply to recommend the wider use of digital tools. Such a recommendation would be too general and would not reflect the practical difficulties of implementing digital environmental management in agriculture and peri-urban territories. The more important question is: under what institutional, technological, economic, and policy conditions can digital tools move from isolated pilot projects to stable systems of sustainable environmental governance?

The central argument of this chapter is that the scaling of digital environmental management depends on four interrelated conditions. First, digital systems must be interoperable. Land data, environmental indicators, remote sensing products, IoT telemetry, routing data, administrative records, and economic indicators must be able to interact through common identifiers, metadata, APIs, geospatial standards, and reproducible workflows. Second, data sovereignty and data governance must be clearly defined. Agricultural and environmental data are economically valuable, legally sensitive, and strategically important. Their use requires rules for access, ownership, sharing, security, reuse, and accountability. Third, institutions and users must be ready to work with digital systems. Even technically strong tools fail if farms, local authorities, public agencies, and advisory services lack sufficient capacity, incentives, trust, and operational routines. Fourth, the cost of digital upgrades must be economically justifiable.

The preceding empirical chapters of this monograph—covering digital land administration, IoT telemetry, environmental monitoring, and spatio-temporal routing—have systematically demonstrated that digital tools possess the theoretical and methodological capacity to deliver significant economic efficiency gains. By reducing transaction costs, predicting agronomic stress, mitigating environmental externalities, and optimizing logistics, the digital toolscape transitions agricultural and peri-urban resource governance from reactive correction to anticipatory optimization. However, the theoretical validation of economic efficiency does not automatically translate into systemic adoption.

Structural implementation barriers constrain the transition to scalable digital environmental management. These barriers cannot be dismissed merely as temporary technological lags; they are profound institutional, economic, and informational frictions. In transition economies, and particularly in Ukraine under the conditions of post-war recovery and European Union integration in 2026, scaling digital environmental management requires confronting four fundamental barriers: the lack of systemic interoperability, unresolved data sovereignty conflicts, uneven institutional readiness, and the comprehensive cost of digital upgrades.

This section systematically dissects these implementation barriers. It models them not as insurmountable obstacles but as quantifiable economic variables to be internalized into strategic roadmaps for scaling.

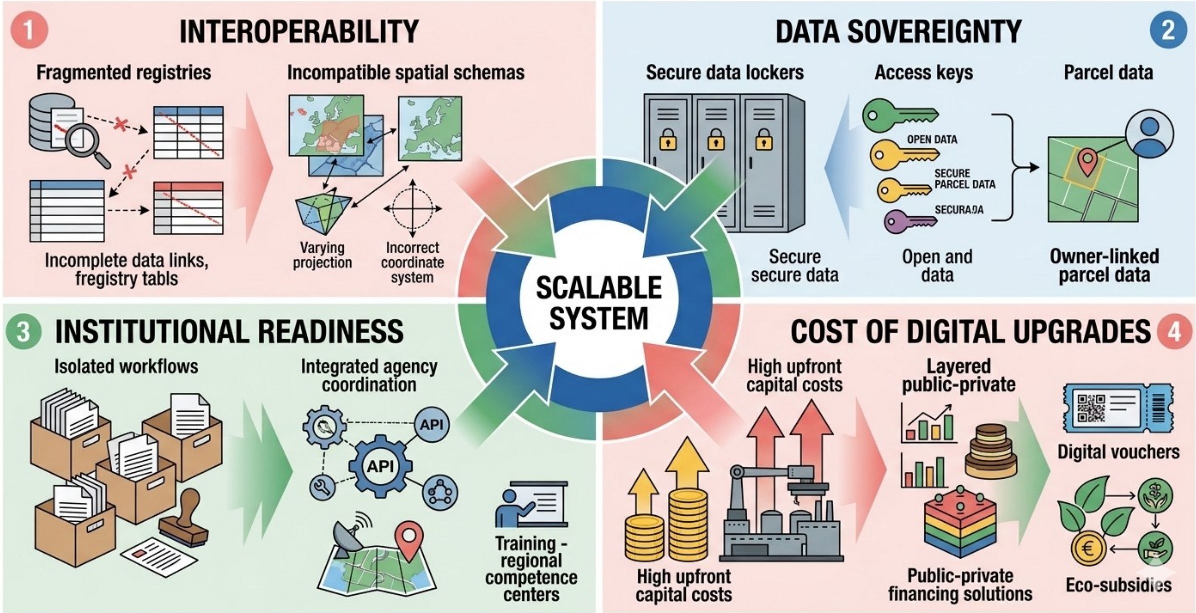


Figure 6.1 Overcoming Implementation Barriers – scalable system concept

The most pervasive barrier to scaling digital environmental management is the absence of deep interoperability among disparate data systems. As established in Chapter 3 and Chapter 4, the economic value of a digital toolscape emerges from its capacity for data fusion—combining cadastral geometries, IoT telemetry, UAV diagnostics, and routing constraints into a unified decision-support fabric. When interoperability fails, the toolscape fractures into isolated data silos.

Interoperability barriers manifest on multiple levels. *Technical interoperability* is frequently hindered by proprietary data formats and closed Application Programming Interfaces (APIs). A farm may deploy state-of-the-art soil moisture sensors. Still, if those sensors cannot automatically feed data into the farm's central geographic information system (GIS) or the local municipality's water-management dashboard, the data must be manually extracted, transformed, and loaded (ETL). *Semantic interoperability* presents an even deeper challenge. Different systems often use conflicting ontologies to describe the same physical reality. For example, a "land parcel" in an agricultural subsidy database (such as the EU's LPIS) may have a different spatial definition and attribute structure than a "land parcel" in the State Land Cadastre.

The economic consequence of this fragmentation is the generation of *interoperability friction costs*. In traditional cost-benefit analyses, data integration is often treated as a negligible, one-time setup fee. In reality, maintaining data pipelines between non-standardized systems requires continuous operational expenditure. We can formalize the total cost of interoperability friction ($C_{interop}$) over a given planning horizon T as:

$$Cinterop = t = 1\sum T(Cmapping, t + Cmaintenance, t + Cerror, t) \quad (6.1)$$

where:

- $C_{mapping, t}$ represents the labor and software costs required to align conflicting data ontologies in period t.
- $C_{maintenance, t}$ denotes the cost of updating custom API connectors when vendor systems change.
- $C_{error, t}$ represents the economic losses incurred due to delayed or inaccurate decisions caused by failed data synchronization (e.g., a routing algorithm utilizing outdated road restriction data).

Overcoming this barrier requires treating interoperability as a good public infrastructure rather than a private software feature. The adoption of FAIR data principles (Findable, Accessible, Interoperable, Reusable) and Open Geospatial Consortium (OGC) standards is not merely a technical preference; it is an economic necessity. For Ukraine's agricultural sector to seamlessly integrate with the European Common Agricultural Policy (CAP) reporting mechanisms, data services must transition toward standardized geospatial APIs (e.g., OGC API - Features). Failure to enforce interoperability at the institutional level results in a "vendor lock-in" paradigm, where the cost of switching to more efficient digital tools becomes prohibitively high due to data hostage situations.

Data sovereignty introduces a complex legal and economic barrier, particularly acute in the context of Ukraine's unique geopolitical and wartime recovery status. Data sovereignty refers to the right of individuals, enterprises, and states to control how their generated data is stored, analyzed, shared, and monetized.

At the enterprise level, the barrier manifests as an asymmetry between agricultural producers and agritech platform providers. Modern agricultural machinery, UAVs, and IoT networks continuously harvest high-resolution agronomic data—yield maps, soil composition, input application rates, and micro-climatic conditions. Frequently, the end-user agreements of multinational agritech platforms transfer the rights to aggregate and monetize this data to the technology provider. The farmer pays for the hardware but loses sovereignty over the informational byproduct. This creates an economic disincentive for digitalization: farmers may resist adopting environmental monitoring tools if they perceive that their proprietary operational data will be exploited by third parties, input suppliers, or market speculators to manipulate pricing.

At the state level, particularly in Ukraine in 2026, data sovereignty intersects with national security. High-resolution spatial data, which is essential for precision agriculture and routing algorithms (Case Study III), also possesses dual-use characteristics. Cadastral maps outlining critical infrastructure, detailed topological models, and real-time logistics telemetry must be protected against malicious exploitation.

The institutional response—restricting access to spatial data during martial law or periods of high security risk—while necessary, creates significant economic friction in environmental management. The barrier lies in the blunt instrument of data restriction. The strategic roadmap must advocate for *differentiated*, *role-based access architectures* (as discussed in Chapter 3), utilizing cryptographic access controls and spatial masking. The economic resilience of the digital system depends on maximizing data utility for legitimate economic actors while maintaining strict sovereignty and security perimeters.

Aligning with the EU Data Act and the concept of Common European Agricultural Data Spaces requires Ukraine to build sovereign data repositories where data usage rights are contractually transparent, legally enforceable, and technologically auditable.

Technologies scale rapidly; institutions evolve slowly. The third implementation barrier is the mismatch between the technical capabilities of digital environmental tools and the institutional readiness of the actors required to govern them.

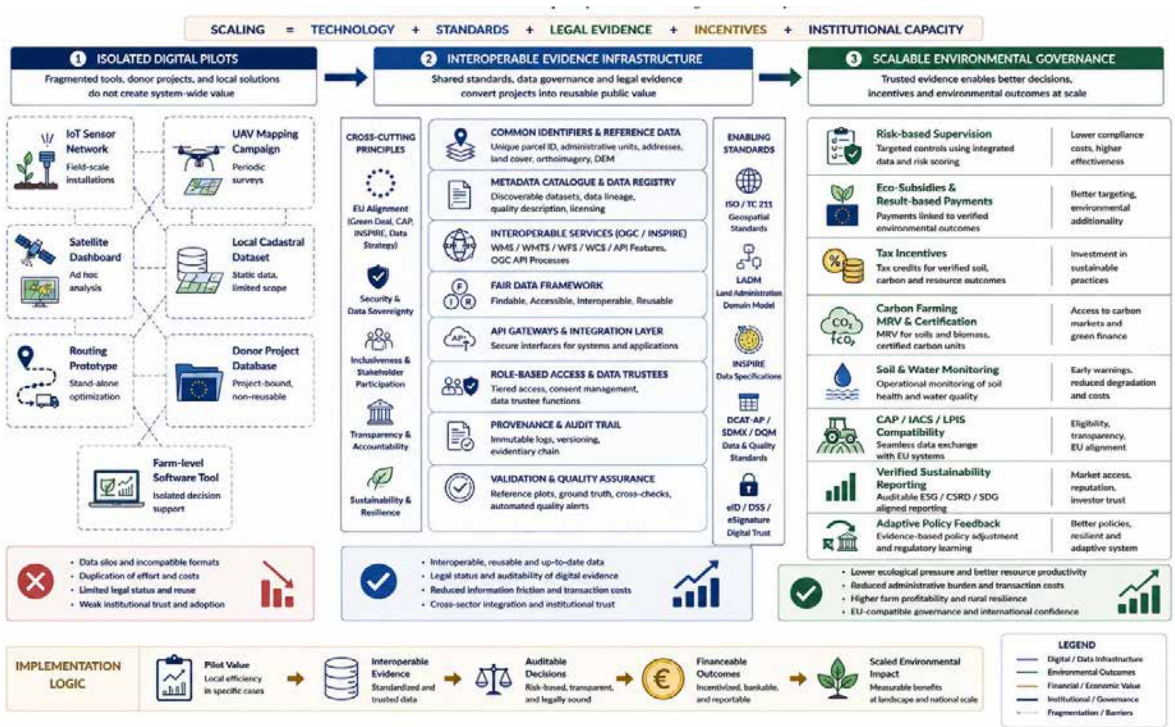


Figure 6.2 From digital pilots to scalable environmental governance

A fundamental premise of this monograph is that digital tools transform hidden environmental externalities into observable variables. However, observation is not synonymous with institutional validation. For a digital signal to alter economic outcomes—such as triggering a financial penalty for a land-use violation, verifying an eco-subsidy claim, or settling a crop insurance dispute—the data must be legally admissible.

Currently, a gap exists between technical facts and institutional evidence. For example, if a multi-spectral UAV image (Case Study II) clearly identifies illegal plowing in a protected water-buffer zone, local environmental authorities may still be legally paralyzed if the procedural code requires a physical, on-site, human-signed inspection to levy a fine. If algorithms are not embedded in evidentiary procedures, their economic value is drastically reduced. They remain diagnostic tools rather than governance instruments.

Institutional readiness is also constrained by human capital. The deployment of advanced spatio-temporal routing optimization or scenario-based multi-criteria decision analysis (MCDA) requires a workforce capable of interpreting probabilistic outputs. Agronomists, local land administrators, and environmental inspectors must transition from deterministic rule-followers to interpreters of data. Furthermore, "algorithmic aversion"—the tendency of human operators to reject machine-generated advice after witnessing a single algorithmic error, even if the algorithm outperforms human baseline accuracy—remains a significant psychological and institutional barrier.

Overcoming institutional friction requires substantial investments in capacity-building and the legal formalization of digital evidence. The regulatory framework must explicitly define the standards for sensor calibration, data provenance, timestamping, and error margins required for digital data to hold evidentiary weight in administrative and legal proceedings.

The final, and often most tangible, barrier to scaling is the economic burden of the digital transition itself. The narrative of digitalization frequently focuses on operational savings (e.g., reduced fuel consumption, optimized fertilizer application), obscuring the heavy capital and ongoing operational requirements of maintaining a digital toolscape.

The cost structure of agricultural and environmental management is fundamentally altered by digitalization. Historically, capital expenditures (CAPEX) in agriculture focused on durable mechanical assets (tractors, silos, irrigation pipes) with long depreciation cycles. Digital upgrades, however, introduce volatile hardware life cycles and a relentless shift towards operational expenditures (OPEX) in the form of Software-as-a-Service (SaaS) subscriptions, cloud storage fees, API call quotas, and continuous connectivity costs.

The Total Cost of Ownership (TCO) for a digital environmental management system over the period T is modeled as:

$$TCOdigital = CAPEXinit + t = 1\sum T(1+r)tOPEXsoftware,t + Ctelecom,t + Cmaintenance,t + Ccalibration,t \quad (6.2)$$

where:

- $CAPEX_{init}$ represents initial hardware (sensors, UAVs, edge computing nodes) and deployment costs.
- $OPEX_{software, t}$ is the recurring licensing and cloud computing expense.
- $C_{telecom, t}$ represents the cost of data transmission (e.g., satellite links, cellular IoT).
- $C_{maintenance, t}$ represents hardware replacement due to harsh field conditions.
- $C_{calibration, t}$ represents the necessary cost of verifying sensor accuracy against ground-truth data to prevent algorithmic drift.
- r is the discount rate reflecting the cost of capital.

For large agro-holdings operating on thousands of hectares, $TCO_{digital}$ is easily offset by marginal percentage gains in yield or input efficiency, spread over a massive operational base. However, for mid-sized farms, local municipalities, and peri-urban cooperatives in transition economies, the initial CAPEX and recurring OPEX represent a prohibitive barrier to entry. The economic models in Case Studies II and III demonstrate high potential returns, but these returns are probabilistic and dependent on optimal execution. If weather events destroy a crop, the digital OPEX remains a fixed liability, amplifying financial distress.

Furthermore, the hardware required for environmental monitoring is highly susceptible to physical degradation. Soil moisture sensors are subject to mechanical damage from tillage equipment; UAVs face rapid obsolescence and battery degradation; and IoT gateways in rural areas face power instability.

To systematically map these barriers against the monograph's evaluation methodology, Table 6.1 summarizes how each implementation friction point explicitly degrades the economic efficiency metrics established in the previous chapters.

Table 6.1. Impact of Implementation Barriers on Economic Efficiency Metrics

Implementation Barrier	Primary Manifestation in Practice	Impact on Economic Evaluation (CBA, MCDA, Routing)	Strategic Mitigation Requirement
Interoperability Friction	Isolated databases; manual data transfer; conflicting cadastral and farm-level maps.	Inflates transaction costs ($C_{interop}$) in CBA; reduces the reliability score of data inputs in MCDA models.	Mandate OGC API standards and FAIR data principles for all state-subsidized digital tools.

Implementation Barrier	Primary Manifestation in Practice	Impact on Economic Evaluation (CBA, MCDA, Routing)	Strategic Mitigation Requirement
Data Sovereignty & Security	Vendor lock-in, farmer reluctance to share data, and state restrictions on high-resolution spatial data.	Limits data availability for routing optimization; increases uncertainty variables in scenario simulations.	Establish sovereign agricultural data spaces with cryptographic role-based access and transparent data-sharing contracts.
Institutional Readiness	Legal inadmissibility of UAV/IoT data; lack of skilled digital agronomists; algorithmic aversion.	Nullifies compliance efficiency metrics; prevents automated pre-checks in digital land governance.	Reform procedural law to accept certified digital provenance; invest in cross-disciplinary agricultural-IT education.
Cost of Digital Upgrades	Prohibitive SaaS subscriptions; hardware wear-and-tear; high cost of capital for digital modernization.	Dramatically increases $TCO_{digital}$, reducing the Net Present Value (NPV) of the digital investment for smaller operators.	Implement targeted eco-subsidies, state-backed digital micro-financing, and open-source public digital infrastructure.

The presence of these four barriers—interoperability, data sovereignty, institutional readiness, and upgrade costs—indicates that the scaling of digital environmental management cannot be left entirely to market forces. If state and institutional actors adopt a passive role, digitalization will occur only in highly capitalized enclaves, creating a bifurcated landscape in which large agroholdings operate in the realm of "Agriculture 4.0." At the same time, peri-urban systems, smaller farms, and municipal environmental authorities remain trapped in legacy, paper-based inefficiencies.

Therefore, overcoming these barriers requires moving beyond technological procurement and stepping into systemic policy design. The friction points identified in this section establish the precise targets for the policy mechanisms, eco-subsidies, and auditable sustainability metrics that will be developed in Section 6.2. Ultimately, the economic efficiency of digital tools is only realized when the friction of the institutional and economic environment is systematically reduced to accommodate them.

Scaling is not about multiplying devices, dashboards, sensors, or software licenses. In environmental management, scaling means that a digital solution becomes part of the ordinary grammar of resource governance: data are collected in comparable formats; institutional actors trust them; economic incentives reward verified outcomes rather than declared intentions; and regulatory control becomes more selective, evidence-based, and auditable. The distinction is decisive. A pilot project demonstrates that technology can work under favorable conditions. A scalable system demonstrates that data, law, finance, and administrative routines can repeatedly convert technology into lower ecological pressure and higher economic efficiency.

The central thesis of this chapter is that scaling digital environmental management in agriculture requires a transition from technology-centered modernization to institution-centered data governance. This is especially important for Ukraine. The Ukrainian case combines high agrarian potential, accelerated digital public administration, wartime constraints, infrastructure damage, environmental degradation, land-market transformation, and a strategic course toward European Union membership. These conditions make the country both vulnerable to failed digitalization and unusually well positioned to leapfrog toward interoperable, risk-oriented, and auditable governance models. The relevant policy horizon is not merely domestic modernization; it is accession-oriented compatibility with the European Green Deal, the Common Agricultural Policy, the EU data strategy, Copernicus-based monitoring, INSPIRE-type geospatial interoperability, and emerging European frameworks for soil health, nature restoration, and carbon farming.

At the European level, digital environmental management is increasingly shaped by a convergence of four policy streams. The first is the environmental stream, represented by the Green Deal, the Nature Restoration Regulation, the Soil Monitoring Law, climate adaptation policy, and the gradual expansion of carbon-farming certification. The second is the agricultural stream, represented by CAP Strategic Plans, eco-schemes, IACS/LPIS, area monitoring, and the search for result-based interventions. The third is the data-governance stream, represented by the Open Data Directive, high-value datasets, the Data Governance Act, the Data Act, Common European Data Spaces, and the Interoperable Europe Act. The fourth is the public-administration stream, where interoperability, administrative simplification, risk-based control, and digital public services are becoming conditions for effective governance rather than optional reforms. Ukraine's roadmap must be read at the intersection of these streams.

This chapter deliberately does not repeat the methodological apparatus of Section 2 or the empirical detail of Sections 3-5. Its object is different. It asks what institutional architecture, incentive design, fiscal mechanism, and audit regime are required so that the demonstrated economic effects of digital land administration, environmental monitoring, and routing optimization can become durable public and private value. The chapter is therefore written as a strategic synthesis: it translates the economic-efficiency logic of the monograph into policy pathways for

The main barriers to scaling digital environmental management are not primarily technological. Most of the technologies discussed in this monograph are already mature enough for operational use: cadastral databases, geospatial services, Sentinel imagery, IoT sensors, UAV diagnostics, spatial optimization engines, cloud repositories, and machine-learning classification tools. The more difficult barriers concern the institutional environment in which these technologies operate. A sensor network that is not linked to a farm-management decision rule remains a technical installation. A remote-sensing product that lacks legal status remains an image, not evidence. A cadastral layer that is not interoperable with planning, environmental, tax, and subsidy systems remains a register, not infrastructure. A routing algorithm that is not tied to compliance mandates and operational requirements remains a convenience, not a governance instrument.

The implementation problem can therefore be conceptualized as a four-dimensional coordination failure. The first dimension is interoperability: data systems cannot create cumulative value if they use incompatible identifiers, schemas, coordinate systems, metadata conventions, APIs, and update cycles. The second dimension is data sovereignty: environmental data must circulate enough to support public value, yet remain protected enough to preserve security, privacy, commercial confidentiality, and farmer trust. The third dimension is institutional readiness: agencies, municipalities, farms, advisory services, inspectors, and technology providers must possess the capacity to interpret and act upon data rather than merely receive it. The fourth dimension is the cost of digital upgrades: the economic burden of adoption is unevenly distributed. It may exclude small and medium farms unless public goods, shared services, and blended finance reduce entry barriers.

Table 6.2. Barrier matrix for scaling digital environmental management in EU-aligned transition economies

Barrier domain	Operational manifestation	Specific risk for Ukraine	EU-aligned strategic response
Interoperability	Fragmented registries; incompatible spatial schemas; absence of stable APIs; repeated manual data transfer.	The State Land Cadastre, agricultural registers, environmental registers, inspection systems, local planning datasets, and remote-sensing products may develop as parallel systems rather than one decision environment.	Adopt an API-first and metadata-first architecture aligned with INSPIRE, high-value dataset obligations, OGC services, LADM-compatible land administration models, and Interoperable Europe principles.
Semantic consistency	Different systems use different definitions of parcel, field, restriction, land cover, land use, environmental zone, and risk event.	The same territory may be legally agricultural, ecologically sensitive, subsidy-eligible, logistically constrained, and environmentally risky, but these meanings are not machine-comparable.	Develop national controlled vocabulary, crosswalks, and code lists for land use, environmental restrictions, soil indicators, field operations, and remote-sensing evidence.
Data sovereignty and trust	Unclear rules on data access, farmer data rights, public-sector use of private data, cloud storage, and wartime restrictions.	Security-sensitive geodata and owner-linked parcel data require differentiated access, while environmental policy requires reusable evidence.	Introduce tiered access, pseudonymized public layers, data trustee functions, audit logs, lawful basis for environmental data processing, and safeguards inspired by the EU Data Governance Act and Data Act.
Legal status of digital evidence	Remote-sensing products and algorithmic classifications are used for information, but not always for legally meaningful decisions.	The analytical note prepared for the modernization of state supervision identifies the lack of definitions for remote-sensing data and information products, as well as rules for desk-based inspections using such products.	Define information products of Earth observation as admissible evidence under specified accuracy, provenance, certification, and contestability conditions.
Institutional readiness	Agencies acquire platforms without redesigning workflows; municipalities lack GIS capacity; farms lack digital advisory support.	Ukraine risks creating advanced national platforms that territorial communities, small farms, or inspection bodies cannot consistently use.	Create readiness tiers, training systems, shared service centers, certified data stewards, and performance contracts tied to actual use rather than to procurement completion.
Cost of digital upgrades	High upfront costs for sensors, telemetry, connectivity, software integration, training, and maintenance.	Small and medium farms may remain outside digital sustainability systems, producing a two-speed agrarian economy.	Use digital vouchers, cooperative service models, accelerated depreciation, concessional loans, and eco-subsidies linked to verified data outputs.
Cybersecurity and continuity	Critical data services become vulnerable to cyberattacks, outages, vendor lock-in, and infrastructure disruption.	Wartime conditions make continuity, backup, and role-based access a national security issue rather than a purely technical concern.	Apply geographically distributed backups, zero-trust access, open standards, public procurement anti-lock-in rules, and emergency data continuity protocols.

Source: prepared by the authors based on the monograph framework and the uploaded analytical note on remote-sensing-based modernization of state supervision.

Interoperability is often misread as a technical question of file formats. In digital environmental management, it is better understood as the institutional capacity of heterogeneous organizations to produce comparable decisions from heterogeneous evidence. Four levels must be distinguished. Syntactic interoperability concerns formats, services, APIs, and machine access. Semantic interoperability concerns shared meanings: what counts as a field, a parcel, a restriction, a buffer zone, a protected feature, a soil-risk event, or a verified environmental outcome. Organizational interoperability concerns the capacity of agencies, municipalities, farms, and service providers to coordinate workflows. Legal interoperability concerns whether data produced in one system can lawfully support a decision in another system.

The EU has gradually shifted from the first level to all four levels. INSPIRE created the geospatial logic of harmonized data themes, metadata, and network services. The Open Data Directive and the High-Value Dataset Implementing Regulation moved certain data categories, including geospatial and Earth observation data, toward machine-readable reuse. The Interoperable Europe Act extends the problem from data availability to the interoperability of public-sector digital services. The Data Governance Act and the Data Act further connect public-sector reuse, private-sector data access, data intermediation, and data-space governance. For Ukraine, the lesson is direct: accession-compatible digital environmental management cannot be built as a collection of national portals. It must be designed as a service architecture in which data are discoverable, reusable, legally traceable, and operationally connected.

A practical roadmap begins with identifiers. Environmental management cannot scale if fields, parcels, rights, restrictions, monitoring events, inspection cases, farm holdings, and subsidy applications are not linked through stable identifiers. The cadastral number can serve as one anchor. Still, it cannot solve all problems because the agricultural field, legal parcel, ecological management unit, and route segment are not identical spatial objects. The policy task is therefore not to force all phenomena into one geometry, but to establish a family of related identifiers and transformation rules. A field used in LPIS, a cadastral parcel in the State Land Cadastre, a protected water buffer, a crop-classification polygon, and an inspection risk object should be capable of being related through controlled spatial joins, metadata, time stamps, and confidence scores.

The second requirement is architecture of minimum viable interoperability. Instead of waiting for complete harmonization, Ukraine can adopt a staged approach: first, publish priority environmental and land-management datasets through documented APIs; second, require metadata, coordinate reference system consistency and machine-readable licensing; third, introduce semantic crosswalks for land use, land cover, restrictions and environmental risk classes; fourth, establish common audit logs and provenance rules for data used in inspection, subsidy, tax or environmental reporting decisions. Such a model is more realistic than an immediate attempt to create one totalizing platform. The strategic objective is not centralization for its own sake, but the reduction of translation costs between systems.

Interoperability also has an economic interpretation. Each time a farm, municipality, inspectorate, or project developer manually reconciles land records, monitoring data, legal restrictions, and operational data, the system pays an invisible transaction cost. These costs are dispersed across offices, consultants, field visits, repeated surveys, delayed decisions, and legal uncertainty; they therefore rarely appear as a single budget line. The previous studies showed how digital cadastral data, monitoring signals, and routing constraints reduce such costs. Section 6 generalizes this result: interoperability is a public investment that converts repeated private reconciliation costs into reusable public infrastructure.

Data sovereignty is the second major barrier. In the agrarian and environmental domain, it cannot be reduced to the slogan of either openness or protection. Excessive closure prevents innovation, verification, public accountability, and cross-sector coordination. Excessive openness can expose personal data, land-market strategies, security-sensitive locations, commercial production information, and ecological vulnerability. The appropriate model is differentiated sovereignty: data should be classified by sensitivity, public value, legal basis, reuse potential, and operational risk.

European data policy provides useful grammar for this differentiation. The Data Governance Act emphasizes trustworthy mechanisms for data sharing, including conditions for the reuse of certain categories of public-sector data and the development of common data spaces. The Data Act addresses access to, and use of data generated by connected products and related services, which are directly relevant to agricultural machinery, sensors, and IoT systems. These instruments do not abolish private interests in data; they create rules under which data can circulate without being appropriate, misused, or locked into proprietary silos. For digital environmental management, the key issue is not ownership in an abstract sense, but accountable stewardship: who may access data, for what purpose, under which conditions, with what safeguards, and with what right of contestation.

Ukraine's wartime context gives data sovereignty a sharper meaning. Cadastral, infrastructure, environmental, and remote-sensing data may have both public value and security sensitivity. This requires role-based access, geospatial generalization for public products, pseudonymization of owner-linked data, separated analytical and identity layers, secure state repositories, and emergency continuity rules. The uploaded analytical note explicitly identifies legal uncertainty around the official receipt and use of Copernicus data, the evidentiary status of remote-sensing products, licensing questions for commercial high-resolution imagery, personal data protection, and API integration with cadastral and LPIS-type systems. These are not secondary legal details. They determine whether digital monitoring becomes an admissible governance instrument or remains an analytical experiment.

Farmer trust is another element of sovereignty. A farm may accept digital sustainability monitoring if data use is predictable, proportional, and economically meaningful. It is unlikely to accept a system in which every sensor reading becomes a potential sanction, every remote-sensing anomaly trigger administrative pressure, and every private operational dataset is made available to competitors or authorities without clear purpose limitation. A scalable system, therefore, needs a data compact: farmers receive better services, incentives, advisory support, and reduced administrative burden; the state receives auditable environmental indicators; the public receives aggregate accountability; and sensitive commercial or personal information is protected by law and by technical design.

This compact is especially important for Ukraine's European integration. EU accession will require the development of systems compatible with CAP administration, environmental reporting, subsidy verification, soil monitoring, and possibly carbon-farming certification. If these systems are experienced only as surveillance, resistance will grow. If they are experienced as a fair exchange between evidence, support, and simplified compliance, digital environmental management can become a source of institutional trust.

Institutional readiness is the third barrier. Many digital reforms fail not because the technology is weak, but because the organization remains analog. Procurement creates a platform; the platform creates a dashboard; the dashboard creates indicators, but field routines, inspection methods, subsidy rules, advisory services, municipal planning, and budget incentives remain unchanged. The result is a pilot trap: impressive demonstrations without durable administrative use.

The pilot trap is particularly dangerous in environmental management because ecological processes are spatially heterogeneous, slow-moving, and cross-sectoral. Soil degradation, water stress, illegal plowing of protected zones, self-afforestation, land abandonment, agrochemical runoff, or field-access constraints cannot be managed by a single agency dashboard. They require coordination between land authorities, environmental agencies, agricultural ministries, water authorities, local governments, researchers, farms, processors, and technology providers. Digital systems become effective only when their outputs are embedded in procedures: subsidy eligibility checks, inspection plans, tax calculations, restoration plans, environmental permits, advisory recommendations, insurance products, and investment decisions.

Institutional readiness should therefore be measured explicitly. A community or agency is ready for digital environmental management when it can maintain geodata, interpret indicators, update registers, procure interoperable services, protect data, explain decisions, handle appeals, and use metrics in budgeting. A farm is ready when it can connect digital records with agronomic decisions, input management, yield protection, compliance reporting, and financial planning. A technology provider is ready when it can deliver documented APIs, metadata, exportable data, audit logs, explainable models, and support for public standards rather than closed products.

For Ukraine, readiness must be understood as a multi-level problem. Large agricultural holdings may have advanced digital systems, while small farms and communities may lack stable connectivity, staff, advisory capacity, or capital. National agencies may have strong registers but weak interagency workflow coordination. Municipalities may receive new planning responsibilities without sufficient geospatial competence. Inspection bodies may be formally digitalized but still rely on manual selection of objects. A strategic roadmap must therefore distribute capacity, not merely building central platforms.

Three institutional instruments are particularly important. The first is the creation of regional digital environmental competence centers that provide shared GIS, remote sensing, and data analysis support to territorial communities and small farms. The second is the professionalization of data stewardship: certified specialists should be responsible not only for mapping, but for metadata, data lineage, quality control, privacy, and interoperability. The third is performance-based administrative reform: agencies should be evaluated not by the number of digital services launched, but by measurable reductions in transaction costs, inspection duplication, response time for environmental risk, data errors, and administrative burden.

Table 6.2. Institutional readiness ladder for digital environmental management

Readiness level	Dominant mode	Typical institutional behavior	Main scaling risk	Required transition
0. Fragmented analog control	Paper, scans, ad hoc spreadsheets	Decisions depend on manual inspection, personal knowledge, and non-reusable documentation.	High discretion, delayed response, limited coverage.	Digitize core records as structured data rather than document images.

Readiness level	Dominant mode	Typical institutional behavior	Main scaling risk	Required transition
1. Digital visibility	Portals and maps	Data is visible but not integrated into workflows or legal procedures.	Transparency without decision capacity.	Introduce APIs, metadata, provenance, and service-level responsibilities.
2. Operational integration	Registers connected to procedures.	Cadastral, monitoring, and inspection data support planning, verification, and reporting.	Partial interoperability and inconsistent semantics.	Adopt common identifiers, controlled vocabularies, and cross-agency protocols.
3. Risk-oriented governance	Automated pre-screening and prioritization	Remote sensing, cadastre, and administrative data generate risk scores and inspection priorities.	Algorithmic opacity and legal contestation.	Certify algorithms, publish validation metrics, and define appeal procedures.
4. Incentive-compatible sustainability management	Payments, taxes, and compliance linked to verified metrics	Eco-subsidies, tax benefits, and regulatory relief depend on auditable environmental outcomes.	Metric gaming and exclusion of smaller actors.	Use independent audits, cooperative services, and proportional requirements.
5. Adaptive data-space governance	Continuous learning system	Environmental, agricultural, and public administration data spaces support policy adjustment, research, and private innovation.	Governance capture and over-centralization.	Maintain pluralistic data stewardship, open standards, and public-interest oversight.

Source: prepared by the authors.

The fourth barrier is cost. The monograph has repeatedly argued that economic efficiency cannot be reduced to acquisition price, yet acquisition price remains politically decisive. Sensors, GNSS equipment, telemetry, drones, cloud services, cybersecurity, data integration, staff training, and software maintenance require capital and operating expenditure. For large farms, these costs may be absorbed into existing management systems. For smaller farms, cooperatives, and municipalities, the same costs may prevent them from entering digital sustainability systems.

The cost barrier has two components. The first is direct investment cost: hardware, connectivity, software, data storage, system integration, and training. The second is organizational transition cost: time spent changing routines, cleaning data, learning procedures, correcting errors, and adapting contracts. In many public digitalization projects, the second component is underestimated, although it determines whether adoption succeeds. A digital system that is inexpensive to buy but expensive to integrate can be economically inefficient; conversely, an expensive public data infrastructure may be highly efficient if reused across many private and public workflows.

This distinction is critical for Ukraine. Digital environmental management should be financed as a layered system. Some layers are public goods and should be publicly funded: base geospatial datasets, cadastral interoperability, open Earth observation products, metadata catalogs, core environmental registers, legal evidence standards, algorithm validation infrastructure, and public dashboards. Some layers are club goods and can be financed through cooperatives, producer organizations, or service subscriptions, such as shared sensors, UAV diagnostics, advisory analytics, field-level monitoring services, and compliance documentation. Some layers are private goods and should be financed by enterprises: farm management software, proprietary optimization models, machinery telemetry, and internal decision dashboards. Confusion among these layers leads either to underinvestment in public infrastructure or unjustified subsidization of private assets.

A strategic approach should avoid two extremes. The first is laissez-faire digitalization, in which only large agribusinesses can afford high-quality environmental data systems, and small producers remain outside measurable sustainability regimes. The second is procurement-heavy statism, in which public authorities buy centralized platforms that do not serve the operational needs of farms and communities. The preferable model is hybrid: public infrastructure establishes standards and shared evidence; private and cooperative services build upon it; incentives reward verified environmental outcomes; and fiscal instruments reduce the cost of adoption for actors that produce public ecological value.

The cost of digital upgrades is also a distributive issue. If digital metrics become the basis for subsidies, certification, export access, credit, or tax benefits, those without digital capacity may be excluded. Therefore, scaling must include safeguards: simplified pathways for small farms, advisory support, cooperative data services, free access to essential public datasets, proportional reporting obligations, and transitional periods. Digital environmental management should increase inclusion and performance, not become a new barrier to market participation.

Table 6.3. Strategic roadmap for overcoming implementation barriers in Ukraine, 2026-2030

Phase	Priority actions	Institutional anchor	Expected output	Risk if neglected
Phase I: 2026 - legal and semantic grounding	Define remote-sensing data and information products; establish desk-based inspection rules; adopt common environmental data dictionaries; classify sensitive geodata.	Cabinet of Ministers, Ministry of Economy, Ministry of Environmental Protection, Ministry of Agrarian Policy, State Regulatory Service, State Space Agency.	Legal admissibility of digital evidence and minimum semantic consistency.	Remote sensing remains advisory only; inspections and subsidies remain legally disconnected from digital evidence.
Phase II: 2026-2027 - minimum viable interoperability	Create API gateways between cadastre, agricultural register, LPIS/IACS-type systems, environmental registers, and inspection systems; publish metadata catalogs and service-level standards.	Ministry of Digital Transformation, State GeoCadastre, sectoral ministries, and registry administrators.	Reusable data flows for land, monitoring, inspection, and support instruments.	Fragmented platforms duplicate costs and create inconsistent decisions.
Phase III: 2027-2028 - risk-oriented environmental control	Implement Earth-observation-based risk scoring; certify algorithms; develop appeal procedures; publish aggregate inspection dashboards.	State Regulatory Service and supervisory authorities.	Selective control focused on high-risk territories, reducing the burden on compliant actors.	Manual inspections continue to dominate, and corruption/discretion risks persist.
Phase IV: 2028-2029 - incentive integration	Link eco-subsidies, tax benefits, concessional credit, and advisory vouchers to auditable metrics and interoperable data submission.	Ministry of Finance, agricultural support agencies, banks, communities, and donor programs.	Economic demand for verified sustainability data.	Digital systems remain cost centers rather than value-generating instruments.
Phase V: 2029-2030 - accession-ready data-space governance	Integrate national systems with EU-compatible data spaces, CAP monitoring logic, soil and nature restoration reporting, and carbon farming certification.	Government of Ukraine, European Commission, national data stewards, and research institutions.	European-compatible digital environmental management ecosystem.	Ukraine faces high adaptation costs at the accession stage and loses opportunities for data-driven support mechanisms.

Source: prepared by the authors.

6.2. Policy Mechanisms for Scaling: Incentives, Eco-Subsidies, Tax Instruments, and Auditable Digital Sustainability Metrics

The preceding chapters have established that the transition to sustainable environmental management requires a fundamental shift in how economic efficiency is measured and operationalized. However, the existence of a robust methodological framework—encompassing extended cost-benefit analysis, multi-criteria decision analysis (MCDA), and shadow pricing—does not automatically guarantee the widespread adoption of digital tools. Digitalization of agrarian systems, often described as Agriculture 4.0 or smart farming, does not inherently produce sustainability through the mere presence of technological devices. To scale these digital toolscapes beyond isolated, capital-rich enterprises, governments and regulatory bodies must deploy targeted policy mechanisms.

This section formulates the strategic roadmaps for scaling digital environmental management through interconnected policy mechanisms. It demonstrates how incentives, eco-subsidies, tax instruments, and auditable sustainability metrics can transform digital tools from optional farm-level upgrades into systemic institutional infrastructure required for European integration and post-war recovery in transition economies like Ukraine.

Digital tools operate within institutions, and their value depends heavily on regulatory stability, property rights, land-use rules, and enforcement mechanisms. Without policy intervention, the agricultural sector often defaults to a linear model of resource use—characterized by extraction, production, consumption, and disposal—which treats natural capital as an expandable or substitutable input. The transition to a circular resource economy, which retains material and informational value within productive systems, requires structural changes in how the state rewards or penalizes agronomic decisions.

The European Union has institutionalized this transition through a dense policy architecture, including the European Green Deal, the Farm to Fork Strategy, and the Common Agricultural Policy (CAP) for 2023-2027. For Ukraine, aligning with these frameworks is not merely an optional modernization effort; it is a mandatory component of EU accession, post-war reconstruction, and the rebuilding of institutional trust. Policy mechanisms must bridge the gap between the private financial costs of implementing digital agritech and the public environmental benefits they generate.

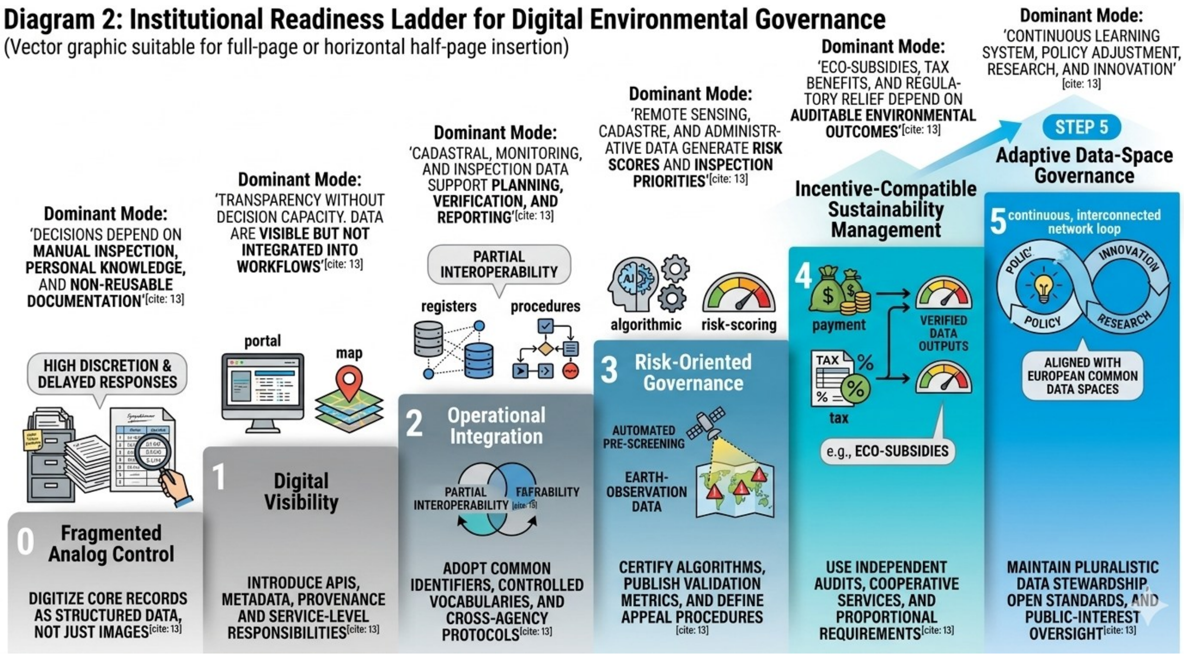


Figure 6.3 Institutional readiness chart

- Bridging the Cost-Benefit Gap: Capital expenditures (CAPEX) for digital systems—such as IoT soil sensors, GIS databases, and routing middleware—are borne directly by the farm or local authority, while environmental benefits like reduced carbon emissions and prevented soil degradation accrue to society.
- Overcoming Institutional Friction: Transition economies often suffer from path dependency, fragmented authority, and incomplete environmental accounting, requiring policy tools to formalize data interoperability and standard compliance.
- Encouraging Data Sovereignty and Sharing: Policies must establish clear data governance rules to prevent platform monopolies and ensure that generated data repositories serve as reusable public and private assets.

Traditional agricultural subsidies have historically been area-based, rewarding the scale of production rather than the sustainability of the practice. The integration of digital environmental tools allows policymakers to transition from area-based payments to performance-based eco-subsidies. Eco-subsidies represent financial transfers explicitly linked to verified environmental improvements, such as optimized nutrient management, water conservation, and biodiversity protection.

Digital monitoring networks, utilizing Sentinel-2 satellite imagery and UAV diagnostics, act as the verification layer for these subsidies. By transforming unpriced ecological effects into measurable evidence, governments can confidently disburse funds based on

actual outcomes.

To formalize the allocation of eco-subsidies, policymakers can adapt the spatial-economic index framework. The subsidy allocation S_{eco} for a given agricultural enterprise can be modeled as a function of its verifiable environmental performance:

$$Seco = j = 1\sum m(\Delta Ej \times wj \times Pshadow) - Cadmin\ (6.3)$$

Where:

- ΔE_{j} represents the verified change in environmental indicator j (e.g., reduced CO_2e emissions or water savings).
- w_{j} is the policy-defined weight of the specific environmental objective.
- P_{shadow} is the shadow price assigned to the environmental externality.
- C_{admin} represents the administrative transaction cost of verifying the data.

The efficiency of this mechanism relies entirely on the digital toolscape. If administrative costs are too high, the subsidy mechanism fails. Interoperable data spaces and OGC-aligned data services drastically lower these transaction costs by automating compliance checks against dynamic cadastral registries. Table 6.1 outlines the structure of performance-based eco-subsidies enabled by digital verification.

Table 6.4. Structure of Digitally Verified Eco-Subsidies

Subsidy Objective	Verifiable Digital Evidence	Policy Implementation Mechanism	Expected Economic Effect
Input-Use Optimization	IoT telemetry logging soil moisture and fertilizer application rates.	Direct payments for reducing agrochemical use below regional baselines.	Reduced input waste and lower localized environmental mitigation costs.
Carbon Sequestration	Integrated farm management logs and Sentinel-2 biomass estimation.	Carbon farming credits are integrated into the CAP framework.	Internalization of CO_2e externalities and yield protection.
Soil Degradation Prevention	UAV diagnostics and multi-criteria spatial-economic assessments.	Targeted financial support for adopting no-till or cover crop practices in high-risk zones.	Preservation of multi-functional soil assets and reduced public remediation expenditures.
Water Stress Mitigation	Automated irrigation scheduling data matched with meteorological APIs.	Premium subsidies for adherence to precision irrigation protocols.	Prevention of irreversible drought stress and optimization of energy costs.

While eco-subsidies act as positive incentives, tax instruments represent the necessary punitive and corrective mechanisms to internalize environmental externalities. The invisibility of ecological costs in market transactions is the primary reason why environmental externalities must be incorporated into economic evaluation. Digital land administration and continuous environmental monitoring allow tax authorities to move from flat-rate land taxes to dynamic, impact-adjusted taxation.

Taxation Based on Shadow Pricing: Shadow pricing assigns monetary values to non-market variables, such as soil degradation, water losses, and ecosystem damage. By legally recognizing shadow prices, the state can levy taxes that accurately reflect the ecological pressure an enterprise places on the peri-urban or rural environment.

- Emissions Taxation: Fuel-driven cost exposure and CO_2e stability can be monitored via spatio-temporal routing middleware. Enterprises that fail to optimize routes or consistently violate agronomic service windows can be subject to localized carbon taxes.
- Degradation Penalties: Utilizing automated spatial constraints in land-use planning, tax systems can issue automated penalties for unauthorized activities in protected environmental zones.
- Resource Depletion Levies: A linear agrarian economy treats soil as a fixed background condition, leading to soil mining and groundwater overuse. Taxes can be calibrated to penalize operations that systematically exceed sustainable water extraction thresholds, using IoT telemetry as definitive proof.

Tax Relief for Digital Upgrades. To mitigate the financial burden of these corrective taxes, the state must simultaneously offer tax relief for the procurement and integration of the digital toolscape. The cost of training, organizational adaptation, and data acquisition often deters small and medium-sized farms from digitalization. Allowing accelerated depreciation on capital expenditures for IoT sensors, GPS units, and routing middleware reduces the financial risk of modernization. Furthermore, tax credits can be issued for integration costs, specifically the harmonization of APIs and the implementation of FAIR data principles.

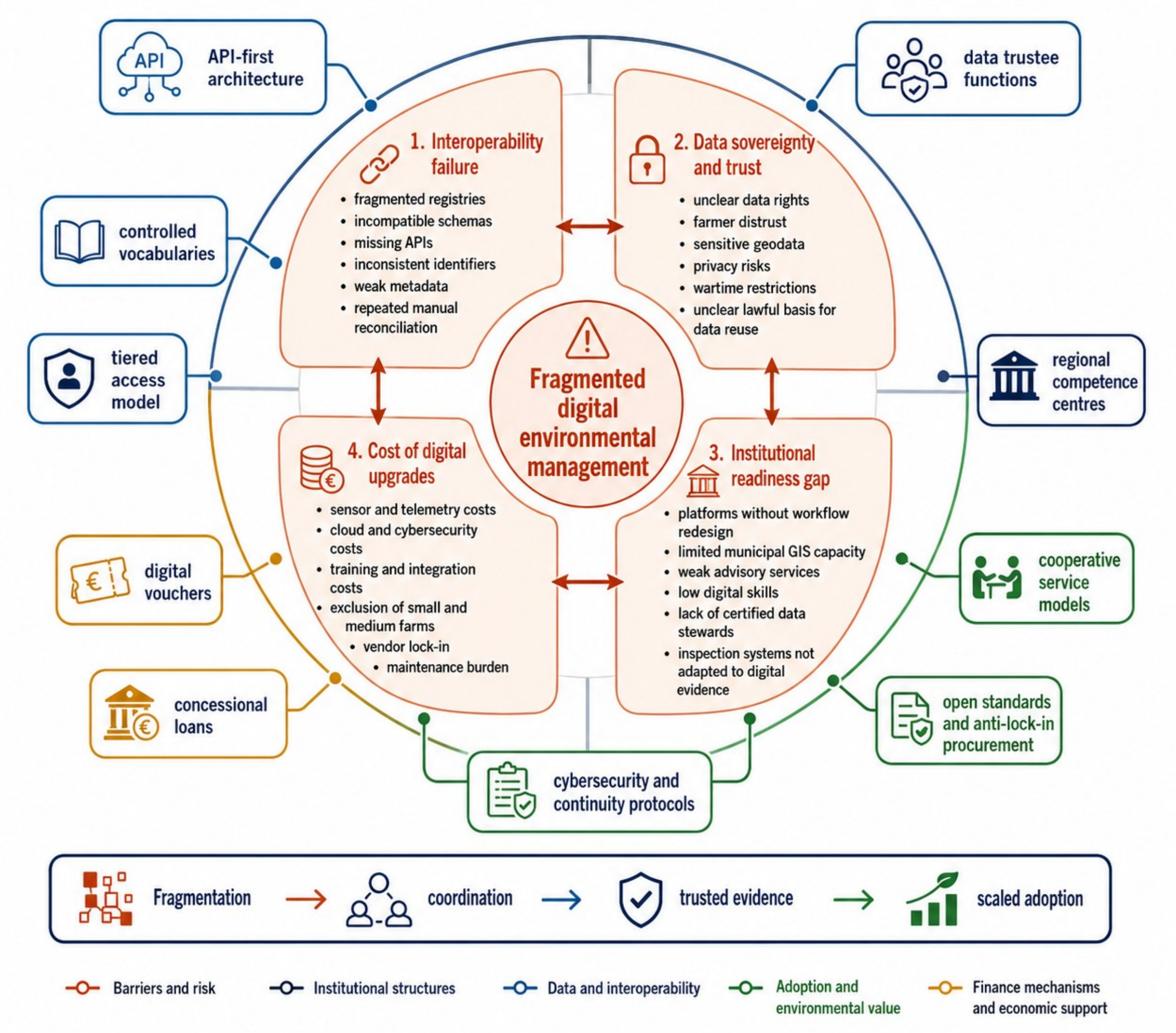


Figure 6.4 Barrier to response architecture for scaling digital environment management

The linchpin connecting incentives, subsidies, and taxes is the existence of auditable digital sustainability metrics. If monitoring data are not integrated with farm management, land records, environmental policy, or economic planning, they remain technical information with little managerial impact. For policy mechanisms to function, data must transition from fragmented signals into legally interpretable and institutionally recognized evidence.

Auditable metrics provide the third analytical layer—the verification layer—of the digital toolscape. Verification is increasingly critical as EU sustainability policy shifts from declaratory commitments to measurable performance.

The Role of FAIR Principles and OGC Standards. The proliferation of disconnected tools creates a paradox of digital inefficiency: more data leads to poorer decisions when it is duplicated, non-standardized, or disconnected from authority.

- Findability and Accessibility: Cadastral systems must function as dynamic spatial databases aligned with FAIR principles, allowing policymakers to locate land rights, restrictions, and environmental obligations easily.
- Interoperability: The use of Open Geospatial Consortium (OGC) services ensures that satellite observations, sensor records, and administrative boundaries can communicate flawlessly. Interoperability reduces the transaction costs of recombining evidence across contexts.
- Reusability: Structured historical datasets enable continuous comparison, anomaly detection, and evidence-based decision-making for future policy formulation.

Institutionalizing Metrics. To utilize these metrics for policy scaling, the state must establish a standardized assessment index. By normalizing heterogeneous indicators (e.g., converting fuel consumption, soil moisture, and spatial compliance into a standard 0 to 1 scale), policymakers can automatically generate compliance scores.

The normalization for a benefit criterion (where higher is better, such as data quality or yield protection) is expressed as:

$$xij' = max(xj) - min(xj)xij - min(xj) \quad (6.4)$$

Conversely, for a cost criterion (where lower is better, such as CO_2e emissions or operational risk):

$$xij' = max(xj) - min(xj)max(xj) - xij \ (6.5)$$

These normalized metrics are directly used to calculate the extended benefit-cost ratio (EBCR) and multi-criteria indices, providing tax authorities and subsidy distributors with an objective, mathematically sound basis for capital allocation.

For Ukraine, the implementation of these policy mechanisms is inextricably linked to post-war recovery and European integration. The war has heavily impacted territories and infrastructure, adding complex layers of security risks, prioritizing demining, and altering logistics and environmental management.

The strategic roadmap for scaling digital environmental management in Ukraine must execute the following interconnected phases:

1. Reconstruction of the Spatial-Economic Base: The state must prioritize upgrading the State Land Cadastre from a static registry to a dynamic, interoperable platform. Without reliable land data and clear environmental protection areas, neither monitoring nor routing tools can produce fully reliable decisions.
2. Deployment of Recovery Eco-Subsidies: Utilizing funds from the Ukraine Facility and international green recovery initiatives, the government must target subsidies toward farms that deploy digital monitoring to restore degraded soils and optimize inputs in war-affected zones.
3. Alignment with EU Reporting Frameworks: Ukrainian agricultural enterprises must adopt sustainability reporting aligned with the EU Farm to Fork Strategy and the CAP. Policies must mandate that digital environmental tools provide verifiable records of greenhouse gas accounting, pesticide reduction, and nutrient management.
4. Managing Uncertainty through Scenario-Based Policy: Given the volatile conditions of wartime and post-war logistics, routing constraints, and market instability, policy mechanisms cannot rely on static baselines. Taxation and subsidy thresholds must be periodically adjusted using scenario-based economic evaluation to ensure they remain fair, resilient, and effective.

Table 6.5. Alignment of Scaling Policies with Sustainable Development Goals

SDG Focus	Policy Mechanism Integration	Strategic Outcome PDF
SDG 2 (Zero Hunger)	Subsidizing precision interventions and monitoring-based crop protection.	Maintained agricultural productivity alongside reduced environmental pressure.
SDG 9 (Innovation & Infrastructure)	Tax relief for API development, cloud storage, and geospatial database preparation.	Development of resilient technological systems and interoperable data spaces.
SDG 11 (Sustainable Cities)	Automated spatial constraints and conflict-prevention mechanisms in peri-urban land allocation.	Balanced urban-rural relations and optimized logistical networks within the Kyiv agglomeration.
SDG 12 (Responsible Consumption)	Imposing levies on linear resource extraction and rewarding circular material retention.	Reduced waste, minimized leakage, and responsible agrarian production.
SDG 17 (Partnerships)	Mandating auditable, OGC-aligned data reporting for international reconstruction financing.	Coordinated institutional trust between farms, state authorities, and European integration bodies.

Sustainable environmental management is economically efficient when it increases the value generated by agrarian systems without reducing the regenerative capacity of the ecological base. The deployment of dynamic incentives, targeted eco-subsidies, precision tax instruments, and rigorously auditable digital metrics provides the institutional architecture necessary to realize this efficiency on a national scale.

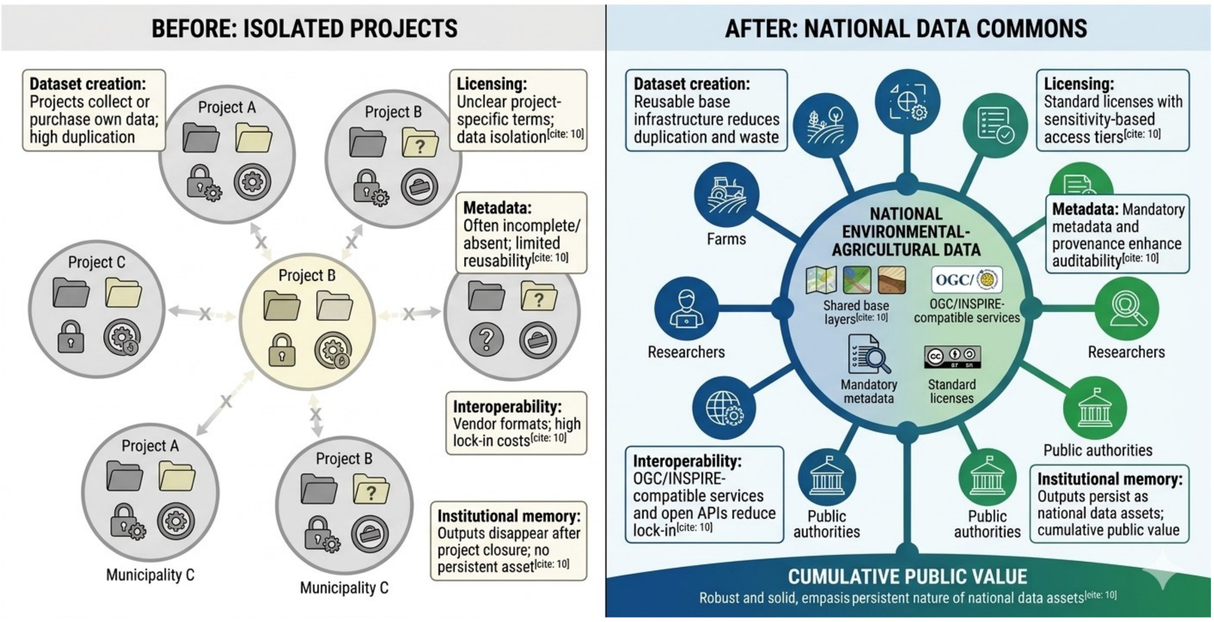


Figure 6.5 Architecture transition and data

The scaling of digital environmental management cannot be ensured only through technological modernization. The previous subsection demonstrated that implementation barriers are linked to interoperability, data sovereignty, institutional readiness, uneven digital capacity, and the real costs of upgrading agricultural and environmental management systems. However, even if these barriers are gradually reduced, digital tools will not automatically become instruments of sustainable development. Their direction of use depends on the policy environment. A farm, cooperative, municipality, technology provider, or public agency will adopt digital tools in a sustainability-oriented way only when incentives, regulatory expectations, financial instruments, and audit mechanisms make such behavior economically rational and institutionally recognized.

This creates a central policy problem. Digital agriculture and environmental monitoring can serve different purposes. The same sensor network can support water saving, but it can also support expansion of water-intensive production. Satellite monitoring can improve environmental control, but it can also remain a passive visualization layer without decision impact. A route system can reduce fuel use and protect service windows. Still, it can also be optimized only for private cost minimization if emissions, restricted zones, and social risks are not included in the objective function. A cadastral platform can reduce transaction costs and prevent land-use conflicts. Still, it can reproduce old institutional fragmentation if restrictions, environmental zones, and public service interfaces are not updated. For this reason, policy mechanisms must not simply encourage the purchase of digital technologies. They must direct digitalization toward measurable environmental, economic, and institutional outcomes.

In this monograph, policy mechanisms for scaling digital environmental management are understood as the set of public, fiscal, regulatory, informational, and institutional instruments that convert digital evidence into economic incentives and governance decisions. Such mechanisms include direct incentives for technology adoption, eco-subsidies linked to verified environmental performance, tax instruments that reward resource efficiency and penalize avoidable ecological pressure, concessional finance for digital infrastructure, public procurement requirements, sustainability reporting systems, digital audit protocols, and data-based eligibility criteria for support programs. The common feature of these mechanisms is that they should be connected to measurable indicators rather than declarative intentions.

The need for such an approach follows from the monograph's general methodology. Earlier chapters showed that the economic efficiency of digital tools must be evaluated through financial, environmental, temporal, operational, informational, and institutional effects. This means that policy should not focus solely on whether a farm has installed a sensor, purchased a platform, used a satellite image, or connected to a dashboard. The more important question is whether the tool has produced measurable changes: lower input use, reduced water stress, protected agronomic service windows, fewer restricted-zone violations, better compliance, lower transaction costs, improved data reliability, reduced risk, or auditable environmental performance. Public support should be linked to these results.

A frequent weakness of technology-support policy is that it subsidizes the acquisition of equipment rather than the verified effect of its use. In agriculture, this may result in farms receiving public support for sensors, drones, software subscriptions, field controllers, or digital platforms without demonstrating whether these tools reduce ecological pressure or improve decision-making. Such an approach creates several risks. First, it may lead to formal digitalization, in which technologies are purchased but poorly integrated into agronomic, land-use, or environmental decision-making. Second, it may favor larger enterprises that already possess technical capacity and can more easily absorb administrative requirements. Third, it may create dependency on vendors without building long-term data capacity. Fourth, it may produce fragmented datasets that cannot support public environmental governance.

An outcome-based policy logic is more appropriate for sustainable environmental management. Under this logic, public support is linked to verified performance. A farm may receive support not only because it installed an IoT soil-moisture network, but because the system generated documented water savings, protected yield under stress, or reduced unnecessary irrigation. A cooperative may receive support not only because it introduced a satellite-monitoring dashboard, but because the dashboard helped prioritize interventions, reduce field-inspection costs, and create a reusable monitoring archive. A local authority may receive support not only because it digitized land records, but because cadastral and environmental layers reduced transaction costs, accelerated verification, prevented incompatible land-use decisions, and improved public accountability.

This does not mean that investment subsidies are unnecessary. In transition economies, including Ukraine, the initial cost of digital upgrades may be too high for many farms, communities, and public institutions. Hardware, software, integration, training, maintenance, data processing, cybersecurity, and interoperability development create real financial barriers. However, investment support should be combined with outcome requirements. The policy mechanism should distinguish between enabling investment and performance payment. The first helps actors access the digital environmental management system. The second rewards the measurable environmental and economic effects produced by the system.

Figure 6.6 Incentive-compatible digital sustainability governance loop

A practical policy architecture may therefore include three levels. The first level is access support. It reduces the initial cost of digital adoption through grants, vouchers, concessional loans, shared-service platforms, cooperative data hubs, and public digital infrastructure. The second level is performance support. It provides eco-subsidies, tax credits, bonus payments, or preferential financing based on verified indicators. The third level is governance support. It creates standards, data protocols, audit systems, interoperability requirements, and legal recognition of digital evidence. These three levels must operate together. Access support without performance criteria may produce inefficient digitalization. Performance support without access support may exclude smaller actors. Governance support without financial instruments may remain declarative.

Incentives are the first group of policy mechanisms for scaling digital environmental management. They include financial and non-financial instruments that make the adoption and effective use of digital tools attractive to farms, cooperatives, local governments, service providers, and public institutions. The purpose of incentives is not only to increase the number of digital tools in use. Their purpose is to establish a stable link between digital evidence and better environmental and economic decisions.

Financial incentives may include partial compensation for digital equipment, grants for pilot implementation, co-financing of monitoring systems, vouchers for advisory services, reduced-interest loans for digital infrastructure, and support for cooperative digital platforms. Such incentives are especially important at the early stage of adoption. Many farms and local authorities understand the potential value of digital tools but cannot absorb the initial cost, integration complexity, or uncertainty of payback. This is particularly relevant for IoT telemetry, UAV diagnostics, cloud platforms, GIS infrastructure, and routing middleware, where the real cost extends beyond equipment to include data preparation, calibration, staff training, maintenance, and integration with existing workflows.

However, financial incentives must be selective. Public resources should not support any digital tool merely because it is new. Eligibility depends on the tool’s connection with sustainable environmental management. Priority should be given to digital systems that can demonstrate at least one of the following functions: reduction of input waste; monitoring of soil, water, vegetation, or emissions; support for compliance with land-use or environmental restrictions; generation of auditable sustainability records; improvement of decision timing; reduction of transport, fuel, or operational risk; or integration with public spatial and environmental data. This prevents technology-neutral support from becoming environmentally blind.

Non-financial incentives are equally important. They include simplified reporting procedures for farms that use verified digital data, faster administrative processing for applications supported by interoperable geospatial evidence, preferential access to public programs for enterprises with auditable sustainability records, recognition of digital monitoring data in compliance procedures, and public certification of farms or communities that implement reliable digital environmental-management systems. Such incentives reduce transaction costs and create reputational value. In some cases, they may be more influential than direct subsidies, especially for export-oriented producers, municipalities seeking investment, or cooperatives seeking access to international programs.

A key policy task is to create incentives for collective digital infrastructure. Many digital tools have strong economies of scale. Satellite monitoring, cadastral integration, route optimization, data storage, advisory services, and sustainability reporting may be too expensive for individual small farms, but economically justified at the level of a cooperative, community, watershed, processing cluster, or peri-urban agricultural zone. Therefore, incentive policy should not focus only on individual enterprise adoption. It should support shared digital services, cooperative sensor networks, regional monitoring platforms, local geodata hubs, and municipal-farm data partnerships. This is especially important for Ukraine, where farm structures are heterogeneous and many communities face limited administrative and financial capacity.

Digital environmental incentives should also be phased out. At the first stage, incentives may support basic digitization: georeferenced field boundaries, digital land-use records, baseline soil and crop monitoring, and basic farm-management data. At the second stage, incentives may support integration: linking cadastral layers, remote sensing, IoT telemetry, weather data, field logs, and economic records. At the third stage, incentives may support optimization: routing, variable-rate interventions, digital twins, scenario modeling, and automated decision-support systems. At the fourth stage, incentives may support verification: sustainability dashboards, audit trails, carbon or soil reporting, compliance evidence, and integration with public policy instruments. This sequence is important because advanced digital tools cannot operate effectively without reliable basic data.

Eco-subsidies are one of the most important instruments for scaling digital environmental management. They can convert environmental benefits into direct economic signals. However, eco-subsidies must be designed carefully. If they are based solely on declared practices, they may lead to weak accountability. If they are based only on complex reporting, they may create excessive administrative burden. If they are based solely on technology ownership, they may reward digital investment regardless of environmental impact. The strongest design is a verified-performance model, where support is linked to measurable and auditable indicators.

In the context of this monograph, eco-subsidies should relate to the same categories used in the methodological framework: financial savings, environmental effects, temporal effects, data value, risk reduction, and institutional benefits. This means that a subsidy may reward not only emission reduction, but also water-use efficiency, soil-risk mitigation, reduced runoff, protected service windows, prevented restricted-zone violations, improved data quality, and verified compliance. Such an approach reflects the multi-dimensional nature of sustainable environmental management.

Eco-subsidies may be designed around several measurable result groups. The first group is input-use efficiency. Farms may receive support for verified reductions in water, fertilizer, fuel, agrochemical use, or unnecessary field operations, if yield and soil quality are not harmed. The second group is environmental-risk reduction. Support may be linked to reduced soil erosion risk, lower water stress, reduced nutrient runoff, protection of green cover, or avoidance of ecologically sensitive areas. The third group is emissions and energy performance. Support may be linked to verified CO_2e reduction from routing, machinery optimization, irrigation energy savings, or reduced repeated field inspections. The fourth group is compliance and spatial responsibility. Support may be linked to zero violations of hard spatial masks, documented respect for protection zones, or use of cadastral and environmental constraints in operational planning. The fifth group is data and audit quality. Support may be linked to complete metadata, reliable monitoring records, interoperable data exports, and digital audit trails.

The advantage of digital tools is that they can reduce verification costs. Traditional eco-subsidies often depend on field inspections, paper reports, or self-declarations. These mechanisms are expensive, slow, and error-prone. Digital systems can provide more frequent and spatially explicit evidence. Satellite imagery can verify vegetation cover, land-use change, and some crop conditions. IoT sensors can document soil moisture and environmental parameters. Farm-management logs can record interventions. Routing systems can document distances, fuel assumptions, service windows, and compliance with restricted-edge requirements. Cadastral systems can verify whether a field or route intersects protected, restricted, or conditional zones. Digital audit trails can preserve time stamps, data sources, model outputs, and decisions.

At the same time, digital verification should not become an uncontrolled surveillance system. Farmers and communities must have clear rights regarding data use, access, correction, appeal, and confidentiality. Eco-subsidy systems should define which data are mandatory, voluntary, aggregated, or sensitive. They should also distinguish between operational data used for farm management and official data used for compliance. Without such distinctions, digital eco-subsidies may face resistance, especially if users perceive them as a mechanism of control rather than support.

A balanced eco-subsidy model should include four principles. First, the indicator must be measurable. It should be possible to observe or calculate the result using agreed data sources. Second, the indicator must be attributable. The result should be reasonably connected to the action of the farm, cooperative, or local authority. Third, the indicator must be auditable. A third party should be able to verify the evidence, assumptions, and calculation procedure. Fourth, the indicator must be proportionate. The administrative cost of proving the result should not exceed the environmental and economic value of the result.

The payment formula for eco-subsidies may combine a base support component and a performance component:

$$EcoSubsidy\_i = Base\_i + α\_1E\_i + α\_2W\_i + α\_3S\_i + α\_4R\_i + α\_5A\_i$$

where EcoSubsidy_i is the total eco-subsidy for farm, cooperative, municipality, or project i; Base_i is the basic support for participation and data-system maintenance; E_i is verified emissions or energy performance; W_i is verified water or input-use efficiency; S_i is soil, land, or ecological sensitivity performance; R_i is risk-reduction or compliance performance; A_i is auditability and data-quality performance; and α_1…α_5 are policy weights.

This formula is not proposed as a rigid payment rule. It is a conceptual structure for translating the monograph's multi-criteria methodology into a policy instrument. Different regions and programs may assign different weights. A drought-prone region may place greater emphasis on water performance. A peri-urban region may place greater weight on land-use compliance and the protection of green zones. A logistics-constrained region may emphasize fuel and routing efficiency. A reconstruction zone may emphasize soil contamination, land restoration, and safety compliance.

Eco-subsidies should also include a safeguard against perverse incentives. For example, a farm should not receive support for reducing fertilizer use if this leads to soil nutrient depletion or yield collapse. A routing system should not be rewarded only for reduced distance if it increases risk, emissions, or restricted-zone violations. A water-saving indicator should not be rewarded with under-irrigation that damages crop productivity. Therefore, eco-subsidy indicators must be evaluated as a balanced set. This is where MCDA and hard-mask logic become policy-relevant. Some conditions should function as eligibility thresholds. A farm that violates legal restrictions, falsifies data, or degrades protected areas should not receive performance payments even if it performs well on one indicator.

Tax instruments provide another mechanism for scaling digital environmental management. Unlike subsidies, which use public expenditure to reward desired behavior, tax instruments modify the cost structure of economic activity. They can reduce the cost of digital investments, reward verified environmental performance or increase the cost of environmentally harmful practices. In the context of this monograph, tax instruments are important because they can connect digital evidence with fiscal incentives.

The first group of tax instruments is investment oriented. These instruments reduce the fiscal burden on farms, cooperatives, or enterprises that invest in eligible digital environmental-management tools. Examples include accelerated depreciation for sensors, monitoring infrastructure, geospatial equipment, data servers, and routing systems; tax credits for certified digital sustainability investments; VAT preferences for approved environmental-monitoring equipment; and deductions for expenditures on data integration, cybersecurity, interoperability, and staff training. Such instruments are particularly useful where direct budget subsidies are limited or administratively difficult.

However, investment-oriented tax instruments must be designed carefully. If eligibility is too broad, they may support ordinary digitalization without environmental effect. If eligibility is too narrow, they may exclude innovative solutions. A practical compromise is to define eligible expenditures by function rather than by brand or technology type. Eligible tools should support environmental monitoring, resource-use optimization, land-use compliance, emissions accounting, soil or water protection, routing efficiency, digital audit trails, or interoperable sustainability reporting. This functional approach prevents policy from becoming obsolete as technologies change.

The second group is performance-oriented tax instruments. These instruments reward verified environmental outcomes. For example, a farm that demonstrates verified reductions in fuel consumption, water use, emissions, or nutrient runoff may receive a tax credit or reduced environmental charge. A cooperative that maintains an auditable environmental data platform may receive fiscal recognition for the public good value of its data. A municipality that integrates cadastral, environmental, and land-use restrictions into digital public services may receive preferential access to intergovernmental transfers or recovery funds. In each case, digital evidence becomes the basis for fiscal differentiation.

The third group is corrective environmental taxation. These instruments increase the cost of environmentally harmful actions. They may include taxes or charges on excessive water use, pollution, emissions, landfill disposal, land degradation, or non-compliance with environmental requirements. Digital tools are relevant because they improve measurement and targeting. Without digital evidence, environmental taxes may be too general, administratively weak, or unfair. With digital evidence, charges can be more closely linked to actual behavior, location, risk, and environmental impact. For example, water-use charges can be better calibrated when irrigation volumes, crop water demand, soil moisture, and weather conditions are monitored. Routing-related fuel and emissions accounting can support more accurate estimates of transport externalities. Land-use decisions can be linked to cadastral and ecological sensitivity data.

The fourth group is tax neutrality and fairness instruments. Digital sustainability policy should avoid penalizing smaller or less digitally mature actors simply because they cannot afford complex monitoring systems. If tax benefits depend solely on sophisticated digital reporting, large enterprises may capture most of the benefits. Therefore, tax instruments should include proportional requirements. Small farms may use simplified reporting, cooperative platforms, or public advisory services. Medium-sized farms may use standard digital templates. Large enterprises may be required to provide more detailed audit trails and sustainability metrics. This differentiated approach improves fairness and reduces the risk that digital policy reinforces structural inequality.

For Ukraine, tax instruments must be considered within the broader context of reconstruction, EU integration, fiscal constraints, and agricultural competitiveness. The state cannot rely only on grants and subsidies. It must develop instruments that mobilize private investment while preserving public accountability. Digital environmental tax incentives can be useful if they are transparent, targeted, and linked to measurable outcomes. At the same time, tax instruments should not create excessive administrative complexity. Their effectiveness depends on simple eligibility rules, reliable digital evidence, clear audit procedures, and coordination between tax authorities, environmental agencies, agricultural institutions, and local governments.

A possible structure for digital environmental tax credit may include the following elements:

$$TaxCredit_i = \beta \times EligibleCost_i \times Q_i \times C_i$$

where $TaxCredit_i$ is the tax credit for project i; $EligibleCost_i$ is the cost of approved digital environmental investments; β is the base credit rate; Q_i is the data-quality and interoperability coefficient; and C_i is the compliance-performance coefficient.

The logic of this structure is that public fiscal support should not depend only on expenditure size. It should also depend on whether the system produces reliable, interoperable, and compliance-relevant data. A project with poor data governance should not receive the same fiscal benefit as a project that generates auditable environmental metrics and can be integrated with public reporting systems.

For corrective charges, a simplified environmental charge may be expressed as:

$$EnvCharge_i = \gamma_1 CO2e_i + \gamma_2 WaterExcess_i + \gamma_3 RunoffRisk_i + \gamma_4 LandRisk_i - Credit_i$$

where EnvCharge_i is the environmental charge for actor i; CO2e_i is measured or estimated emissions; WaterExcess_i is excess water use relative to a justified benchmark; RunoffRisk_i is a nutrient or agrochemical runoff-risk indicator; LandRisk_i is the land-use or ecological-risk indicator; γ_1…γ_4 are policy coefficients; and Credit_i is the verified reduction or mitigation credit.

Such formulas should not be introduced mechanically. They require high-quality data, sector consultation, gradual implementation, and sensitivity analysis. Their main value in this monograph is conceptual: they show how digital evidence can transform environmental taxation from broad administrative categories into more precise ecological-economic instruments.

The central condition for outcome-based incentives, eco-subsidies, and tax instruments is the existence of auditable digital sustainability metrics. Without auditable metrics, policy mechanisms remain declarative. With auditable metrics, environmental performance can be measured, compared, verified, and linked to economic instruments. This is one of the key practical conclusions of the monograph.

Auditable digital sustainability metrics are indicators that satisfy six conditions. First, they are clearly defined. The metric must have an explicit meaning, a calculation method, a unit, and an interpretation. Second, they are data-supported. The metric must be based on identifiable data sources, such as satellite imagery, IoT telemetry, cadastral layers, farm logs, routing outputs, emission factors, or administrative records. Third, they are reproducible. Another analyst should be able to calculate the metric using the same data and method. Fourth, they are traceable. The data lineage, time stamp, processing steps, and assumptions should be documented. Fifth, they are comparable. The metric should be usable across farms, fields, communities, routes, or time periods, with appropriate normalization. Sixth, they are policy relevant. The metric should support decisions, incentives, compliance, or investment evaluation.

The monograph’s empirical cases suggest several groups of such metrics. For digital land management, the relevant metrics include parcel data completeness, restriction-layer coverage, average land-use verification time, number of detected spatial conflicts, share of decisions checked against hard masks, interoperability score, cadastral update frequency, and audit-trail completeness. These metrics show whether digital land administration reduces transaction costs and improves spatial certainty.

For IoT telemetry and environmental monitoring, the relevant metrics include sensor uptime, field coverage, soil-moisture threshold exceedance, irrigation response time, NDVI/EVI anomaly detection rate, verified intervention response, input-use change, water-saving estimate, yield-protection estimate, and environmental risk reduction score. These metrics show whether monitoring creates action rather than only data.

For spatio-temporal routing, the relevant metrics include direct logistics cost, fuel use, route distance, travel time, service-window feasibility, CO_2e emissions, restricted-edge violations, risk-weighted route score, cost per kilometer, and scenario stability. These metrics show whether routing supports economic efficiency, environmental accounting, and compliance.

A general digital sustainability metric can be expressed as:

DSM_i = f(D_i, M_i, Q_i, R_i, A_i)

where DSM_i is the digital sustainability metric for object i; D_i is the underlying data; M_i is the calculation method; Q_i is the data-quality coefficient; R_i is the reliability or uncertainty adjustment; and A_i is the auditability status.

This expression emphasizes that the metric is not only a number. It is a combination of data, method, quality, uncertainty, and auditability. A metric without metadata and an audit trail is weak for policy use. A metric with high technical precision but unclear legal status may also be weak. A metric that is less detailed but authoritative, comparable, and auditable may be more useful for governance.

Digital sustainability metrics should also be distinguished between primary, derived, and composite indicators. Primary indicators are measured directly or closely to directly: fuel consumed, route distance, sensor uptime, field area, irrigation volume, or service-window completion. Derived indicators are calculated from primary data: CO_2e emissions, cost per kilometer, water-use efficiency, or delay-loss estimate. Composite indicators aggregate several dimensions: sustainability score, land-use suitability index, intervention priority index, routing utility, or institutional-readiness score. Policy instruments should be cautious with composite indicators. They are useful for ranking and decision support, but financial payments should be based as much as possible on transparent primary and derived indicators.

The auditability of metrics requires a digital evidence chain. The evidence chain begins with data capture. Data may come from satellite observation, IoT telemetry, UAV diagnostics, cadastral systems, field logs, machinery telemetry, routing engines, or administrative records. The second stage is data validation. This includes quality checks, calibration, cloud masking, outlier detection, spatial matching, and consistency tests. The third stage is processing. This includes calculation of indices, emissions, costs, risks, penalties, and scenario results. The fourth stage is interpretation. The system determines whether a threshold has been met, whether an improvement has occurred, or whether a violation has been avoided. The fifth stage is reporting. Results are exported in a form suitable for farms, public authorities, auditors, or policy programs. The sixth stage is audit. A third party can verify the source data, method, assumptions, and result.

A policy-ready metric should therefore accompany a digital passport. The passport should include the metric name, definition, unit, data source, spatial resolution, temporal resolution, update frequency, method, responsible institution, quality score, uncertainty range, eligibility use, audit procedure, and privacy classification. This may appear administratively demanding, but it is necessary if digital sustainability metrics are to support public money, tax preferences, market claims, or compliance decisions.

Table 6.6. Recommended auditable digital sustainability metrics for scaling digital environmental management

Policy domain	Metric group	Example metric	Data source	Policy use
Digital land management	Spatial certainty	Parcel/restriction completeness index	Cadastre, GIS, municipal layers	Eligibility for land-use planning support
Digital land management	Transaction-cost reduction	Average verification time per land-use decision	Workflow logs, administrative records	Evaluation of digital cadastre efficiency
Digital land management	Compliance	Share of decisions checked against hard masks	Cadastral and environmental restrictions	Eco-subsidy and permitting control
Environmental monitoring	Water efficiency	Irrigation water saved per hectare	IoT sensors, irrigation logs, weather data	Eco-subsidy for water efficiency
Environmental monitoring	Soil and crop condition	Stress detection and intervention-response time	Sentinel-2, UAV, IoT, field logs	Support for precision interventions
Environmental monitoring	Input-use efficiency	Fertilizer or agrochemical reduction without yield loss	Farm logs, yield records, EO indicators	Tax credit or subsidy eligibility
Routing and logistics	Fuel and cost efficiency	Cost per kilometer and fuel per route	Routing engine, fleet logs, fuel price	Logistics-efficiency support
Routing and logistics	Service-window feasibility	Share of jobs completed within the agronomic window	Task logs, routing schedule	Performance payment for resilience
Routing and logistics	Compliance	Restricted-edge violations	Hard-mask routing logs	Mandatory eligibility condition
Sustainability reporting	Emissions	CO_2e per hectare, route, or operation	Fuel, machinery, emission factors	Carbon accounting and reporting
Institutional governance	Auditability	Metadata and provenance completeness	System logs, data catalogs	Public program eligibility
Institutional governance	Interoperability	FAIR/OGC compliance score	API, metadata, standards audit	Digital infrastructure support

Source: prepared by the authors.

This table shows that digital sustainability metrics should not be limited to environmental indicators in a narrow sense. They must also include institutional and operational indicators, because sustainable environmental management depends on whether data are usable, trustworthy, and connected to decisions.

The policy mechanisms proposed in this subsection should be directly linked to the three empirical case studies in the monograph. Otherwise, Chapter 6 would remain too general. The purpose of the chapter is to show how methodological and empirical findings can be translated into scaling instruments.

In the case of digital land management and cadastral systems, policy mechanisms should focus on spatial certainty, transaction-cost reduction, and compliance-aware land allocation. Incentives may support integrating cadastral data with environmental restrictions, land-use planning documents, soil maps, infrastructure data, and public service workflows. Eco-subsidies may reward communities or land users that maintain complete and auditable restriction layers, use hard-mask screening before land-use decisions, and reduce conflicts or delays in verification. Tax instruments may support investment in geospatial databases, API services, and digital audit trails. Sustainability metrics may include restriction-layer coverage, cadastral completeness, verification time, dispute reduction, and land-use compatibility.

In the case of IoT telemetry and environmental monitoring, policy mechanisms should focus on transforming monitoring signals into precision interventions. Incentives may support installation and maintenance of soil sensors, weather stations, field telemetry, satellite-processing workflows, and shared monitoring services. Eco-subsidies may reward verified water savings, earlier stress response, reduced input waste, lower runoff risk, or documented yield protection. Tax instruments may support monitoring infrastructure and data services if they meet interoperability and auditability standards. Sustainability metrics may include soil-moisture threshold response, irrigation optimization, NDVI/EVI anomaly handling, intervention timing, and input-use efficiency.

In spatio-temporal routing and optimization, policy mechanisms should focus on fuel-driven cost exposure, emissions accounting, feasibility of agronomic service windows, and compliance with spatial restrictions. Incentives may support routing middleware, fleet telemetry, road graph preparation, and the integration of cadastral restrictions into logistics systems. Eco-subsidies may reward verified reduction in fuel use, improved service-window performance, and zero restricted-edge violations. Tax instruments may support low-emission logistics upgrades or digital route accounting. Sustainability metrics may include route cost, travel time, CO_2e, service-window feasibility, and hard-mask compliance.

These applications show that policy mechanisms should be differentiated by function. A cadastral system, a monitoring system, and a routing system should not be evaluated using the same narrow indicator. However, all three should follow the same governance principle: public support should be linked to measurable, auditable, and environmentally meaningful performance.

Measurement, reporting, and verification, or MRV, form the institutional core of digital environmental policy. Measurement produces evidence. Reporting translates evidence into a form usable by farms, agencies, markets, and public programs. Verification confirms that the evidence is reliable. Without MRV, incentives and subsidies cannot be trusted. Without digitalization, MRV may become expensive, slow, and administratively burdensome. The challenge is to design digital MRV systems that are credible but not excessive.

Digital MRV should be based on several principles. The first principle is proportionality. The level of detail required should correspond to the scale of support and risk. A small farm applying for a modest water-efficiency incentive should not face the same reporting burden as a large enterprise claiming major carbon or sustainability benefits. The second principle is interoperability. MRV data should be reusable across programs where possible. A field boundary, crop record, or sensor dataset should not have to be submitted separately in incompatible formats for each program. The third principle is transparency. The calculation method should be available to participants and auditors. The fourth principle is contestability. Users should have a procedure for correcting errors, challenging interpretations, and providing additional evidence. The fifth principle is security. Sensitive farm, land, and infrastructure data must be protected.

A digital MRV workflow for eco-subsidies may include the following stages:

1. Registration of the participant, land parcels, fields, or operational units.
2. Connection of data sources, including cadastral layers, remote sensing, IoT telemetry, field logs, or routing outputs.
3. Establishment of baseline conditions.
4. Definition of eligible sustainability indicators.
5. Monitoring during the reporting period.
6. Calculation of performance metrics.
7. Automated quality control and anomaly detection.
8. Submission of digital report.
9. Independent or administrative verification.
10. Payment, tax credit, or compliance recognition.
11. Archiving digital evidence for future audit and longitudinal analysis.

This workflow illustrates that digital MRV is not only a reporting tool. It is a governance infrastructure. It allows policy to move from paper declarations to evidence-based performance. At the same time, it creates a historical dataset for future planning, research, and evaluation. This data value must be recognized as part of the economic effect of digital environmental management.

In Ukraine, digital MRV is particularly important given the post-war recovery and EU integration. Reconstruction programs, environmental damage assessment, agricultural modernization, and access to European markets will increasingly require reliable evidence. Ukraine will need to demonstrate not only that reforms have been adopted, but that they produce measurable results. Digital MRV can support this by connecting field-level evidence with municipal, regional, national, and international reporting needs. However, this requires strong institutional design. Data must be credible, secure, interoperable, and legally recognized.

Policy mechanisms for scaling digital environmental management must reflect uncertainty. In stable environments, incentives can be designed around predictable costs, yields, logistics, and institutional procedures. In Ukraine, uncertainty is higher. War and post-war recovery affect land access, infrastructure conditions, logistics routes, environmental damage, data availability, investment capacity, labor mobility, and public finance. Climate change and market volatility add further uncertainty. Therefore, policy mechanisms must be resilient and adaptive.

The first requirement is scenario-based policy design. Incentives and eco-subsidies should be tested under alternative scenarios: normal conditions, fuel-price stress, drought stress, infrastructure disruption, restricted access, sensor failure, and data gaps. This is consistent with the monograph's methodological emphasis on scenario analysis and robustness testing. A policy instrument that works only under ideal data conditions may fail in practice. For example, a subsidy that requires UAV verification may be unusable in areas where UAV flights are restricted. A monitoring payment that depends on continuous IoT data may fail where connectivity is unstable. A routing incentive may need alternative evidence when GPS or road-access data are incomplete.

The second requirement is redundancy. Digital environmental policy should allow multiple evidence pathways. Water-efficiency performance may be verified through IoT telemetry, irrigation logs, weather data, and crop indicators. Land-use compliance may be verified through cadastral data, satellite imagery, field records, and administrative decisions. Routing compliance may be verified through route logs, hard-mask outputs, task records, and fuel data. Redundancy reduces dependency on a single technology and increases resilience.

The third requirement is risk-adjusted support. Farms and communities operating in high-risk territories may need greater support or more flexible eligibility criteria. A uniform policy may unintentionally disadvantage actors facing war-related restrictions, damaged infrastructure, or higher data-collection costs. This does not mean weakening accountability. It means adapting the verification method to real conditions. The same sustainability objective may require different digital pathways depending on the level of territorial risk.

The fourth requirement is protection against opportunism. Uncertainty can create opportunities for manipulation. If payments are based on self-reported data without verification, the system becomes vulnerable. If models are too opaque, users may not trust them. If audits are too weak, false claims may spread. Therefore, policy mechanisms must combine flexibility with traceability. Every claim should include a data source, method, timestamp, and audit path. Where data are estimated rather than measured, this should be declared.

The fifth requirement is gradual implementation. Digital environmental policy should not impose full-scale requirements before institutions and users are ready. A phased roadmap is more appropriate. The first phase may establish baseline data and voluntary reporting. The second phase may introduce pilot incentives and simplified metrics. The third phase may introduce performance-based payments for verified indicators. The fourth phase may integrate digital metrics into tax instruments, environmental compliance, and market certification. This sequence allows learning and reduces resistance.

Scaling digital environmental management requires a clear distribution of roles among public authorities, local governments, farms, cooperatives, technology providers, auditors, universities, and international partners. Without such distribution, policy mechanisms become fragmented.

The state should define the legal framework, data-governance rules, interoperability requirements, fiscal instruments, subsidy principles, and audit procedures. It should also ensure that public registries and environmental data infrastructures are reliable. The state should not attempt to control every operational dataset. Still, it must define which data are official, which data can be used for policy purposes, and how digital evidence is verified.

Local governments and territorial communities should play a key role in land-use planning, local environmental monitoring, public-service digitization, and coordination with farms. They are closest to the territories where land-use conflicts, water stress, infrastructure gaps, and ecological risks occur. Digital environmental management at the community level may include cadastral integration, green-zone monitoring, environmental-risk mapping, local dashboards, and support for cooperative digital services.

Farms and agricultural enterprises are the primary operational users of digital tools. They generate data, implement interventions, adjust production practices, and bear many adoption costs. Policy mechanisms should recognize their role not only as beneficiaries but also as data producers and environmental managers. This requires fair rules for data ownership, access, consent, and value sharing.

Cooperatives and producer organizations can reduce the cost of digital adoption. They can operate shared monitoring systems, advisory services, data platforms, machinery-routing systems, and sustainability reporting tools. For small and medium-sized farms, cooperative digital infrastructure may be the most realistic scaling pathway. Policy should support this model through targeted grants, tax recognition, and simplified collective reporting.

Technology providers should be required to meet interoperability, cybersecurity, data portability, and auditability standards. Public support should not create vendors lock-in. A farm or municipality receiving public funds for digital environmental tools should not be trapped in a closed platform that prevents data export, verification, or integration with public systems. Therefore, procurement and subsidy rules require open interfaces, metadata, and documented data models.

Universities and research institutions should contribute methodology, validation, training, and independent evaluation. They can help design indicators, test shadow-price assumptions, validate remote sensing and IoT methods, develop MCDA models, and support pilot projects. In the Ukrainian context, universities can serve as bridges between public policy, local communities, farms, and international scientific standards.

Independent auditors and certification bodies should verify claims where financial payments, tax benefits, or market labels are involved. However, audit systems must be proportionate and risk based. Not every small claim requires a full audit. Digital systems can automate part of the verification, while more complex cases require expert review.

International partners can support infrastructure, standards, capacity building, and alignment with European policy requirements. However, external support should strengthen national data sovereignty and institutional capacity rather than create parallel systems that disappear after project funding ends.

A practical roadmap for scaling digital environmental management through policy mechanisms may be organized into five stages. The first stage is diagnostic. At this stage, the state, regions, and communities identify priority environmental management problems, including water stress, soil degradation, land-use conflicts, logistics inefficiencies, emissions, data fragmentation, and weak reporting. Existing digital tools, data sources, institutional capacities, and cost barriers are mapped. The output of this stage is a national and regional digital environmental-readiness profile.

The second stage is standardization. At this stage, common data standards, metadata requirements, interoperability protocols, definitions of digital sustainability metrics, and audit principles are developed. The objective is not to centralize all data, but to ensure that data can be interpreted and reused. The output is a set of policy-ready digital metric passports and data-governance rules.

The third stage is piloting. At this stage, selected communities, farms, cooperatives, and public agencies test the effectiveness of incentive mechanisms. Pilots should include farms of different sizes, regions, environmental challenges, and digital maturity levels. The purpose is to test not only technical feasibility but also administrative cost, user acceptance, data quality, and policy relevance. The output is evidence of which mechanisms work, under what conditions, and for whom.

The fourth stage is performance-based scaling. At this stage, eco-subsidies, tax credits, concessional finance, and procurement preferences are linked to verified digital sustainability metrics. Programs should use a combination of baseline support and performance payments. The output is a functioning system were digital environmental data influences economic decisions.

The fifth stage is institutional integration. At this stage, digital sustainability metrics become part of regular agricultural policy, environmental reporting, land-use planning, reconstruction finance, and EU-aligned governance. The objective is to move from pilot projects to institutional routines. The output is a stable digital ecosystem for environmental management.

Table 6.7. Strategic roadmap for policy scaling of digital environmental management

Stage	Main objective	Policy instruments	Key outputs	Main risk
1. Diagnostic	Identify problems, data gaps, and institutional capacity	Readiness assessment, stakeholder mapping, baseline studies	Digital environmental-readiness profile	Underestimating hidden costs
2. Standardization	Define metrics, data rules, and audit logic	Metric passports, FAIR/OGC requirements, metadata rules	Common sustainability metric framework	Over-complex standards
3. Piloting	Test instruments in real conditions	Pilot eco-subsidies, digital vouchers, cooperative platforms	Evidence on feasibility and cost	Pilot capture by large actors

Stage	Main objective	Policy instruments	Key outputs	Main risk
4. Performance scaling	Link support to verified outcomes	Eco-subsidies, tax credits, concessional finance	Outcome-based policy system	Weak verification or excessive bureaucracy
5. Institutional integration	Embed digital metrics into governance	Reporting systems, public registries, EU-aligned MRV	Stable digital environmental governance	Fragmentation and loss of trust

Source: prepared by the authors.

This roadmap should be interpreted as a governance sequence rather than a rigid plan. Regions and sectors may move at different speeds. Some communities may already be ready for performance-based support. Others may first need basic data infrastructure and training. The key is to avoid two extremes: waiting for perfect digital capacity before acting and scaling financial incentives before the evidence system is reliable.

Policy mechanisms for scaling digital environmental management must include safeguards. Without safeguards, digital environmental policy can produce new inequalities, privacy risks, excessive bureaucracy, or false environmental claims. The first safeguard is data protection. Agricultural and environmental data may reveal sensitive information about production, land value, infrastructure, logistics, ecological risks, and business strategy. Policy systems must define access levels, anonymization rules, aggregation procedures, and cybersecurity requirements. The second safeguard is farmer autonomy and consent. Digital systems should support decision-making, not replace the agency of land users and managers. Where data is used for public payments or compliance, consent and legal obligations must be clear. Farmers should know which data are used, why, by whom, and with what consequences.

The third safeguard is anti-greenwashing control. Digital dashboards and sustainability labels can create an appearance of environmental performance without real change. Policy should require evidence of outcomes, not only attractive visualizations or declarations. Auditable metrics are essential for preventing greenwashing. The fourth safeguard is inclusiveness. Small farms, communities with weak infrastructure, and high-risk regions should not be excluded from support because they cannot meet advanced digital requirements immediately. Policy should provide simplified pathways, cooperative models, and capacity-building support.

The fifth safeguard is algorithmic transparency. If public payments or compliance decisions depend on digital models, the model's logic must be explainable. This does not require publishing all software code in every case, but it does require clear documentation of indicators, weights, thresholds, assumptions, and appeal procedures.

The sixth safeguard is separation between advisory and enforcement functions where appropriate. Farmers may be more willing to share data for advisory purposes than for enforcement. If every data point is treated as a compliance risk from the outset, users may avoid participation. Policy design must balance trust and accountability.

For Ukraine and other transition economies, scaling digital environmental management requires a delicate balance among modernization, institutional trust, and economic feasibility. It is not sufficient to copy instruments from more institutionally mature systems. Policy mechanisms must account for fragmented data, uneven digital infrastructure, differences in farm size, wartime and post-war constraints, fiscal limitations, and the strategic importance of EU integration.

Ukraine has several advantages. It has strong agricultural capacity, developed geospatial and land-management expertise, growing experience with digital public services, and a clear strategic incentive to align with European standards. It also has urgent practical needs: environmental damage assessment, land restoration, reconstruction planning, agricultural resilience, logistics optimization, and transparent use of public and international funds. Digital environmental management can serve all these needs if coherent policy mechanisms support it.

However, the risk of fragmented digitalization remains high. Separate projects may create dashboards, platforms, registries, monitoring tools, and reporting forms without interoperability. Such fragmentation would reduce the economic value of digital tools and increase transaction costs. Therefore, public policy should prioritize shared standards, reusable data infrastructure, and auditable metrics. The objective is not to create a single centralized system for everything, but to build a coordinated ecosystem in which different systems can exchange evidence and support decisions.

The Ukrainian policy model should therefore combine investment support, performance incentives, tax instruments, digital MRV, cooperative platforms, and institutional safeguards. It should support both farm-level efficiency and public environmental governance. It should recognize data as a productive and institutional asset. It should connect sustainability metrics with EU integration, recovery finance, land-use planning, and agricultural competitiveness. Most importantly, it should reward verified outcomes rather than formal digital adoption.

The analysis of policy mechanisms for scaling digital environmental management confirms that digital tools become economically and environmentally significant only when they are embedded in an appropriate incentive system.

Technologies alone do not guarantee sustainability. They must be connected to policy instruments that reward measurable resource efficiency, environmental risk reduction, compliance, data quality, and institutional transparency.

Incentives are needed to reduce the initial cost and uncertainty of adoption. Eco-subsidies are needed to reward verified environmental performance. Tax instruments are needed to modify the cost structure of digital investment and ecological pressure. Auditable digital sustainability metrics are needed to transform data into policy-relevant evidence. Digital MRV is needed to make payments, reporting, and compliance credible. Institutional safeguards are needed to protect data rights, avoid greenwashing, preserve trust, and ensure inclusiveness.

For Ukraine, the strategic importance of these mechanisms is especially high. Digital environmental management can support agricultural modernization, land governance, post-war recovery, environmental damage assessment, EU integration, and resilient regional development. However, this will occur only if digital tools are not treated as isolated innovations. They must be integrated into a policy architecture that combines economic efficiency, environmental responsibility, institutional readiness, and auditable evidence.

The general policy conclusion can therefore be formulated as follows: the scaling of digital environmental management requires a transition from technology-based support to evidence-based support. Public policy should not reward the mere possession of digital tools. It should reward the verified capacity of those tools to reduce environmental pressure, improve decision timing, protect natural resources, lower transaction costs, support compliance, and create reusable data for sustainable governance. In this sense, incentives, eco-subsidies, tax instruments, and digital sustainability metrics are not separate instruments. They are components of one strategic mechanism for converting digital evidence into sustainable economic development.

The policy problem of scaling digital environmental management is not only about regulating technologies. It is about making environmentally desirable behavior economically rational, administratively simple, and empirically verifiable. Traditional environmental policy often oscillates between two instruments: command-and-control regulation and general financial support. The first can define obligations but may become burdensome if verification is manual and poorly targeted. The second can encourage adoption but may subsidize activity without measuring results. Digital environmental management enables a third model: incentive-compatible governance based on auditable metrics.

Incentive-compatible governance means that public support, regulatory relief, tax benefits, or market access are linked to evidence that can be independently verified. The evidence does not need to be perfect; it must be sufficiently reliable, proportionate to the decision, contestable, and reproducible. This is the point at which digital land administration, remote sensing, telemetry, and routing become policy infrastructure. They allow the state and market actors to move from declared practices to measured performance.

The EU is moving in this direction, though unevenly. CAP 2023-2027 introduced eco-schemes as a major instrument for rewarding climate, environmental, and animal-welfare practices. IACS and LPIS increasingly provide the data infrastructure for payment verification, while area monitoring based on Sentinel imagery reduces dependence on physical field checks. The Carbon Removals and Carbon Farming Regulation establishes a voluntary certification framework for carbon removals and carbon farming. The Soil Monitoring Law creates a harmonized soil-monitoring horizon for Member States, and the Nature Restoration Regulation requires area-based restoration measures. Together, these instruments do not yet form one unified system, but they create a policy environment in which environmental payments, monitoring data, and digital auditability are becoming increasingly inseparable.

For Ukraine, the relevance is twofold. First, accession requires institutional alignment: cadastral, LPIS, IACS, environmental, soil, climate, and subsidy systems must be compatible with EU expectations. Second, reconstruction and modernization require cost-effective instruments that can channel public, donor, and private finance toward measurable environmental outcomes. Ukraine cannot afford a model in which each subsidy, restoration project, land-control action, or agrarian investment builds its own evidence chain. The country needs a shared audit architecture.

Eco-subsidies should not be designed as payments for possessing digital tools. A farm should not be rewarded merely for buying sensors, subscribing to satellite analytics, or installing software. These are inputs. The public interest lies in outcomes and credible practices: reduced nutrient losses, preserved soil cover, lower water stress, verified buffer zones, avoided plowing of protected areas, improved trajectories of organic matter, reduced fuel intensity, protected service windows, and documented compliance with land-use restrictions. Digital tools should be subsidized only to the extent that they reduce the cost of producing trustworthy evidence or enable practices that would otherwise be difficult to verify.

This distinction is important because vendors or large farms can capture technology subsidies without generating public ecological value. A better design is a two-layer subsidy. The first layer supports digital capacity where market failure is clear: small farms, cooperatives, municipalities, advisory services, and public-good data infrastructure. The second layer rewards verified environmental performance. For example, a cooperative may receive support for a shared remote-sensing and soil-monitoring service, while farms receive payments only when the service documents eligible practices or outcomes. This design reduces exclusion while maintaining performance discipline.

Result-based payments are attractive but cannot be applied mechanically. Some environmental outcomes, such as changes in soil organic carbon, are slow and uncertain; others, such as the presence of vegetative cover during erosion-risk periods, can be monitored more directly. A mature system should combine practice-based, result-based, and risk-based elements. Practice-based payments are suitable where practices are known to produce environmental benefits, but outcomes are difficult to measure annually. Result-based payments are suitable where metrics can be measured with sufficient reliability. Risk-based instruments are suitable for inspection and control, where digital evidence identifies areas that require attention rather than automatically imposing sanctions.

Digital metrics can also reduce the administrative burden of environmental support. If evidence is automatically generated through LPIS, satellite time series, cadastral restrictions, farm logs, and sensor data, farmers should not be required to submit the same information repeatedly in different formats. The policy principle should be once-only reporting with controlled reuse. This principle is central to a fair digital transition: the state receives better evidence, but the compliant farmer receives fewer forms, fewer duplicate inspections, and faster payments.

Table 6.8. Policy mechanisms for scaling digital environmental management

Mechanism	Economic logic	Digital evidence required	Ukraine-specific design note
Eco-subsidies for verified practices	Internalize positive externalities that markets do not pay for: soil protection, reduced runoff, biodiversity support, and lower emissions.	Remote-sensing indicators, cadastral restrictions, land-cover classification, farm operation logs, and periodic field validation.	Start with practices that can be verified reliably: buffer-zone protection, cover crops, grassland preservation, non-plowing of protected areas, and digital nutrient plans.
Result-based payments	Reward measured environmental outcomes rather than inputs or declarations.	Indicator baselines, monitoring time series, confidence intervals, validation samples, and audit rules.	Use cautiously for slow variables such as soil carbon; combine with practice requirements and multi-year baselines.
Digital vouchers and advisory credits	Lower adoption barriers for small and medium farms and communities.	Proof of service use, interoperable data output, and documented advisory recommendations.	Target cooperatives, communities, and farms below a defined scale; require open export formats and anti-lock-in clauses.
Accelerated depreciation and green tax credits	Reduce the after-tax cost of digital upgrades that produce public environmental data or verified resource savings.	Invoices, technical specifications, data output evidence, and a sustainability use case.	Limit eligibility to interoperable equipment and services that produce auditable data.
Concessional loans and guarantees	Address high upfront capital costs and credit constraints.	Investment plan, expected environmental indicators, data governance plan, and reporting protocol.	Combine with the Ukraine Facility, reconstruction finance, and development-bank instruments.
Risk-based inspection relief	Reward compliant actors with fewer physical inspections while focusing control on high-risk cases.	Risk scores, remote-sensing anomaly detection, inspection history, and cadastral/legal context.	Implement desk-based checks for low- and medium-risk, with field inspections for verified high-risk anomalies and appeal rights.
Public procurement of data commons	Create reusable base infrastructure rather than repeating project-specific datasets.	Metadata, APIs, data lineage, accuracy reports, licenses, and service-level agreements.	Prioritize national geospatial layers, soil monitoring, crop maps, water-stress indicators, and restriction datasets.
Carbon-farming certification support	Farms enabled to participate in emerging carbon and climate-finance mechanisms.	Baseline, additionality evidence, permanence/risk assessment, monitoring data, and independent verification.	Avoid premature carbon-credit claims; build national MRV capacity aligned with the EU CRCF logic.

Source: prepared by the authors.

Tax instruments can support scaling when they are transparent, targeted, and linked to measurable public value. The simplest instrument is accelerated depreciation for eligible digital environmental equipment, including sensors, telemetry, GNSS, weather stations, data storage systems, environmental monitoring devices, and interoperable software. This reduces the cost of capital without requiring the state to select individual vendors. However, eligibility must be tied to technical standards and data-output requirements. Otherwise, depreciation becomes a general technology subsidy unrelated to sustainability.

A second instrument is a tax credit or deduction for verified environmental-management services. Instead of subsidizing hardware, the tax system can support recurring services that maintain data quality: soil testing, remote-sensing analytics, calibration, environmental advisory, audit preparation, and certified data stewardship. This is often more economically rational because the value of digital environmental management lies in continuous use rather than one-time acquisition.

A third instrument is differentiated land or environmental taxation. In principle, land-tax adjustments can reward compliance with verified protective regimes or penalize persistent degradation. In practice, such instruments require caution. Tax incentives based on environmental indicators must be predictable, legally robust, and resistant to measurement error. They should not punish a farmer for weather-driven anomalies, war-related constraints, or inherited degradation that cannot be corrected in the short term. The preferred first step is not punitive environmental taxation but reducing administrative burdens and providing targeted benefits for participation in auditable sustainability systems.

A fourth instrument is fiscal conditionality for public support. Public investment grants, reconstruction funds, irrigation modernization, rural infrastructure projects, or concessional loans should include digital evidence obligations where relevant. This does not mean excessive reporting. It means that publicly supported projects should produce reusable geospatial and environmental data, including updated boundaries, infrastructure layers, water-use indicators, soil-risk data, compliance records, and route or logistics data, where appropriate. In this way, public money builds data capital and physical assets.

Ukraine's fiscal roadmap should also account for donor and EU financing. The Ukraine Facility and other reconstruction instruments can support green and digital transition, but their effectiveness will depend on whether financed projects are interoperable with national systems. Each project that creates a closed dataset or proprietary monitoring architecture increases future integration costs. Therefore, interoperability and data reuse should be eligibility criteria for public- and donor-funded digital environmental projects.

Auditable metrics are the foundation of incentive-compatible scaling. A metric is auditable when its definition is clear, its data sources are known, its calculation is reproducible, its uncertainty is stated, its spatial and temporal boundaries are explicit, and its result can be contested or independently verified. This is more demanding than producing a dashboard. A dashboard may visualize data; an audit metric must support a decision.

The monograph's previous chapters identified several families of metrics: transaction-cost reduction, input savings, yield protection, CO_2e stability, service-window feasibility, compliance with hard masks, and reduced operational risk. At the scaling stage, these metrics must be translated into policy categories. Some metrics are operational and useful for farms. Some are administrative and useful for agencies. Some are environmental and useful for subsidy or reporting systems. Some are institutional and useful for measuring the performance of digital governance itself. A mature roadmap must avoid the error of one universal sustainability index. Different decisions require different metrics with different evidentiary thresholds.

The first family is land-governance metrics: completeness of cadastral coverage, share of restrictions represented as machine-readable layers, number of procedures completed without manual document exchange, average time for parcel verification, rate of boundary conflicts, and rate of automated consistency checks. These metrics are part of the institutional infrastructure for sustainability. They do not directly measure soil or water conditions, but they determine whether environmental rules can be applied in space.

The second family is environmental condition metrics: soil-cover duration, erosion-risk exposure, water-stress indicators, vegetation-anomaly persistence, nutrient-loss proxies, protected-area disturbance, land-cover conversion, and field-level carbon-related indicators. These metrics require remote sensing, field validation, historical baselines, and uncertainty management. They should be used differently for advisory, subsidy, and enforcement purposes. Advisory use may tolerate lower certainty; sanctions require stronger evidence and due-process safeguards.

The third family is resource-efficiency metrics: water use per hectare, fertilizer intensity adjusted for yield, pesticide application intensity, fuel per ton-kilometer or hectare serviced, machinery idle time, and input reduction without yield loss. These metrics are close to economic efficiency and can often be integrated with farm records. Their policy value is high because they connect environmental performance to cost savings.

The fourth family is compliance and risk metrics: share of high-risk anomalies inspected, confirmation rate of digital risk alerts, average time from detection to administrative action, share of repeated violations, and proportion of inspections replaced by desk-based checks. These metrics are particularly relevant to the uploaded analytical notes, which proposes a risk-scoring model based on remote-sensing indicators, API exchange with cadastral and LPIS-type systems, and public performance dashboards.

The fifth family is governance metrics: interoperability compliance, percentage of datasets with metadata, API uptime, number of reusable data services, algorithm validation accuracy, appeal outcomes, data-breach incidents, and cost per verified environmental outcome. These metrics measure the state itself. Without them, digital environmental management risks evaluating farmers while leaving public systems unevaluated.

Table 6.9. Auditable sustainability metric families for scaled digital environmental management

Metric family	Illustrative indicators	Primary data sources	Main policy use	Audit safeguard
Land-governance metrics	Machine-readable restrictions; parcel verification time; boundary conflict frequency; completeness of functional zones.	Cadastre, planning datasets, restriction registers, transaction logs.	Land-use planning, compliance pre-checks, and investment screening.	Versioned geodata, legal provenance, and change history.
Environmental condition metrics	Soil cover, vegetation anomalies, erosion-risk exposure, water-buffer disturbance, and land-cover conversion.	Sentinel-1/2, Copernicus layers, UAV imagery, field samples, soil datasets.	Eco-subsidies, advisory services, environmental control, and restoration planning.	Validation samples, uncertainty bands, temporal baselines, and appeal procedures.
Resource-efficiency metrics	Water use per hectare, fertilizer intensity, fuel per service unit, and input savings without yield loss.	IoT telemetry, farm logs, machinery data, irrigation records, yield maps.	Tax incentives, credit scoring, advisory programs, and enterprise efficiency evaluation.	Cross-checks with production records and proportional privacy protection.
Compliance and risk metrics	Risk score, confirmed violation rate, detection-to-action time, and share of desk-based checks.	Inspection systems, remote sensing, cadastre, and environmental registers.	Risk-based supervision and reduction of administrative burden.	Algorithm certification, human review for high-consequence decisions, and transparent rules.
Governance metrics	API uptime, metadata completeness, interoperability compliance, cost per verified outcome, and appeal success rate.	Registry logs, service monitoring, audit reports, and procurement records.	Evaluation of public digital infrastructure and donor-funded programs.	Independent audit, open technical documentation, and public aggregate dashboards.

Source: prepared by the authors.

One of the most important applications of digital environmental management in Ukraine is modernizing state supervision. Traditional inspection models are spatially limited, expensive, and vulnerable to discretion. They depend on inspectors' ability to physically visit territories and detect violations in a timely manner. This model is poorly suited to a country with extensive agricultural land, wartime safety constraints, environmental damage, limited administrative resources, and the need to reduce regulatory pressure on compliant businesses.

Remote-sensing-based supervision changes the inspection logic. Instead of selecting objects primarily through plans or complaints, the state can pre-screen territories using Sentinel imagery, land-cover classification, NDVI or SAR change indicators, cadastral restrictions, water-protection zones, and historical land-use baselines. The result is not automatic punishment, but risk prioritization. High-risk anomalies receive attention; low-risk objects face fewer unnecessary visits. This logic is consistent with the analytical note's proposal to move toward a risk-oriented digital model in which Earth-observation data, algorithmic classification, R1-R5 risk gradation, API exchange, and performance dashboards support supervisory planning.

The legal design must be careful. Remote-sensing evidence should have different legal weights depending on the decision. For advisory warnings, preliminary detection may be sufficient. For inspection scheduling, a validated anomaly and cadastral context may be sufficient. For sanctions, the evidence should meet higher standards: documented data source, acquisition time, processing method, algorithm version, accuracy assessment, human review, opportunity for the land user to respond, and compatibility with procedural law. This hierarchy prevents both underuse and misuse of digital evidence.

The economic value of risk-oriented supervision is threefold. First, it reduces control costs by replacing part of the physical inspection with desk-based screening. Second, it reduces the burden on compliant actors by focusing field visits on higher-risk cases. Third, it increases deterrence because violations that are visible from space become harder to hide. The uploaded analytical note estimates potential reductions in administrative burden and budget savings under such a model; these estimates should be treated not as guaranteed outcomes but as policy-relevant benchmarks requiring empirical validation during implementation.

For EU alignment, Ukraine should avoid building remote-sensing supervision as an isolated enforcement tool. It should be connected to LPIS/IACS-type area monitoring, environmental reporting, soil monitoring, agricultural advisory services, and subsidy verification. The same data event may have several meanings: a crop-classification anomaly may be an advisory signal, a subsidy cross-check issue, an environmental risk, or a land-use compliance concern. A well-designed system legally separates these uses while technically reusing the underlying evidence.

The most advanced stage of scaling is data-space governance. A data space is not simply a database. It is an institutional environment in which data holders, users, intermediaries, and public authorities exchange data under agreed technical, legal, and governance conditions. For digital environmental management, data spaces can connect public geodata, farm-level data, remote-sensing products, environmental observations, research datasets, machinery data, and policy metrics without forcing them into one ownership regime.

European policy increasingly treats data spaces as instruments of strategic autonomy, innovation, and sustainability. The Green Deal Data Space, the agricultural data space, and other common European data spaces are designed to make data available in secure, trustworthy environments. Ukraine's accession-oriented roadmap should therefore consider not only alignment with individual EU regulations but participation in the broader data-space paradigm. This requires more than data publication. It requires trusted access control, interoperability standards, metadata, licensing, identity management, data intermediaries, certification, and dispute-resolution mechanisms.

In agriculture, the data-space approach can address a recurring conflict. Farmers generate valuable operational data but may fear losing control over it. Public authorities need reliable indicators but cannot collect all information directly. Researchers and technology providers need access to data for innovation but cannot rely on informal exchanges. A data space can create controlled sharing: aggregated indicators for public reporting, pseudonymized datasets for research, verified metrics for subsidies, and private operational data retained under farmer control. This architecture is more compatible with sovereignty than either full openness or full closure.

Ukraine can begin with a national environmental-agricultural data commons. The commons would not absorb all private data. It would define priority public layers and shared services: cadastral base layers, land-cover maps, crop classification, soil-risk layers, water-stress indicators, protected-zone layers, field-boundary services, historical change detection, metadata catalogs, and algorithm validation datasets. Around this commons, private and cooperative services could build specialized analytics, advisory tools, and compliance products. The public sector would finance and govern the commons; the market would innovate on top of it.

This model also helps to manage donor coordination. International reconstruction and environmental programs often create project datasets that disappear after implementation or remain inaccessible. A national data commons would require funded projects to deliver reusable outputs in standard formats, with metadata and licensing. Each project would therefore contribute to cumulative national capacity rather than isolated reports. For Ukraine, where reconstruction and EU integration will involve many donors, this requirement is not technical bureaucracy; it is a condition for avoiding waste.

Table 6.10. From isolated digital projects to a national environmental-agricultural data commons

Element	Isolated project model	Data commons model	Scaling implication
Dataset creation	Each project collects or purchases its own data.	Projects use and improve shared base layers.	Lower duplication and stronger data continuity.
Licensing	Unclear project-specific terms.	Standard licenses with sensitivity-based access tiers.	Higher reuse and lower legal uncertainty.
Metadata	Often incomplete or absent.	Mandatory metadata and provenance.	Auditability and scientific reproducibility.
Interoperability	Vendor-specific formats and interfaces.	OGC/INSPIRE-compatible services and open APIs.	Reduced switching costs and vendor lock-in.
Validation	Project-specific accuracy claims.	Shared validation datasets and certified methods.	Comparable trust across agencies and regions.
Institutional memory	Outputs disappear after project closure.	Outputs persist as national data assets.	Cumulative public value.

Source: prepared by the authors.

The strategic roadmap for Ukraine should not mechanically imitate EU systems. EU Member States themselves differ in cadastral traditions, LPIS design, administrative capacity, environmental priorities, and data-governance maturity. The relevant objective is functional equivalence: Ukraine should be able to produce reliable, interoperable, and auditable environmental-agricultural data for decision-making comparable to that required in the EU. Functional equivalence is more important than institutional mimicry.

By 2030, Ukraine should aim to operate a digital environmental management system that meets five criteria. First, land, environmental, and agricultural data should be connected through stable identifiers and interoperable services. Second, remote sensing should have a clear legal status for advisory, supervisory, and evidentiary purposes. Third, eco-subsidies, tax incentives, and reconstruction finance should require auditable digital outputs. Fourth, small and medium farms should have access to shared digital services so that sustainability metrics do not become a barrier to inclusion. Fifth, public systems themselves should be measured through governance metrics: API availability, metadata completeness, processing time, appeal outcomes, inspection efficiency, and cost per verified outcome.

The EU dimension should be treated as a learning frontier rather than a static target. CAP policy is evolving toward simplification, performance, and stronger use of data. The Vision for Agriculture and Food emphasize competitiveness, resilience, and reduced administrative burden. The Carbon Removals and Carbon Farming Regulation creates incentives for robust MRV. Soil and nature-restoration policies require spatially explicit monitoring. Data legislation expands interoperability and trusted sharing. Ukraine's advantage is that it can design its accession systems after these trends have become visible, rather than retrofitting legacy systems built for older policy paradigms.

This advantage is not automatic. It will be lost if digital systems are procured as closed products, if data sovereignty is confused with data isolation, if remote sensing is introduced without due process, if eco-subsidies pay for technology rather than outcomes, or if small farms are excluded from digital support. It will be realized only if scaling is understood as institutional design. The essential unit of reform is not the sensor, satellite image, dashboard, or algorithm. It is the decision rule that converts evidence into fair, efficient, and environmentally meaningful action.

The final implication is conceptual. Economic efficiency in digital environmental management should be evaluated not only at the project level but also at the governance system level. A digital platform is efficient when it reduces repeated information costs, increases compliance reliability, improves environmental targeting, lowers administrative burden, enables fair incentives, and produces data that can be reused across policy cycles. The strategic roadmap is therefore an investment in state capacity. For Ukraine, this is also an accession strategy: a way to translate European environmental and digital standards into a national architecture suited to recovery, agrarian competitiveness, and long-term stewardship of land, soil, and water resources.

This chapter argued that scaling digital environmental management requires institutionalizing data-driven resource stewardship. The principal barriers are interoperability, data sovereignty, institutional readiness, and the cost of upgrades. These barriers are mutually reinforcing fragmented data reduces trust; weak trust prevents sharing; limited sharing reduces the economic value of digital tools; and low value undermines adoption. Overcoming them requires not a single platform but a layered governance model built on open standards, differentiated access, data stewardship, legal evidence rules, and capacity distribution.

The policy mechanisms proposed in the chapter are designed to turn digital environmental management from an expense into a value-generating system. Eco-subsidies should reward verified practices and outcomes rather than the possession of technology. Tax instruments should reduce the cost of interoperable and auditable digital upgrades. Risk-based supervision should reduce unnecessary inspections while increasing the probability of detecting real environmental violations. Public and donor finance should create reusable data assets rather than isolated project outputs. Sustainability metrics should be auditable, decision-specific, and proportionate to the legal consequences attached to them.

For the European Union, the Ukrainian case illustrates the strategic importance of connecting agricultural policy, environmental monitoring, geospatial data, carbon farming, and digital public administration. For Ukraine, the EU policy environment provides a roadmap but not a template. The task is to build an accession-ready digital environmental management architecture that is lawful, secure, interoperable, economically inclusive, and capable of producing measurable environmental value. This is the point at which the monograph's empirical cases become strategic: land administration, environmental monitoring, and routing optimization are not isolated tools, but components of a governance system in which sustainability becomes measurable, financeable, and enforceable.

Figure 6.7 Digital Twin Visualization concept

CONCLUSIONS

The research conducted in this monograph confirms that the economic efficiency of digital tools in sustainable environmental management cannot be adequately assessed through a narrow financial or technological lens. Digitalization in agriculture, land management, environmental monitoring, and routing is not valuable simply because it introduces new software, sensors, maps, platforms, or algorithms. Its value emerges when digital systems change the quality, timing, reliability, and institutional usability of decisions. In this sense, digital environmental management should be understood as a system of evidence-based coordination among natural resource processes, economic calculation, technological infrastructure, and public governance.

The central conclusion of the monograph is that digital tools enhance economic efficiency by transforming ecological and operational uncertainty into measurable, interpretable, and actionable information. A satellite image, an IoT sensor, a cadastral database, a routing engine, or an analytical dashboard has no independent economic meaning outside the decision process in which it is used. Its efficiency depends on whether it helps reduce resource losses, prevent ecological damage, improve agronomic timing, decrease transaction costs, avoid legal conflicts, support compliance, and strengthen the resilience of agricultural and peri-urban systems. Therefore, digital tools should be evaluated not as isolated technologies, but as components of a broader environmental-economic decision infrastructure.

The theoretical analysis demonstrated that sustainable environmental management requires an expanded understanding of efficiency. Classical economic approaches often treat efficiency as the relation between output and paid inputs, or as the ratio between monetary benefits and monetary costs. Such an interpretation remains important, but it is insufficient for environmental management because many of the highest costs are not immediately reflected in market prices. Soil degradation, water stress, carbon emissions, biodiversity loss, landscape fragmentation, delayed agronomic interventions, and weak institutional trust can remain invisible in short-term accounts while generating substantial long-term losses. The monograph, therefore, argues that economic efficiency must include not only current financial performance but also preservation of ecological productivity, reduction of externalities, and the ability of institutions to use reliable evidence for decision-making.

The transition from linear resource use to circular resource economies is one of the conceptual foundations of this expanded approach. In a linear agrarian model, economic growth is often achieved by increasing throughput: more inputs, more energy, more machinery movement, more extraction, and more pressure on soils, water, and ecosystems. Such a model may produce short-term private gains, but it postpones costs into the future and transfers them to society, communities, public budgets, and future producers. In contrast, a circular, sustainability-oriented model seeks to retain ecological and material value within the productive system. It reduces leakage, prevents avoidable waste, supports nutrient and water efficiency, preserves soil quality, and makes environmental performance part of the management logic. Digital tools are relevant to this transition only when they help close this gap between production and ecological accounting.

The analysis of Agriculture 4.0 and smart farming further showed that digital agriculture should not be interpreted as a collection of independent technical devices. It is more accurately understood as a digital toolscape: a layered configuration of sensors, satellite data, UAV diagnostics, cadastral layers, machinery telemetry, cloud infrastructure, artificial intelligence, decision-support models, dashboards, standards, and institutional users. The economic value of this toolscape lies in the chain that links measurement, interpretation, prescription, and verification. Measurement expands the range of observable signals. Interpretation converts raw data into indicators, thresholds, risks, and classifications. Prescription supports operational or policy decisions. Verification documents what was done, where, when, and with what result. Only this full chain creates sustainable digital value.

The monograph also demonstrates that environmental externalities must be incorporated into economic evaluation before they become visible as direct damage, penalties, yield losses, or public remediation costs. CO_2e emissions, soil degradation, water stress, resource depletion, and loss of ecosystem functions are not supplementary environmental indicators added after the main calculation. They are constitutive variables of long-term economic efficiency. Digital environmental management creates value when it makes these externalities observable and connects them to decision rules. In this respect, digital evidence is not merely a reporting instrument; it is a mechanism for internalizing costs that would otherwise remain hidden, delayed, or transferred to other actors.

A particularly important conclusion concerns the role of institutions in transition economies. Digital tools cannot generate sustainable efficiency if they operate in an environment of fragmented data, weak registries, unclear rights, poor interoperability, low trust, or unstable regulatory incentives. In Ukraine, this issue is especially significant because agricultural modernization, land reform, environmental recovery, EU integration, and wartime resilience are interconnected. Digital environmental management must therefore be assessed not only by technical accuracy or farm-level savings, but also by institutional credibility, data sovereignty, legal traceability, transparency, and compatibility with European policy frameworks. The efficiency of a digital tool is reduced when its data cannot be trusted, audited, legally interpreted, or reused.

The methodological framework developed in the monograph responds to this complexity by combining extended cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario simulation. This combination is necessary because no single method can fully capture the economic effect of digital environmental tools. Classical cost-benefit analysis can measure investment and operating costs, as well as direct savings, but it often underestimates environmental, temporal, informational, and institutional effects. Multi-criteria decision analysis allows the comparison of alternatives when cost, time, CO_2e emissions, risk, spatial constraints, data quality, and institutional feasibility must be considered simultaneously. Shadow pricing enables assigning monetary value to non-market effects, such as avoided ecological damage, protected service windows, reduced risk, and improved compliance. Scenario simulation tests whether digital tools remain efficient under uncertainty.

The adapted cost-benefit logic proposed in the monograph expands the benefit side of digital agritech evaluation. It includes direct financial benefits, environmental benefits, time benefits, data benefits, risk-reduction benefits, and institutional benefits. This structure reflects the real way in which digital systems produce value. An IoT monitoring system may save water, protect yield, reduce unnecessary field visits, create historical data, support sustainability reporting, and reduce uncertainty. A digital cadastre may reduce administrative time but also prevent land-use conflicts, improve tax and valuation functions, increase legal certainty, and support recovery planning. A route system may reduce fuel costs while also preserving agronomic service windows, avoiding restricted areas, stabilizing logistics, and providing auditable operational records. These combined effects justify the use of an extended evaluation framework.

The monograph’s multi-criteria spatial-economic assessment confirms that sustainable environmental decisions rarely rest on a single dominant criterion. The cheapest option is not necessarily the most efficient if it increases environmental risk, violates spatial restrictions, delays intervention, or produces unreliable data. The shortest route is not necessarily optimal if it crosses a restricted area, increases risk, or misses an agronomic time window. The most detailed monitoring system is not necessarily the most efficient if it is too expensive, difficult to maintain, legally unusable, or poorly integrated. MCDA is therefore not only a mathematical instrument; it is a method for making decision priorities transparent. It shows which criteria matter, how they are weighted, and how alternatives change under different policies or operational assumptions.

The distinction between hard masks and soft penalties is one of the most important methodological results of the monograph. Environmental and land-use governance cannot treat all constraints as ordinary trade-offs. Some restrictions are non-negotiable because they reflect legal prohibitions, safety requirements, protected areas, military restrictions, unresolved cadastral status, or ecological thresholds. These must be modeled as hard masks that remove an alternative from the feasible set before optimization. Other factors, such as poor road quality, moderate ecological sensitivity, higher transaction costs, uncertainty, or lower accessibility, should be treated as soft penalties that reduce attractiveness without automatically excluding the alternative. This hierarchical logic is essential for compliance-aware digital environmental management.

Shadow pricing provides the third methodological pillar of the monograph. Its use is justified by the fact that many environmental and temporal effects have measurable economic consequences even when they lack direct market prices. Avoided CO_2e emissions, reduced soil degradation, saved irrigation water, protected agronomic windows, avoided restoration costs, and reduced probability of legal or ecological violations all have economic value. The proposed framework does not use shadow pricing to artificially inflate the benefits of digital tools. On the contrary, it requires that each shadow price be transparent, justified, and tested through sensitivity analysis. Direct financial results and shadow-adjusted results should be presented separately so that decision-makers can distinguish between narrow financial efficiency and extended environmental-economic efficiency.

Scenario analysis and simulation complete the methodological framework by addressing uncertainty. Agriculture and environmental management operate under conditions of weather variability, market volatility, fuel-price changes, sensor failures, cloud cover, data gaps, road restrictions, and institutional uncertainty. In Ukraine, these uncertainties are intensified by war-related risks, damaged infrastructure, restricted access to some territories, and rapidly changing logistics. A digital tool that appears efficient under one deterministic assumption may become weak under stress conditions. Conversely, a tool that appears costly under normal conditions may become highly valuable when fuel prices rise, access becomes restricted, or service-window timing becomes critical. Scenario analysis, therefore, allows the researcher to evaluate robustness rather than only average performance.

The first empirical case study, devoted to digital land management and cadastral systems, confirms that environmental-economic efficiency begins with the quality of the spatial-legal representation of land. A digital cadastre is not merely a register of parcels. It is a spatial-economic infrastructure that defines how land rights, restrictions, valuation, planning regimes, environmental obligations, taxation, and investment decisions are represented and reused. The economic effect of such a system is realized through reduced search costs, shorter verification times, reduced conflict, improved compliance, better land allocation, and greater institutional transparency. The value of cadastral digitalization is therefore not limited to the cost of extracts or administrative services. Its deeper value lies in spatial certainty.

The Ukrainian cadastral context demonstrates the importance of this conclusion. Under conditions of land reform, decentralization, wartime risk, post-war recovery, agricultural-market development, and EU approximation, the cadastre must function as more than a departmental information system. It should become a dynamic, interoperable, versioned, and service-oriented spatial core that connects parcels, rights, restrictions, buildings, addresses, valuation, taxation, functional zones, planning decisions, natural-resource data, and environmental constraints. Such a system reduces uncertainty across many economic sectors: agriculture, infrastructure, energy, municipal planning, compensation, taxation, mortgage lending, environmental control, and reconstruction.

The case study also shows that cadastral efficiency must be measured by transaction-cost reduction, conflict prevention, compliance efficiency, fiscal and valuation support, and peri-urban allocation quality. In fragmented land-information environments, actors repeatedly reconstruct the same facts: parcel boundaries, ownership or use rights, restrictions, intended use, valuation, and access conditions. Each reconstruction requires time, expert labor, field checks, document comparison, and legal verification. A reliable digital cadastre reduces this duplication by creating reusable authoritative geodata. Its value grows as the same spatial facts support multiple decisions. This is the infrastructure logic of cadastral efficiency.

The second empirical case study, devoted to IoT telemetry and environmental monitoring, confirms that monitoring becomes economically valuable only when signals are converted into interventions. Satellite imagery, UAV diagnostics, IoT sensors, weather data, and dashboards provide data, but data alone does not save water, protect yield, or reduce environmental pressure. The economic value appears when monitoring supports timely decisions: irrigation, fertilization, spraying, inspection, risk alerts, or localized mitigation. This means that monitoring systems must be evaluated based on input-use reduction, yield protection, avoided delay, improved environmental targeting, reduced field-inspection costs, and the quality of the generated evidence.

The monitoring case also demonstrates the importance of threshold logic and event classification. Environmental and agronomic data must be interpreted through decision rules. A soil-moisture value becomes economically meaningful when it indicates whether irrigation is necessary. A vegetation index anomaly becomes valuable when it indicates the need for a field inspection or a crop protection intervention. UAV imagery becomes useful when it verifies a stress pattern that satellite data cannot explain. Monitoring efficiency, therefore, depends not only on sensor accuracy but also on the quality of the decision rule that links data to action. Without this link, digital monitoring risks becoming a technically impressive but economically underused layer.

The third empirical case study, devoted to spatio-temporal optimization and routing, demonstrates how digital land constraints and monitoring signals can be transformed into operational logistics decisions. Agricultural operations are not only spatially distributed but also time sensitive. Machinery, transport, fuel, labor, road conditions, field accessibility, and agronomic service windows must be coordinated. In peri-urban territories, routing is further complicated by congestion, land-use pressure, environmental restrictions, safety constraints, and competition between urban and agricultural functions. Therefore, routing cannot be reduced to shortest-path calculation. The efficient route is the route that balances direct cost, travel time, CO_2e emissions, risk, compliance, and service-window feasibility.

The Kyiv peri-urban routing simulation confirms this logic. The comparison of baseline, stress, and sustainability-adjusted scenarios shows that fuel-driven cost volatility significantly affects logistics costs, but weighted routing can preserve operational feasibility and spatial compliance. The stress scenario increases direct cost exposure, while the sustainability-adjusted scenario introduces a moderate cost premium. At the same time, travel-time performance remains stable, service-window feasibility stays within acceptable limits, and hard-mask violations remain absent. These results show that the routing model does not eliminate external economic shocks, but it can absorb part of their operational impact by maintaining feasibility, compliance, and decision transparency.

The routing case is especially important because it illustrates how economic, environmental, and institutional criteria can be integrated in a practical operational model. Fuel costs, travel time, emissions, operational risk, service windows, and restricted-edge compliance are integrated into a single decision-support logic. This confirms the monograph’s broader argument: digital environmental tools are most valuable when they connect data, constraints, economic indicators, and actionable decisions. Routing becomes not merely a logistics function, but a practical demonstration of digital environmental management under uncertainty.

Across the three case studies, a common pattern emerges. Digital land management provides the official spatial and institutional base. IoT and remote monitoring provide environmental and operational signals. Routing transforms these signals and constraints into time-sensitive decisions. Strategic roadmaps then define how such tools can be scaled through policy, incentives, data governance, interoperability, and auditable sustainability metrics. This sequence is central to the monograph's scientific novelty. It moves beyond analyzing isolated technologies and instead evaluates digital environmental management as an integrated system.

The strategic scaling analysis confirms that the main barriers to digital environmental management are not only technological. They include interoperability gaps, data sovereignty concerns, cybersecurity risks, institutional fragmentation, uneven digital readiness, financing limitations, maintenance capacity constraints, weak incentives, and insufficient trust in data. These barriers are especially important in transition economies because digital systems often depend on public registries, legal recognition, administrative coordination, and long-term institutional stability. A digital tool that cannot be connected to existing governance systems may produce useful data but fail to create systemic efficiency.

The monograph therefore recommends that digital environmental management be scaled through a combination of technological, institutional, and policy mechanisms. Technological scaling requires interoperable architecture, open standards, APIs, metadata, spatial databases, secure data storage, and reproducible analytical workflows. Institutional scaling requires clear responsibilities, data rights, audit trails, role-based access controls, trusted public registries, and cooperation among farms, local authorities, research institutions, technology providers, and state agencies. Policy scaling requires incentives that reward verified environmental performance, input savings, emissions reduction, compliance, and data-based transparency.

Eco-subsidies, tax instruments, sustainability reporting, and digital audit mechanisms should be designed to reward measurable outcomes rather than the mere purchase of technology. A farm should not be supported only because it installs sensors or uses a platform. Support should be linked to verified reductions in water use, avoided emissions, protected soil, improved compliance, yield protection, or data-sharing practices that strengthen public environmental governance. This shift from technology acquisition to outcome verification is essential for avoiding superficial digitalization.

For Ukraine, the monograph's practical implications are significant. Digital environmental management can support agricultural modernization, land-use governance, post-war recovery, reconstruction planning, environmental damage assessment, and EU integration. However, this requires that digital tools be embedded in a coherent data-governance framework. Cadastral data, satellite observations, IoT telemetry, UAV diagnostics, routing data, environmental restrictions, and economic indicators must be connected through common identifiers, metadata, interoperability standards, and legal procedures. Without such integration, Ukraine risks accumulating disconnected digital modules that do not produce cumulative value.

The European integration dimension reinforces this conclusion. EU policy increasingly requires measurable, comparable, auditable, and interoperable environmental performance. Agriculture, land governance, climate policy, soil monitoring, data regulation, and sustainability reporting are increasingly interconnected. For Ukraine, approximation to this environment requires not only the formal adoption of legal norms, but also practical digital capacity. The country must be able to represent land, resources, restrictions, emissions, interventions, and outcomes as reliable data objects. This is not simply a technical requirement; it is a condition for policy credibility, market access, public investment, and international cooperation.

The scientific contribution of the monograph lies in developing an integrated framework for evaluating digital tools for sustainable environmental management. The work combines environmental economics, institutional economics, land management, spatial analysis, digital agriculture, and decision science. It demonstrates that economic efficiency should be evaluated through direct financial effects, environmental externalities, time-sensitive operational effects, data value, risk reduction, and institutional benefits. It also shows how these dimensions can be operationalized through adapted cost-benefit analysis, multi-criteria decision analysis, shadow pricing, and scenario simulation.

The practical contribution lies in the ability to apply the framework to real decision-making. Farms and cooperatives can use it to justify investments in monitoring, routing, or digital land-management tools. Local authorities can use it to evaluate cadastral modernization, environmental monitoring, and peri-urban planning instruments. Policymakers can use it to design eco-subsidies, tax incentives, and sustainability-reporting mechanisms based on auditable metrics. Researchers can use it to structure empirical studies that combine spatial data, environmental indicators, economic valuation, and simulation. Technology providers can use it to demonstrate value in a transparent and verifiable way.

At the same time, the monograph recognizes several limitations. First, valuing environmental and institutional effects requires assumptions, which may vary by region, crop, market, policy context, and data quality. Second, shadow pricing remains sensitive to selected carbon prices, restoration costs, delay-loss coefficients, and risk probabilities. Third, many digital tools generate long-term data benefits that are difficult to monetize in the short term. Fourth, Ukrainian wartime and post-war conditions create data access restrictions, operational risks, and uncertainty about infrastructure, complicating empirical validation. Fifth, the economic value of digital systems depends strongly on adoption behavior, human capacity, and institutional readiness.

These limitations do not weaken the need for integrated evaluation. On the contrary, they show why narrow deterministic calculations are insufficient. The appropriate response is not to abandon economic evaluation, but to make it more transparent, scenario-based, and sensitive to uncertainty. Future research should therefore expand empirical testing across different regions, farm sizes, crop systems, monitoring configurations, and routing environments. It should also develop stronger local shadow-price databases for soil degradation, water stress, carbon emissions, biodiversity pressure, land-use conflicts, and delay-induced agronomic losses. In addition, future work should strengthen the link between digital environmental metrics and public policy instruments.

A further direction for research is the development of digital twins and interoperable environmental data spaces for Ukrainian agriculture and peri-urban territories. Such systems could combine cadastral parcels, land-use restrictions, Sentinel-based indicators, IoT telemetry, UAV diagnostics, machinery data, weather forecasts, market information, and policy constraints in a single decision environment. Their value would not lie solely in visualization, but also in the ability to test scenarios, estimate costs, evaluate externalities, prioritize interventions, and document compliance. This direction is especially relevant for Ukraine's recovery, EU integration, and sustainable agricultural modernization.

The monograph also points to the importance of data ethics and digital sovereignty. Agricultural and environmental data are economically valuable and institutionally sensitive. They concern land, production, infrastructure, ecological risks, public subsidies, and private business decisions. Therefore, digital environmental management must protect data rights, privacy, cybersecurity, and fair access. Efficiency cannot be achieved by creating dependency on opaque platforms or by transferring data value away from the actors who produce and need the data. Sustainable digitalization requires governance arrangements that balance openness, security, reuse, and accountability.

In conclusion, the monograph confirms its central hypothesis: the economic efficiency of digital tools for sustainable environmental management can be assessed more accurately when financial, environmental, temporal, operational, informational, and institutional effects are evaluated together. Digital land management, environmental monitoring, and spatio-temporal routing become economically meaningful when they reduce uncertainty, improve timing, protect natural resources, prevent conflicts, support compliance, and generate reusable evidence. Their value is not exhausted by direct savings. It lies in transforming environmental management from reactive correction to anticipatory, data-driven, and institutionally accountable decision-making.

The general scientific result of the monograph can be formulated as follows: digital environmental management is economically efficient when it increases the value generated by agrarian and land-use systems without reducing the ecological and institutional conditions on which future value depends. This requires not only technologies, but also methods, standards, incentives, trust, and governance. In the Ukrainian context, such an approach is particularly important because sustainable agriculture, land governance, environmental recovery, digital transformation, and European integration are no longer separate agendas. They form one strategic task: to build a resilient, evidence-based, and economically justified system of environmental management capable of supporting both national recovery and long-term sustainable development.

Project Acknowledgment and Publication Funding Statement

The authors acknowledge that the research presented in this monograph was developed within the scientific and thematic context of the Digi Agrar UA program - *Digital Transformation for Sustainable Development: German-Ukrainian Perspectives for Future Agricultural and Food Systems in Europe*. The program relates to the thematic complex “Diffusion of innovations and knowledge” and covers the project period from 01.01.2025 to 31.12.2025. The investigated geographical and institutional context of the program includes Ukraine, Germany, and the European Union.

The monograph’s research direction aligns with the program's broader objectives by examining the roles of digital transformation, data-driven decision-making, innovation diffusion, and sustainable development in agricultural and food systems. In particular, the work contributes to the analysis of digital tools for sustainable environmental management, land-use planning, agrarian monitoring, and spatio-temporal optimization in the context of Ukrainian and European agricultural transformation.

At the same time, the authors explicitly state that all publication-related expenses, including preparation, editing, formatting, submission, publication, and dissemination costs connected with the authors’ publications and this monograph, were self-funded by the authors. Unless otherwise stated in a specific publication or project document, the scientific publications resulting from this research were not financed from the Digi Agrar UA project budget.

The authors remain fully responsible for the scientific content, methodology, interpretations, conclusions, and recommendations presented in this monograph.

Fair Use, AI-Assisted Tools, and Author Responsibility Statement

All images and diagrams were prepared by the authors based on their research data, unless otherwise noted.

During the preparation of this monograph, the authors used selected digital and AI-assisted tools, including Gemini 3.1, ChatGPT 5.5, and Grammarly, for auxiliary tasks related to text formatting, language refinement, structural organization, editorial consistency, and partial visualization support. These tools were used as supportive instruments in the writing and presentation process, not as autonomous sources of scientific data, empirical findings, or final scholarly interpretation.

All empirical data, case-study materials, numerical indicators, routing-scenario values, land-use data, environmental and economic interpretations, methodological decisions, and scientific conclusions presented in the monograph are based on the authors' own research, prior publications, calculations, analytical materials, and professional expertise. The AI-assisted tools did not generate the underlying datasets, did not replace the authors' scientific analysis, and did not independently determine the research results.

Where AI-assisted tools were used to support visual structuring, diagram preparation, text polishing, or formatting, the resulting materials were reviewed, corrected, selected, and approved by the authors. The authors verified the consistency of the final text with the monograph's research objectives, empirical evidence, and methodological logic.

The use of AI-assisted tools in this work should therefore be understood as part of a transparent, author-controlled editorial and visualization workflow. The authors retain full responsibility for the accuracy, originality, scholarly integrity, ethical use of sources, and final form of all materials included in the monograph.

REFERENCES

Agrawal, J., & Arafat, M. Y. (2024). Transforming farming: A review of AI-powered UAV technologies in precision agriculture. Drones, 8(11), Article 664. https://doi.org/10.3390/drones8110664

Aich, S., Chakraborty, S., Lee, Y.-K., & Kim, H.-C. (2022). Digital twins in agriculture: A state-of-the-art review. ICT Express, 8(3), 300–312. https://doi.org/10.1016/j.icte.2021.11.006

Atik, C. (2022). Towards comprehensive European agricultural data governance: Moving beyond the "data ownership" debate. International Review of Intellectual Property and Competition Law, 53(5), 701–742. https://doi.org/10.1007/s40319–022–01191-w

Avgoustaki, D. D., & Xydis, G. (2020). Indoor vertical farming in the urban nexus: Contextualising alternative food niches in the smart city. Land Use Policy, 97, Article 104780. https://doi.org/10.1016/j.landusepol.2020.104780

Awais, M., Wang, X., Hussain, S., Aziz, F., & Mahmood, M. Q. (2025). Advancing precision agriculture through digital twins and smart farming technologies: A review. AgriEngineering, 7(5), Article 137. https://doi.org/10.3390/agriengineering7050137

Bahmutsky, S., Grassauer, F., Arulnathan, V., & Pelletier, N. (2024). A review of life cycle impacts and costs of precision agriculture for cultivation of field crops. Sustainable Production and Consumption, 52, 347–362. https://doi.org/10.1016/j.spc.2024.11.010

Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agricultural systems. Nature Sustainability, 3, 254–256. https://doi.org/10.1038/s41893–020–0510–0

Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. Transportation Research Part B: Methodological, 45(8), 1232–1250. https://doi.org/10.1016/j.trb.2011.02.004

Bellon-Maurel, V., Lutton, E., Bisquert, P., Brossard, L., Chambaron-Ginhac, S., Labarthe, P., Lagacherie, P., Martignac, F., Molenat, J., Parisey, N., Picault, S., Piot-Lepetit, I., & Veissier, I. (2022). Digital revolution for the agroecological transition of food systems: A responsible research and innovation perspective. Agricultural Systems, 203, Article 103524. https://doi.org/10.1016/j.agsy.2022.103524

Bennett, R. M., van Gils, H. A., Zevenbergen, J. A., Lemmen, C. H. J., & Wallace, J. (2021). Land administration maintenance: A review of the empirical literature. Land Use Policy, 105, Article 105410. https://doi.org/10.1016/j.landusepol.2021.105410

Bennett, R., Wallace, J., & Williamson, I. (2008). Organizing land information for sustainable land administration. Land Use Policy, 25(1), 126–138. https://doi.org/10.1016/j.landusepol.2007.03.006

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Computers, Environment and Urban Systems, 65, 126–139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004

Boggia, A., Massei, G., Pace, E., Rocchi, L., Paolotti, L., & Attard, M. (2018). Spatial multicriteria analysis for sustainability assessment of agricultural land use. Land Use Policy, 72, 400–410. https://doi.org/10.1016/j.landusepol.2017.12.062

Boulding, K. E. (1966). The economics of the coming spaceship Earth. In H. Jarrett (Ed.), Environmental quality in a growing economy (pp. 3–14). Johns Hopkins University Press.

Boursianis, A. D., Papadopoulou, M. S., Diamantoulakis, P., Liopa-Tsakalidi, A., Barouchas, P., Salahas, G., Karagiannidis, G., Wan, S., & Goudos, S. K. (2022). Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. Internet of Things, 18, Article 100187. https://doi.org/10.1016/j.iot.2020.100187

Brewster, C., Roussaki, I., Kalatzis, N., Doolin, K., & Ellis, K. (2017). IoT in agriculture: Designing a Europe-wide large-scale pilot. IEEE Communications Magazine, 55(9), 26–33. https://doi.org/10.1109/MCOM.2017.1600528

Bronson, K., & Knezevic, I. (2016). Big Data in food and agriculture. Big Data & Society, 3(1). https://doi.org/10.1177/2053951716648174

Cabinet of Ministers of Ukraine. (2012). Resolution No. 1051 of 17 October 2012 on approval of the Procedure for maintaining the State Land Cadastre. https://zakon.rada.gov.ua/go/1051–2012-%D0%BF

Cabinet of Ministers of Ukraine. (2017). National Waste Management Strategy in Ukraine until 2030. https://zakon.rada.gov.ua/laws/show/820–2017-%D1%80

Caffaro, F., & Cavallo, E. (2019). The effects of individual characteristics and external support on smart farming adoption. Technology in Society, 57, 111–120. https://doi.org/10.1016/j.techsoc.2018.12.006

Carolan, M. (2017). Publicising food: Big Data, precision agriculture, and co-experimental techniques of addition. Sociologia Ruralis, 57(2), 135–154. https://doi.org/10.1111/soru.12120

Chen, D., Bodirsky, B. L., Krueger, T., Mishra, A., & Popp, A. (2020). The world's growing municipal solid waste: Trends and impacts. Environmental Research Letters, 15(7), Article 074021. https://doi.org/10.1088/1748–9326/ab8659

Cicciù, B., Schramm, F., & Schramm, V. B. (2022). Multi-criteria decision making/aid methods for assessing agricultural sustainability: A literature review. Environmental Science & Policy, 138, 85–96. https://doi.org/10.1016/j.envsci.2022.09.020

Cinelli, M., Coles, S. R., & Kirwan, K. (2014). Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. Ecological Indicators, 46, 138–148. https://doi.org/10.1016/j.ecolind.2014.06.011

Coase, R. H. (1960). The problem of social cost. Journal of Law and Economics, 3, 1–44. https://doi.org/10.1086/466560

Commission Implementing Regulation (EU) 2023/138 of 21 December 2022 laying down a list of specific high-value datasets and the arrangements for their publication and re-use. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2023/138/oj

Copernicus Climate Change Service. (n.d.). ERA5 hourly data on single levels from 1940 to present. Climate Data Store. Retrieved June 8, 2026, from https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels

Copernicus Data Space Ecosystem. (n.d.-a). APIs. Retrieved June 8, 2026, from https://dataspace.copernicus.eu/analyse/apis

Copernicus Data Space Ecosystem. (n.d.-b). Copernicus Data Space Ecosystem. Retrieved June 8, 2026, from https://dataspace.copernicus.eu/

Copernicus Data Space Ecosystem. (n.d.-c). openEO API. Retrieved June 8, 2026, from https://dataspace.copernicus.eu/analyse/apis/openeo-api

Copernicus Data Space Ecosystem Documentation. (n.d.-a). Digital elevation model (DEM) data. Retrieved June 8, 2026, from https://documentation.dataspace.copernicus.eu/APIs/SentinelHub/Data/DEM.html

Copernicus Data Space Ecosystem Documentation. (n.d.-b). Sentinel-2. Retrieved June 8, 2026, from https://documentation.dataspace.copernicus.eu/Data/SentinelMissions/Sentinel2.html

Copernicus SentiWiki. (n.d.). Sentinel-2 mission. Retrieved June 8, 2026, from https://sentiwiki.copernicus.eu/web/s2-mission

Dale, P., & McLaughlin, J. (1999). Land administration. Oxford University Press.

Daly, H. E. (1991). Steady-state economics (2nd ed.). Island Press.

Daly, H. E. (1996). Beyond growth: The economics of sustainable development. Beacon Press.

De Clercq, M., Vats, A., & Biel, A. (2018). Agriculture 4.0: The future of farming technology. World Government Summit.

Deininger, K. (2003). Land policies for growth and poverty reduction. World Bank and Oxford University Press.

Dibbern, T., Romani, L. A. S., & Massruhá, S. M. F. S. (2024). Main drivers and barriers to the adoption of digital agriculture technologies. Smart Agricultural Technology, 8, Article 100459. https://doi.org/10.1016/j.atech.2024.100459

Duhan, H., Singh, A., Kumar, M., & Singh, P. (2024). Economic valuation of IoT-enabled precision agronomy: ROI mapping. Precision Agriculture, 25, 412–430.

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. IEEE Internet of Things Journal, 5(5), 3758–3773. https://doi.org/10.1109/JIOT.2018.2844296

Ellen MacArthur Foundation. (2013). Towards the circular economy: Economic and business rationale for an accelerated transition. Ellen MacArthur Foundation.

Enemark, S., Bell, K. C., Lemmen, C., & McLaren, R. (2014). Fit-for-purpose land administration. International Federation of Surveyors and World Bank.

Eshetie, G. G., Alemie, B. K., & Wubie, A. M. (2024). Geospatial technologies in support of responsible land tenure governance: A systematic review. Geomatica, 76(2), Article 100014. https://doi.org/10.1016/j.geomat.2024.100014

European Commission. (2019). The European Green Deal (COM(2019) 640 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52019DC0640

European Commission. (2020a). A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system (COM(2020) 381 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0381

European Commission. (2020b). A new Circular Economy Action Plan for a cleaner and more competitive Europe (COM(2020) 98 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2020:98:FIN

European Commission. (2024a). EU opens accession negotiations with Ukraine. Directorate-General for Neighbourhood and Enlargement Negotiations. https://enlargement.ec.europa.eu/news/eu-opens-accession-negotiations-ukraine-2024–06–25_en

European Commission. (2024b). Ukraine 2024 Report (SWD(2024) 699 final). https://enlargement.ec.europa.eu/document/download/1924a044-b30f-48a2–99c1–50edeac14da1_en

European Commission. (2025). Ukraine 2025 Report. Directorate-General for Enlargement and Eastern Neighbourhood. https://enlargement.ec.europa.eu/ukraine-report-2025_en

European Commission. (2026). How the EU Space Programme supports agriculture. Copernicus Observer. https://www.copernicus.eu/en/news/news/observer-how-eu-space-programme-supports-agriculture

European Environment Agency. (2024a). Europe's state of water 2024: The need for improved water resilience. Publications Office of the European Union. https://doi.org/10.2800/02236

European Environment Agency. (2024b). Soil. https://www.eea.europa.eu/en/topics/in-depth/soil

European Parliament and Council of the European Union. (2007). Directive 2007/2/EC establishing an Infrastructure for Spatial Information in the European Community (INSPIRE). Official Journal of the European Union.

European Parliament and Council of the European Union. (2019). Directive (EU) 2019/1024 on open data and the re-use of public sector information. Official Journal of the European Union. https://eur-lex.europa.eu/eli/dir/2019/1024/oj

European Parliament and Council of the European Union. (2021a). Regulation (EU) 2021/2115 establishing rules on support for CAP Strategic Plans. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2021/2115/oj/eng

European Parliament and Council of the European Union. (2021b). Regulation (EU) 2021/2116 on the financing, management and monitoring of the common agricultural policy. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2021/2116/oj

European Parliament and Council of the European Union. (2023). Regulation (EU) 2023/2854 on harmonised rules on fair access to and use of data (Data Act). Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2023/2854/oj/eng

European Parliament and Council of the European Union. (2024a). Regulation (EU) 2024/1991 on nature restoration. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/1991/oj/eng

European Parliament and Council of the European Union. (2024b). Regulation (EU) 2024/792 establishing the Ukraine Facility. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/792/oj/eng

European Parliament and Council of the European Union. (2024c). Regulation (EU) 2024/903 laying down measures for a high level of public sector interoperability across the Union (Interoperable Europe Act). Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/903/oj

European Parliament and Council of the European Union. (2025). Directive (EU) 2025/2360 on soil monitoring and resilience. Official Journal of the European Union. https://eur-lex.europa.eu/eli/dir/2025/2360/oj/eng

Falcão, L., Matar, S., Rauch, E., Elberzhager, F., & Koch, K. (2023). Next-generation interoperability: A framework for data spaces and OPC UA-based automations. Information, 14(8), Article 440. https://doi.org/10.3390/info14080440

FAO. (2014). Building a common vision for sustainable food and agriculture: Principles and approaches. Food and Agriculture Organization of the United Nations. https://www.fao.org/3/i3940e/i3940e.pdf

FAO. (2023). The State of Food and Agriculture 2023: Revealing the true cost of food to transform agrifood systems. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/cc7724en

FAO. (2024). The State of Food and Agriculture 2024: Value-driven transformation of agrifood systems. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/cd2616en

Ferla, G., Mura, B., Falasco, S., Caputo, P., & Matarazzo, A. (2024). Multi-Criteria Decision Analysis (MCDA) for sustainability assessment in food sector: A systematic literature review on methods, indicators and tools. Science of the Total Environment, 946, Article 174235. https://doi.org/10.1016/j.scitotenv.2024.174235

Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. European Review of Agricultural Economics, 50(4), 1277–1309. https://doi.org/10.1093/erae/jbad021

Flevy. (2025). IoT integration in precision agriculture: Cost-benefit analysis and ROI. Internet of Things Case Studies.

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Research Policy, 31(8–9), 1257–1274. https://doi.org/10.1016/S0048–7333(02)00062–8

Georgescu-Roegen, N. (1971). The entropy law and the economic process. Harvard University Press.

GeoServer. (n.d.). GeoServer documentation. Retrieved June 8, 2026, from https://docs.geoserver.org/

GO FAIR. (n.d.). FAIR principles. Retrieved June 8, 2026, from https://www.go-fair.org/fair-principles/

Google for Developers. (n.d.). OR-Tools. Retrieved June 8, 2026, from https://developers.google.com/optimization

GraphHopper. (n.d.-a). GraphHopper Directions API. Retrieved June 8, 2026, from https://docs.graphhopper.com/

GraphHopper. (n.d.-b). GraphHopper routing engine [Computer software]. GitHub. Retrieved June 8, 2026, from https://github.com/graphhopper/graphhopper

Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), Transdisciplinary perspectives on complex systems (pp. 85–113). Springer. https://doi.org/10.1007/978–3–319–38756–7_4

Guebsi, R., Mami, S., & Chokmani, K. (2024). Drones in precision agriculture: A comprehensive review of applications, technologies, and challenges. Drones, 8(11), Article 686. https://doi.org/10.3390/drones8110686

Ihuoma, S. O., & Madramootoo, C. A. (2021). Recent advances in crop water stress detection. Computers and Electronics in Agriculture, 188, Article 106377. https://doi.org/10.1016/j.compag.2021.106377

Ihuoma, S. O., Madramootoo, C. A., & Kalacska, M. (2021). Integration of satellite imagery and in situ soil moisture data for estimating irrigation water requirements. International Journal of Applied Earth Observation and Geoinformation, 102, Article 102396. https://doi.org/10.1016/j.jag.2021.102396

IPCC. (2022). Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. https://doi.org/10.1017/9781009157926

Ismail, F. Z., Halog, A., & Smith, C. (2017). How sustainable is disaster resilience? An overview of sustainable construction approach in post-disaster housing reconstruction. International Journal of Disaster Resilience in the Built Environment, 8(5), 555–572.

ISO. (2024). ISO 19152–1:2024 Geographic information - Land Administration Domain Model (LADM) - Part 1: Generic conceptual model. International Organization for Standardization. https://www.iso.org/standard/81263.html

Jahani Chehrehbargh, F., Rajabifard, A., Atazadeh, B., Steudler, D., Shahidinejad, J., & Nugraha, B. W. (2025). A feasibility assessment of an extended LADM: Enhancing land administration systems through object-relational database management. Transactions in GIS, 29(4), Article e70083. https://doi.org/10.1111/tgis.70083

Jawad, H. M., Nordin, R., Gharghan, S. K., Jawad, A. M., & Ismail, M. (2017). Energy-efficient wireless sensor networks for precision agriculture: A review. Sensors, 17(8), Article 1781. https://doi.org/10.3390/s17081781

Kaufmann, J., & Steudler, D. (1998). Cadastre 2014: A vision for a future cadastral system. International Federation of Surveyors.

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. Resources, Conservation and Recycling, 127, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and Agriculture 4.0: New contributions and a future research agenda. NJAS: Wageningen Journal of Life Sciences, 90–91, Article 100315. https://doi.org/10.1016/j.njas.2019.100315

Korhonen, J., Honkasalo, A., & Seppälä, J. (2018). Circular economy: The concept and its limitations. Ecological Economics, 143, 37–46. https://doi.org/10.1016/j.ecolecon.2017.06.041

Kragt, M. E., & Robertson, M. J. (2014). Quantifying ecosystem services trade-offs from agricultural practices. Ecological Economics, 102, 147–157. https://doi.org/10.1016/j.ecolecon.2014.03.013

Krigsholm, P., Riekkinen, K., & Ståhle, P. (2018). The changing uses of cadastral information: A user-driven case study. Land, 7(3), Article 83. https://doi.org/10.3390/land7030083

Krisnawijaya, N. N. K., Tekinerdogan, B., Catal, C., van der Tol, R., & Herdiyeni, Y. (2025). Implementing FAIR principles in data management systems: A multi-case study in precision farming. Computers and Electronics in Agriculture, 230, Article 109855. https://doi.org/10.1016/j.compag.2024.109855

Lajoie-O'Malley, A., Bronson, K., van der Burg, S., & Klerkx, L. (2020). The future(s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. Ecosystem Services, 45, Article 101183. https://doi.org/10.1016/j.ecoser.2020.101183

Lan, J., & Ban, Q. (2025). The farm-level economic and environmental benefits of precision agriculture technology adoption: A meta-analysis of global evidence. Sustainability, 17(24), Article 11223. https://doi.org/10.3390/su172411223

Lemmen, C., van Oosterom, P., & Bennett, R. (2015). The Land Administration Domain Model. Land Use Policy, 49, 535–545. https://doi.org/10.1016/j.landusepol.2015.01.014

Li, J., Wang, Z., & Chen, H. (2023). Farmers' policy satisfaction and willingness to adopt smart farming. Agricultural Economics, 54(2), 215–228.

Li, X., Mieno, T., & Bullock, D. S. (2023). The economic performances of different trial designs in on-farm precision experimentation: A Monte Carlo evaluation. Precision Agriculture, 24(6), 2500–2521. https://doi.org/10.1007/s11119–023–10050–8

Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2014). Survey of green vehicle routing problem: Past and future trends. Expert Systems with Applications, 41(4), 1118–1138. https://doi.org/10.1016/j.eswa.2013.07.107

Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2020). Green vehicle routing problem: A state-of-the-art review. International Journal of Production Economics, 228, Article 107749. https://doi.org/10.1016/j.ijpe.2020.107749

Lin, Y., Zhang, Y., & Yang, X. (2022). The challenge of regional disparities in the adoption of smart farming technologies. Journal of Rural Studies, 92, 154–165.

Liu, J., Zhang, D., Li, X., & Wang, L. (2024). Distribution path optimization of carbon emission-reducing agricultural cold chain logistics based on improved GA. Cleaner Logistics and Supply Chain, 12, Article 100164. https://doi.org/10.1016/j.clscn.2024.100164

Liu, Z., Chen, Y., Li, J., & Zhang, D. (2021). Spatiotemporal-dependent vehicle routing problem considering carbon emissions. Discrete Dynamics in Nature and Society, 2021, Article 9729784. https://doi.org/10.1155/2021/9729784

Macháč, J., Trantinová, M., & Zaňková, L. (2021). Externalities in agriculture: How to include their monetary value in decision-making? International Journal of Environmental Science and Technology, 18, 3–20. https://doi.org/10.1007/s13762–020–02752–7

Macioszek, E. (2018). First and last mile delivery: Problems and issues. In Advances in interdisciplinary engineering (pp. 147–154). Springer.

MacPherson, J., Voglhuber-Slavinsky, A., Olbrisch, M., Schöbel, P., Dönitz, E., Mouratiadou, I., & Helming, K. (2022). Future agricultural systems and the role of digitalization for achieving sustainability goals: A review. Agronomy for Sustainable Development, 42, Article 70. https://doi.org/10.1007/s13593–022–00792–6

Markard, J., Raven, R., & Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. Research Policy, 41(6), 955–967. https://doi.org/10.1016/j.respol.2012.02.013

Martyn, A., Hunko, L., Medynska, N., Poltavets, A., & Kolosa, L. (2026). Engineering-economic assessment of Ukraine's digital land cadastre: Quantifying added value from geodata across agriculture, energy, and transport projects. Engineering for Rural Development, Jelgava, 27–29 May 2026.

Martyn, A., Trevoho, I., & Yevsiukov, T. (2024). Modernization of state control (supervision) over land use and protection in Ukraine: Prospects for using Earth remote sensing information products. Manuscript supplied by the authors.

Metaferia, M. T., Bennett, R., Alemie, B. K., & Koeva, M. N. (2023). Fit-for-purpose land administration and the Framework for Effective Land Administration: Synthesis of contemporary experiences. Land, 12(1), Article 58. https://doi.org/10.3390/land12010058

Millennium Ecosystem Assessment. (2005). Ecosystems and human well-being: Synthesis. Island Press.

Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in agriculture: The time is now-A systematic review of smart sensing technologies. Sensors, 25(12), Article 3583. https://doi.org/10.3390/s25123583

Ministry of Economy of Ukraine. (2024). Ukraine Plan 2024–2027. https://www.ukrainefacility.me.gov.ua/wp-content/uploads/2024/03/ukraine-facility-plan.pdf

Moghdani, R., Salimifard, K., Demir, E., & Benyettou, A. (2021). The green vehicle routing problem: A systematic literature review. Journal of Cleaner Production, 279, Article 123691. https://doi.org/10.1016/j.jclepro.2020.123691

Moldavan, L., Pimenowa, O., Wasilewski, M., & Wasilewska, N. (2023). Sustainable development of agriculture of Ukraine in the context of climate change. Sustainability, 15(13), Article 10517. https://doi.org/10.3390/su151310517

Moore, F. C., Baldos, U., Hertel, T., & Diaz, D. (2017). New science of climate change impacts on agriculture implies higher social cost of carbon. Nature Communications, 8, Article 1607. https://doi.org/10.1038/s41467–017–01792-x

NASA POWER Project. (n.d.). Prediction of Worldwide Energy Resources (POWER) data access viewer. NASA Langley Research Center. Retrieved June 8, 2026, from https://power.larc.nasa.gov/data-access-viewer/

National University of Life and Environmental Sciences of Ukraine, Department of Land Cadastre, & Department of Land-Use Planning. (2026). Land cadastre in Ukraine: Vision to 2030. Strategic framework for public policy, legislative decisions, digital transformation and European integration.

Navas de Maya, B., & Rodríguez García, M. (2023). Spatio-temporal economic planning in agri-food supply chains. European Journal of Operational Research, 305(1), 120–136.

Nazarenko, V. A. (2020). Economic aspects of land use in the Kyiv and suburban areas. Bioeconomics & Agrarian Business, 11(3), 100–113. https://doi.org/10.31548/bioeconomy2020.03.077

Nazarenko, V. A. (2021a). Research of the urban development in connection to food processing and agricultural companies in Ukraine. In Industry research in the 21st century: Agricultural sciences, zoology and veterinary medicine, manufacturing and technology (pp. 33–47). Publishing House "UKRLOGOS Group". https://doi.org/10.36074/hdsanzvvt.ed-1.04

Nazarenko, V. A. (2021b). System modeling of the smart city in context of land management e-service. Land Science, 3(1), 22–35. https://doi.org/10.30560/ls.v3n1p22

Nazarenko, V. A. (2021c). Urbanization: Definition, components, and classification in context of land and economics sciences. Land Management, Cadastre and Land Monitoring, (1), 114–123. https://doi.org/10.31548/zemleustriy2021.01.10

Nazarenko, V. A. (2023). Web service system model for ecological and economic monitoring under urbanization. Land Management, Cadastre and Land Monitoring, (4), 31–39. https://doi.org/10.31548/zemleustriy2023.04.03

Nazarenko, V. A. (2024a). Model systemy sotsialno-ekonomichnykh posluh dlia rozumnykh mist z aktsentom na ekolohichnyi monitorynh ta upravlinnia zemelnymy resursamy [Model of a socio-economic service system for smart cities with emphasis on ecological monitoring and land-resource management]. Grail of Science, 46, 287–294. https://doi.org/10.36074/grail-of-science.29.11.2024.033

Nazarenko, V. A. (2024b). Sustainable land use framework: Ukraine case study. Land Management, Cadastre and Land Monitoring, (1), 59–65. https://doi.org/10.31548/zemleustriy2024.01

Nazarenko, V. A. (2025a). Digital agronomy: Smart decision-support workflow for climate-resilient farming in the Kyiv agglomeration. Land Management, Cadastre and Land Monitoring, (3), 33–42. https://doi.org/10.31548/zemleustriy2025.03.04

Nazarenko, V. A. (2025b). Distributed information systems in smart cities: A comprehensive economic data framework for Kyiv. Grail of Science. https://doi.org/10.36074/grail-of-science.01.11.2024.015

Nazarenko, V. A. (2025c). Main factors of economic, land, and environmental impact due to rapid technological advancements. Land Management, Cadastre and Land Monitoring, (1), 94–103. https://doi.org/10.31548/zemleustriy2025.01

Nazarenko, V. A. (2025d). Urban futures reimagined: Advanced ecological-economic frameworks for sustainable growth. NULES of Ukraine Publishing House.

Nazarenko, V. A. (2025e). Weights-based real-time routing platform for digital agriculture in Ukraine. Grail of Science, 57, 185–194. https://doi.org/10.36074/grail-of-science.17.10.2025.018

Nazarenko, V. A. (2026). Spatio-temporal economic planning weighted routing model for agricultural land-use management in peri-urban zones: A case study of the Kyiv agglomeration [Manuscript].

Nazarenko, V. A., & Martyn, A. G. (2024a). Geospatial technologies in post-war reconstruction: Challenges and innovations in Ukraine. Land Management, Cadastre and Land Monitoring, (4), 89–96. https://doi.org/10.31548/zemleustriy2024.03.07

Nazarenko, V. A., & Martyn, A. G. (2024b). Information systems for modeling land prices under the urbanization process. Economics and Business Management, 15(1), 45–55. https://doi.org/10.31548/economics15(1).2024.039

Nazarenko, V. A., & Martyn, A. G. (2025). Urban growth and agrarian dynamics: Evaluating the Kyiv agglomeration's economic landscape. Economics and Business Management, 16(2), 24–41. https://doi.org/10.31548/economics/2.2025.24

Nazarenko, V. A., Martyn, A. G., Klikh, L., & Pashchenko, O. (2024). Green metrics: Internet of Things based ecological monitoring and management for sustainable urban living in Kyiv. In Proceedings of the 2024 International Conference "Economic Science for Rural Development" (No. 58, pp. 220–230). Latvia University of Life Sciences and Technologies. https://doi.org/10.22616/ESRD.2024.58.022

Nazarenko, V. A., & Ostroushko, B. P. (2024). Smart city management system utilizing micro-services and IoT-based systems. Energy and Automation, 1(71), 29–38. https://doi.org/10.31548/energiya1(71).2024.029

Nazarenko, V. A., Smolii, V., Onyshchenko, B., & Misiura, M. (2024). System model of e-services for suburban area management. Engineering for Rural Development, 23, 135–141. https://doi.org/10.22616/ERDev.2024.23.TF030

Nazarenko, V. A., & Voitovych, O. (2024a). Ecological and economic profile of cities: On the way to sustainable development. Land Management, Cadastre and Land Monitoring, (4), 80–90. https://doi.org/10.31548/zemleustriy2024.04

Nazarenko, V. A., & Voitovych, O. (2024b). Kontseptsiia systemy upravlinnia mistom u konteksti prohramy staloho rozvytku [Concept of a city management system in the context of the sustainable development program]. Grail of Science, 47, 117–124. https://doi.org/10.36074/grail-of-science.20.12.2024.013

Nazarenko, V. A., & Voitovych, O. (2025). Model ekoloho-ekonomichnoho profiliu mist: Na shliakhu do staloho rozvytku [Model of the ecological-economic profile of cities: On the way to sustainable development]. Land Management, Cadastre and Land Monitoring, (4), 80–89. https://www.journals.nubip.edu.ua/index.php/Zemleustriy/article/viewFile/51159/15957

North, D. C. (1990). Institutions, institutional change and economic performance. Cambridge University Press.

Obayi, R., Choudhary, S., Nayak, R., & Ramanjaneyulu, G. V. (2025). Pragmatic interoperability for human-machine value creation in agri-food supply chains. Information Systems Frontiers. Advance online publication. https://doi.org/10.1007/s10796–024–10567-x

Open Geospatial Consortium. (n.d.). OGC API - Features. https://www.ogc.org/standards/ogcapi-features/

Open Geospatial Consortium. (2023, December 5). OGC to form Land Administration Domain Model Standards Working Group; Public Comment sought on Charter. https://www.ogc.org/requests/ogc-to-form-land-administration-domain-model-standards-working-group-public-comment-sought-on-charter/

Open Geospatial Consortium. (2016). OGC SensorThings API Part 1: Sensing (OGC 15–078r6). https://docs.ogc.org/is/15–078r6/15–078r6.html

Open Geospatial Consortium. (2022). OGC SensorThings API Part 1: Sensing, version 1.1 (OGC 18–088). https://docs.ogc.org/is/18–088/18–088.html

OpenStreetMap Foundation. (n.d.). OpenStreetMap. Retrieved June 8, 2026, from https://www.openstreetmap.org/

Ostrom, E. (1990). Governing the commons: The evolution of institutions for collective action. Cambridge University Press.

Panagos, P., Borrelli, P., Poesen, J., Ballabio, C., Lugato, E., Meusburger, K., Montanarella, L., & Alewell, C. (2015). The new assessment of soil loss by water erosion in Europe. Environmental Science & Policy, 54, 438–447. https://doi.org/10.1016/j.envsci.2015.08.012

Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., & Fountas, S. (2024). Economic and environmental benefits of digital agricultural technologies in crop production: A review. Smart Agricultural Technology, 8, Article 100441. https://doi.org/10.1016/j.atech.2024.100441

Pearce, D. W., & Turner, R. K. (1990). Economics of natural resources and the environment. Johns Hopkins University Press.

Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013). Drivers of precision agriculture technologies adoption: A literature review. Procedia Technology, 8, 61–69. https://doi.org/10.1016/j.protcy.2013.11.010

Pignatti, E., Carli, G., & Canavari, M. (2015). What really matters? A qualitative analysis on the adoption of innovations in agriculture. Journal of Agricultural Informatics, 6(4), 73–84.

Pigou, A. C. (1920). The economics of welfare. Macmillan.

PostGIS. (n.d.). Documentation. Retrieved June 8, 2026, from https://postgis.net/documentation/

Purnomo, A., Rosyid, A., & Hidayat, T. (2026). Digital twin for agricultural land monitoring system. Pertanika Journal of Science & Technology, 34(1), 1–18.

QGIS.org. (n.d.). Documentation for QGIS 3.44. Retrieved June 8, 2026, from https://docs.qgis.org/latest/en/docs/index.html

Qiao, Y., Ren, P., Tang, H., & Li, Z. (2023). An interoperable and service-oriented approach for real-time environmental modeling by coupling OGC WPS and SensorThings API. Environmental Modelling & Software, 162, Article 105651. https://doi.org/10.1016/j.envsoft.2023.105651

Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S. E., Donges, J. F., Druke, M., Fetzer, I., Bala, G., von Bloh, W., Feulner, G., Fiedler, S., Gerten, D., Gleeson, T., Hofmann, M., Huiskamp, W., Kummu, M., Mohan, C., Nogués-Bravo, D., ... Rockström, J. (2023). Earth beyond six of nine planetary boundaries. Science Advances, 9(37), Article eadh2458. https://doi.org/10.1126/sciadv.adh2458

Roccatello, E., Pagano, A., Levorato, N., & Rumor, M. (2025). State of the art in Internet of Things standards and protocols for precision agriculture with an approach to semantic interoperability. Network, 5(2), Article 14. https://doi.org/10.3390/network5020014

Rockström, J., Steffen, W., Noone, K., Persson, A., Chapin, F. S., III, Lambin, E., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., ... Foley, J. A. (2009). A safe operating space for humanity. Nature, 461, 472–475. https://doi.org/10.1038/461472a

Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. Frontiers in Sustainable Food Systems, 2, Article 87. https://doi.org/10.3389/fsufs.2018.00087

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., LeBlanc, J., Martin, R., Neufeld, H. T., Nixon, A., Pant, L., Shalla, V., & Fraser, E. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. Journal of Rural Studies, 68, 112–122. https://doi.org/10.1016/j.jrurstud.2019.01.023

Sartori, M., Ferrari, E., M'Barek, R., Philippidis, G., Boysen-Urban, K., Borrelli, P., Montanarella, L., & Panagos, P. (2024). Remaining loyal to our soil: A prospective integrated assessment of soil erosion on global food security. Ecological Economics, 219, Article 108103. https://doi.org/10.1016/j.ecolecon.2023.108103

Shadkam, E., & Irannezhad, E. (2025). A comprehensive review of simulation optimization methods in agricultural supply chains and transition towards an agent-based intelligent digital framework for Agriculture 4.0. Engineering Applications of Artificial Intelligence, 143, Article 109930. https://doi.org/10.1016/j.engappai.2024.109930

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies: Integrating farm-level evidence and system interaction. Agricultural Systems, 190, Article 103074. https://doi.org/10.1016/j.agsy.2021.103074

Sher, A., Mazhar, S., & Li, X. (2025). Driving mechanism of Internet use on vegetable farmers' smart farming adoption. Frontiers in Sustainable Food Systems, 8, Article 1687446. https://doi.org/10.3389/fsufs.2025.1687446

Siksnelyte, I., Zavadskas, E. K., Stringer, L. C., & Hegedűs, M. (2018). Sustainable decision-making in agriculture: A review of multi-criteria decision-making methods. Sustainability, 10(12), Article 4381. https://doi.org/10.3390/su10124381

State Service of Ukraine for Geodesy, Cartography and Cadastre. (n.d.). Electronic services of the StateGeoCadastre. Retrieved June 15, 2026, from https://e.land.gov.ua/services

State Service of Ukraine for Geodesy, Cartography and Cadastre. (n.d.-a). Derzhavna sluzhba Ukrainy z pytan heodezii, kartohrafii ta kadastru [State Service of Ukraine for Geodesy, Cartography and Cadastre]. Retrieved June 8, 2026, from https://land.gov.ua/

State Service of Ukraine for Geodesy, Cartography and Cadastre. (n.d.-b). Elektronni servisy Derzhheokadastru [StateGeoCadastre e-services]. Retrieved June 8, 2026, from https://e.land.gov.ua/services

State Service of Ukraine for Geodesy, Cartography and Cadastre. (2025). In Ukraine, information on functional zones was entered into the State Land Cadastre for the first time on the basis of a comprehensive spatial-development plan. https://land.gov.ua/v-ukrayini-vpershe-vneseno-do-dzk-vidomosti-pro-funkczionalni-zony-na-pidstavi-kompleksnogo-planu-prostorovogo-rozvytku/

State Service of Ukraine for Geodesy, Cartography and Cadastre. (2026). The head of the StateGeoCadastre presented the results of the StateGeoCadastre's work in 2025. https://land.gov.ua/golova-derzhgeokadastru-dmytro-makarenko-prezentuvav-rezultaty-roboty-derzhgeokadastru-u-2025-roczi/

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. Science, 347(6223), Article 1259855. https://doi.org/10.1126/science.1259855

Talukder, B., Hipel, K. W., & vanLoon, G. W. (2017). Elimination method of Multi-Criteria Decision Analysis (MCDA): A simple methodological approach for assessing agricultural sustainability. Sustainability, 9(2), Article 287. https://doi.org/10.3390/su9020287

Tzounis, A., Katsoulas, N., Bartzanas, T., & Kittas, C. (2017). Internet of Things in agriculture: Recent advances and future challenges. Biosystems Engineering, 164, 31–48. https://doi.org/10.1016/j.biosystemseng.2017.09.007

U.S. Government Accountability Office. (2024). Precision agriculture: Benefits and challenges for technology adoption and use (GAO-24–105962). https://www.gao.gov/products/gao-24–105962

Ukrainian Parliament. (2011). Law of Ukraine No. 3613-VI of 7 July 2011 on the State Land Cadastre. https://zakon.rada.gov.ua/go/3613–17

Ukrainian Parliament. (2020). Law of Ukraine No. 554-IX of 13 April 2020 on the National Spatial Data Infrastructure. https://zakon.rada.gov.ua/go/554–20

United Nations. (2015). Transforming our world: The 2030 Agenda for Sustainable Development. https://sdgs.un.org/2030agenda

United Nations University. (2025). Urban and peri-urban agriculture: A pathway to sustainable cities. UNU Institute for Integrated Management of Material Fluxes and of Resources.

Urdu, D., Berre, A. J., Sundmaeker, H., Rilling, S., Roussaki, I., Marguglio, A., & Wolfert, S. (2024). Aligning interoperability architectures for digital agri-food platforms. Computers and Electronics in Agriculture, 224, Article 109194. https://doi.org/10.1016/j.compag.2024.109194

Ustaoglu, E., Sisman, S., & Aydınoglu, A. C. (2021). Determining agricultural suitable land in peri-urban geography using GIS and Multi Criteria Decision Analysis (MCDA) techniques. Ecological Modelling, 455, Article 109610. https://doi.org/10.1016/j.ecolmodel.2021.109610

van Oosterom, P., Unger, E. M., & Lemmen, C. (2022). The second themed article collection on the Land Administration Domain Model (LADM). Land Use Policy, 120, Article 106287. https://doi.org/10.1016/j.landusepol.2022.106287

Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. Agricultural Systems, 189, Article 103046. https://doi.org/10.1016/j.agsy.2020.103046

Vranić, S., Matijević, H., Roić, M., & Cetl, V. (2022). Land Administration Domain Model (LADM) and OGC standards: Making geospatial data FAIR. LADM 2022 Workshop Proceedings.

Walter, A., Finger, R., Huber, R., & Buchmann, N. (2017). Smart farming is key to developing sustainable agriculture. Proceedings of the National Academy of Sciences, 114(24), 6148–6150. https://doi.org/10.1073/pnas.1707462114

Wang, T., Jin, H., Sieverding, H., Kumar, S., Miao, Y., Rao, X., Obembe, O., Mirzakhani Nafchi, A., Redfearn, D., & Cheye, S. (2023). Understanding farmer views of precision agriculture profitability in the U.S. Midwest. Ecological Economics, 213, Article 107950. https://doi.org/10.1016/j.ecolecon.2023.107950

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J. W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., ... Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data, 3, Article 160018. https://doi.org/10.1038/sdata.2016.18

Williamson, I., Enemark, S., Wallace, J., & Rajabifard, A. (2010). Land administration for sustainable development. ESRI Press.

Williamson, O. E. (1985). The economic institutions of capitalism. Free Press.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in smart farming: A review. Agricultural Systems, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

World Bank. (2026). State and Trends of Carbon Pricing 2026. World Bank. https://www.worldbank.org/en/publication/state-and-trends-of-carbon-pricing

Wu, D., Li, J., Cui, J., & Hu, D. (2023). Research on the time-dependent vehicle routing problem for fresh agricultural products based on customer value. Agriculture, 13(3), Article 681. https://doi.org/10.3390/agriculture13030681

Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computers & Operations Research, 39(7), 1419–1431. https://doi.org/10.1016/j.cor.2011.08.013

Yao, Q., Zhu, S., & Li, Y. (2022). Green vehicle-routing problem of fresh agricultural products considering carbon emission. International Journal of Environmental Research and Public Health, 19(14), Article 8675. https://doi.org/10.3390/ijerph19148675

Yousaf, H., Kayvanfar, V., Mazzoni, S., & Elomri, A. (2023). From decision support to Agriculture 4.0: A systematic review of data-driven systems and adoption challenges. Frontiers in Sustainable Food Systems, 7, Article 1107026. https://doi.org/10.3389/fsufs.2023.1107026

Zevenbergen, J., Augustinus, C., Antonio, D., & Bennett, R. (2013). Pro-poor land administration: Principles for recording the land rights of the underrepresented. Land Use Policy, 31, 595–604. https://doi.org/10.1016/j.landusepol.2012.09.005

Zhai, Z., Martínez, J. F., Beltran, V., & Martínez, N. L. (2020). Decision support systems for Agriculture 4.0: Survey and challenges. Computers and Electronics in Agriculture, 170, Article 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. Precision Agriculture, 13(6), 693–712. https://doi.org/10.1007/s11119–012–9274–5

Zhang, J., Zhao, Y., Xue, W., & Li, J. (2015). Vehicle routing problem with fuel consumption and carbon emission. International Journal of Production Economics, 170, 234–242. https://doi.org/10.1016/j.ijpe.2015.09.031

Zou, X., & Li, Y. (2022). Shadow pricing of agricultural environmental externalities: A systematic literature review. Journal of Environmental Management, 314, Article 115064. https://doi.org/10.1016/j.jenvman.2022.115064