Multi-Sensor Approach for Early Crop Disease Detection: Socio-Economic and Ecological Implications.

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Abstract

This study analyses an innovative multi-sensor remote-sensing approach for early and accurate crop disease detection and explores its economic, environmental, and social implications through the Business Process Modelling Cost-Benefit Analysis framework. This represents a novel methodological approach that enables the integrated evaluation of the multidimensional impacts of digital technologies within agricultural processes and decision-making systems. The analysis highlights that the multi-sensor approach can facilitate anticipatory and targeted interventions, thereby reducing agrochemical use and associated costs, improving environmental and human health and promoting the transition towards

biodiversity-aligned sustainable agriculture. However, this approach also presents challenges including high capital investments, advanced infrastructure requirements, the need for novel skills, system interoperability barriers and data privacy concerns. Furthermore, the analysis characterises that impacts vary over time and differ across stakeholder groups. Because the study was conducted in a controlled environment at the technology design stage, the results are limited in terms of their transferability to other contexts. Further research in diverse real-world settings is therefore recommended to support the sustainable integration of this technology.

1. INTRODUCTION

Smart farming technologies are increasingly transforming agricultural practices and reshaping how farming systems operate. While these changes manifest at the farm level, their impacts extend across the broader Socio-Ecological System (SES), resulting in a systemic change (Rijswijk et al., 2021). Digital tools alter how different entities interact (Cowie et al., 2020; Klerkx & Rose, 2020) and produce outcomes that span across economic, environmental, social, and governance levels (Rijswijk et al., 2023). Reports show that they foster sustainable farming by increasing efficiency, productivity, accuracy, transparency, and traceability (European Union, 2023). However, this shift is also framed as 'Green Revolution 2.0' due to the emerging trade-offs and undesirable consequences that arise when these technologies are implemented without examination (Klerkx & Rose, 2020).

Specifically, digital technologies are becoming increasingly critical to pest and disease management as they can enable more efficient pesticide use (Finger, 2026). Despite an annual global agrochemical usage of 3.7 million tonnes (FAO, 2024), pests and diseases destroy an estimated 40% of global crop production, costing the economy over $220 billion (FAO, 2022). Therefore, early detection is becoming crucial as it helps in initial containment of the disease, reducing both yield loss and excessive chemical treatments (Buja et al., 2021).

To this end, remote sensing technologies are highly efficient at mapping the spatial distribution of diseases (Calzone et al., 2021; Cotrozzi, 2022). By providing precise data, they enable timely, targeted interventions and remove the need for broadcast chemical application (Oerke, 2020). In addition, because sensors gather information without physical contact (Colwell, 1983), they cause minimal disturbance to crop environment. When combined with site-specific management, they can significantly reduce the agrochemical use (Anastasiou et al., 2023) and deliver clear benefits for agricultural sustainability (Coman et al., 2025; Martos et al., 2021).

However, several barriers undermine their widespread adoption at farm level. These include the high cost of digital innovations (Finger, 2023; Yang, 2020), performance uncertainties and strict regulations particularly regarding Unmanned Aerial Vehicles (UAVs). (Klerkx & Rose, 2020; Shepherd et al., 2020) . Moreover, digital tools can be energy-intensive (García-Martín et al., 2019), which increases their environmental footprint. Without appropriate regulatory policies and frameworks, they may also trigger serious ethical and social issues such as a widening digital divide and a concentration of corporate power (Bampasidou et al., 2024; Finger, 2023). Often, these unintended effects materialise over the long-term and become visible only after the technology is implemented in practice (Pansera et al., 2019). However, stakeholders can minimise the intensity of these impacts by anticipating potential risks, trade-offs and costs prior to technological integration into farming systems (Wuepper et al., 2026). Hence, understanding these context-specific (Schnebelin, 2022), multi-dimensional implications (Rolandi et al., 2021) allows for a holistic assessment of the technology's value, which can help identify pathways for its sustainable integration.

Therefore, the main objective of this study is to provide an integrated assessment of the economic, environmental, and social implications of using a multi-sensor remote sensing approach for early crop disease detection. Importantly, it aims to identify the associated risks, trade-offs, and sustainability challenges that emerge when implementing this technology within agricultural systems.

2. CONTEXT OF THE STUDY

The technology under analysis combines several sensor types including hyperspectral reflectance, solar-induced fluorescence (SIF), thermal infrared (TIR), and light detection and ranging (LiDAR) observations to achieve early and precise plant disease detection. This approach was developed within the Italian national project 'MUSELY', where the primary objective is to establish an integrated framework for diagnosing plant diseases at an early stage.

The multi-sensor approach provides complementary insights into plant health, with each sensor capturing a distinct variable (Zhang & Zhu, 2023). The specifications of the digital tools used are detailed in the Table S1 (see Supplementary material). When implemented, this approach provides novel insights into plant structural, biochemical, and physiological responses across three distinct phases of disease progression:

- Pre-symptomatic detection (hours-days): Captures early physiological indicators.
- Disease progression (days-weeks): Focuses on symptom-specific identification by utilising hyperspectral reflectance.
- Potential recovery phase: Monitors the restoration of baseline conditions.

The multi-sensor approach was selected as a case study because it represents a significant technological advancement in early disease detection. Consequently, it provides an excellent context for assessing the overall implications of advanced digital monitoring systems in agriculture. Moreover, experimental projects often provide a setting where technological niches can evolve, helping actors manage uncertainty while establishing new roles and routines

(Bacco et al., 2019; Geels, 2004). An analysis at this stage can help identify potential positive and negative impacts ex-ante. In evaluation studies, this early assessment is considered crucial for designing an effective digitalisation strategy (Kaplan et al., 2021). Therefore, this evaluation provides insights into the potential implications of the technology for different stakeholders, while guiding the design and scaling of sustainable digitalisation strategies.

3. METHODOLOGY

3.1 Data Collection

Rather than focusing on technical efficiency, this study investigates the broader socio-economic and environmental implications of the multi-sensor approach. For this purpose, data were collected iteratively from technology users through in-depth semi-structured interviews conducted from November, 2024 to May, 2025. Initially, a one-day workshop was organised to gather information on the actors involved, the physical and technological resources used and the activities. This workshop included two remote sensing professionals, two crop protection specialists, and three social scientists. Further data regarding costs and benefits were collected through individual online video interviews, each lasting 45-60 minutes. Following the analysis, the findings were discussed with the interviewed stakeholders and validated to produce the results.

3.2 Integrated Analytical Framework

Drawing on Socio-Technical Systems (STS) theory (Bijker et al., 1987), this analysis assumes that technological innovations cannot be evaluated in isolation; rather, they are deeply rooted within the broader social system. To operationalise this perspective in the digital era, this study adopts the lens of a Social-Cyber-Physical System (SCPS) framework (Rijswijk et al., 2021). It evaluates the impacts arising from the complex, mutual interactions between cyber-physical (digital equipment, data infrastructure, natural resources) and social components (people, institutions) (Szabo et al., 2023).

Previously, the SCPS framework has been integrated with other models to examine how cyber-physical elements influence changes among different entities, their relationships, and activities (Metta et al., 2022, 2024). Here, the framework is explicitly combined with the 'action situation' concept from Ostrom's Institutional Analysis and Development (IAD) framework (Ostrom, 2010). The IAD framework provides a structured institutional lens to systematically identify the actors involved in the digitalisation process, their operational roles, the formal and informal rules governing their behaviour, and the resulting structural outcomes (Ciliberti et al., 2024).

The impacts produced by these process-level dynamics were then subsequently assessed at the SES level (Ostrom, 2009) to validate and extrapolate the findings across wider agricultural landscapes (Klerkx et al., 2019; Metta et al., 2022). Overall, this multi-layered analysis is situated within the sustainable digitalisation framework (Soma et al., 2024). By combining these complementary models, the integrated framework offers a systems approach to evaluate digital technologies, thereby situating this research within a broader effort to evaluate the systemic, long-term consequences of digital innovations in agriculture.

3.3 Data Analysis

To transform these theoretical concepts (STS, SCPS, IAD) into verifiable empirical data, the BPM-CBA was employed as the primary evaluative methodology. While the macro-level frameworks identify which systemic elements interact, they lack the granular tools to measure these interactions in the field. The BPM-CBA framework bridges this gap by serving as the operational engine of the theoretical model. It specifically analyses the interactions among the technical, operational, environmental, and socio-economic dimensions of the experimental SCPS. This approach was developed within the research activities of the Horizon Europe CODECS project[1] and is conceptually aligned with the systemic and socio-technical perspective proposed by Soma et al., (2024). Further, this framework was subsequently applied in empirical research on agricultural digitalisation, robotics, and Artificial Intelligence (AI) - enabled management systems (Luglio, 2026).

Methodologically, BPM-CBA combines Business Process Modelling (BPM) with Cost–Benefit Analysis (CBA) to create an integrated and process-oriented evaluation approach. Specifically, BPM enables the mapping and visualisation of the cyber-physical workflows of the SCPS and the institutional 'action situations' of the IAD framework before and after the introduction of digital technologies. Simultaneously, CBA operationalises the outcomes of these socio-technical transitions by identifying and assessing the associated costs, benefits, risks, and trade-offs.

Unlike conventional CBA methods, which mainly focus on monetised impacts and static economic evaluation, BPM-CBA explicitly links process-level transformations to broader economic, environmental, social, and governance implications. This capability allows the framework to capture implementation dynamics, stakeholder-specific effects, and operational changes. It also accounts for non-monetised impacts and temporal dimensions that are often overlooked in traditional evaluation methods. In this study, BPM-CBA was applied as a pilot methodological approach to evaluate how integrating the multi-sensor remote sensing system reshapes operational practices and generates multidimensional implications within the agricultural system under analysis.

3.3.1 Business Process Modelling (BPM)

[1]CODECS – Maximising the CO-benefits of agricultural Digitalisation through conducive digital ECoSystems, Horizon Europe project, Grant Agreement No. 101060179. See: CODECS project website; CORDIS project page.

BPM (Mannari, Oronzo Spagnolo, et al., 2023) helps analyse how a specific context is reshaped by the introduction of a digital technology. It highlights actors, resources, actor-technology interactions, and workflows before (the AS-IS scenario) and after (the TO-BE scenario) technology implementation. Specifically, BPM visualises the SCPS and action situations through three types of diagrams that cover complementary dimensions (Mannari, Bacco, et al., 2023):

- Goal and structure: These map technological and social entities, along with their interactions and interdependencies.
- Process-before and process-after: These outline specific operational activities with and without the multi-sensor approach.
- Process overlap: It provides a comprehensive visualisation of the transformation process by illustrating all actors, resources, and activities that are added, removed and retained during the digital transition.

This layered visual representation enables researchers to identify the exact points where costs and benefits emerge, thereby streamlining a qualitative assessment of their nature and magnitude.

3.3.2 CBA Framework

Following the process diagrams, a Cost-Benefit (CB) map was used to explicitly visualise the entities generating costs and benefits. With the CB map as reference, the CBA framework (Vergamini, 2025) was utilised to identify the implications of the multi-sensor approach across different sustainability dimensions. This framework is built on a multi-layered taxonomy of costs and benefits derived from a systematic literature review of 439 studies (Rolandi et al., 2021). This approach ensures that both tangible and intangible impacts are captured. Importantly, it provides a multidimensional analytical framework that organises these impacts across technical, socio-economic and ecological dimensions.

Unlike traditional CBA, BPM-CBA incorporates real-time data by adapting to the changing dynamics of the SES. This capability is particularly relevant in experimental contexts, where emerging technologies often operate under uncertain conditions. Because the multi-sensor disease detection system operates within an SCPS environment, the systemic and participatory logic of BPM-CBA is highly valuable. It centres stakeholder participation, which helps uncover hidden co-benefits and clarifies how costs and benefits are distributed among different actors.

Moreover, this approach accounts for the temporal distribution of impacts, acknowledging that costs and benefits do not always occur simultaneously but instead they evolve across three distinct phases:

- Set-up (S): The initial phase of system design and preparation.
- Implementation (I): The rollout and integration phase.
- Operation (O): Ongoing activities once the system is fully functional.

The integrated BPM–CBA approach was adopted to evaluate this case because it enables sustainable digitalisation through inclusive and adaptive impact evaluation. Figure 1 illustrates the detailed workflow of the empirical analysis.

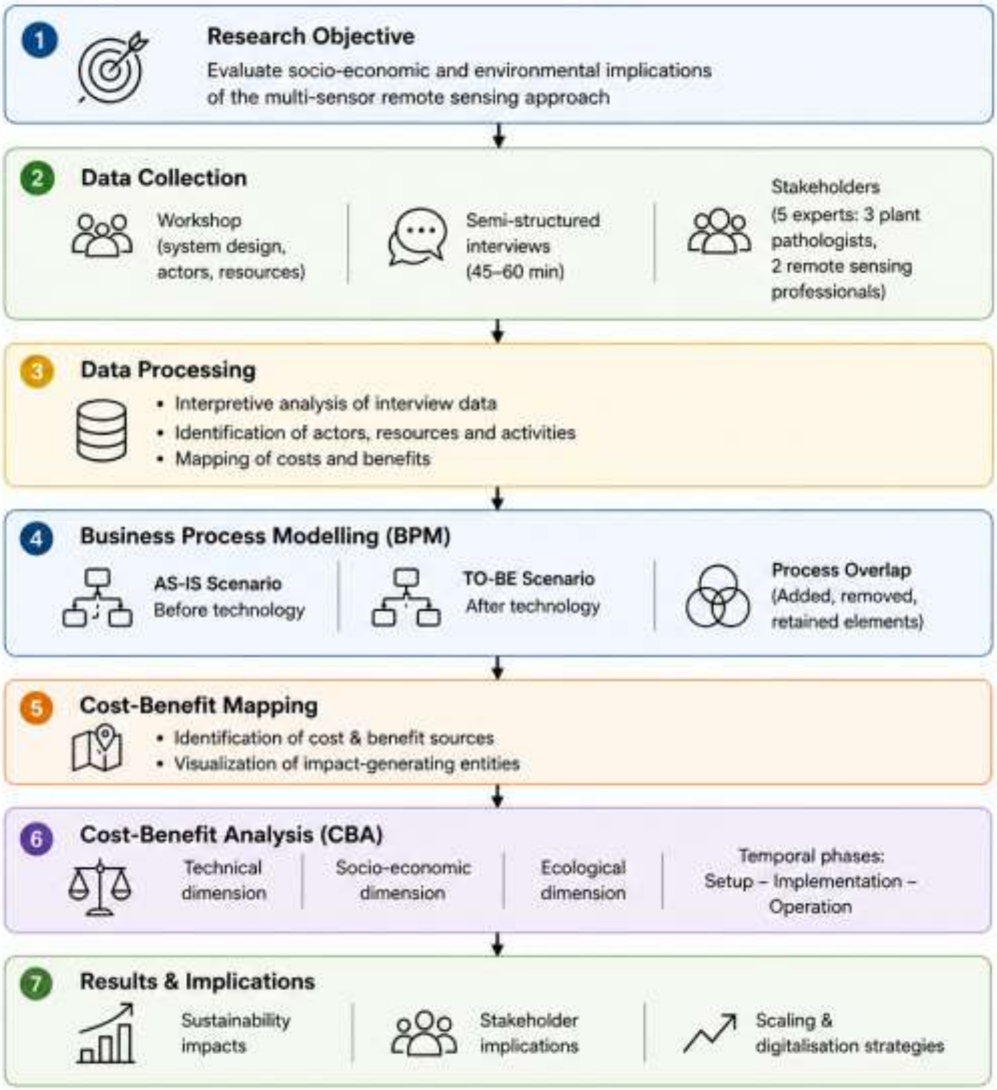

Figure 1: Workflow of the empirical analysis

4. RESULTS

4.1 Business Process Modelling of Multi-sensor approach

4.1.1 System Components and their Interactions

As shown in Figure 2, the process after the multi-sensor approach involved four stakeholder groups: agri-environmental researchers, technology providers, instrument technicians, and data processing specialists. Each group brings distinct expertise and objectives to the system:

- Agri-environmental researchers: Enable early disease detection by combining data from different sensors.

- Technology providers: Supply the multi-sensor system, which comprises an assemblage of various digital tools that together form the broader technological system.
- Instrument technicians: Assemble the system and manage flight operations.
- Data processing specialists: Analyse the data and generate an AI-based disease incidence map.

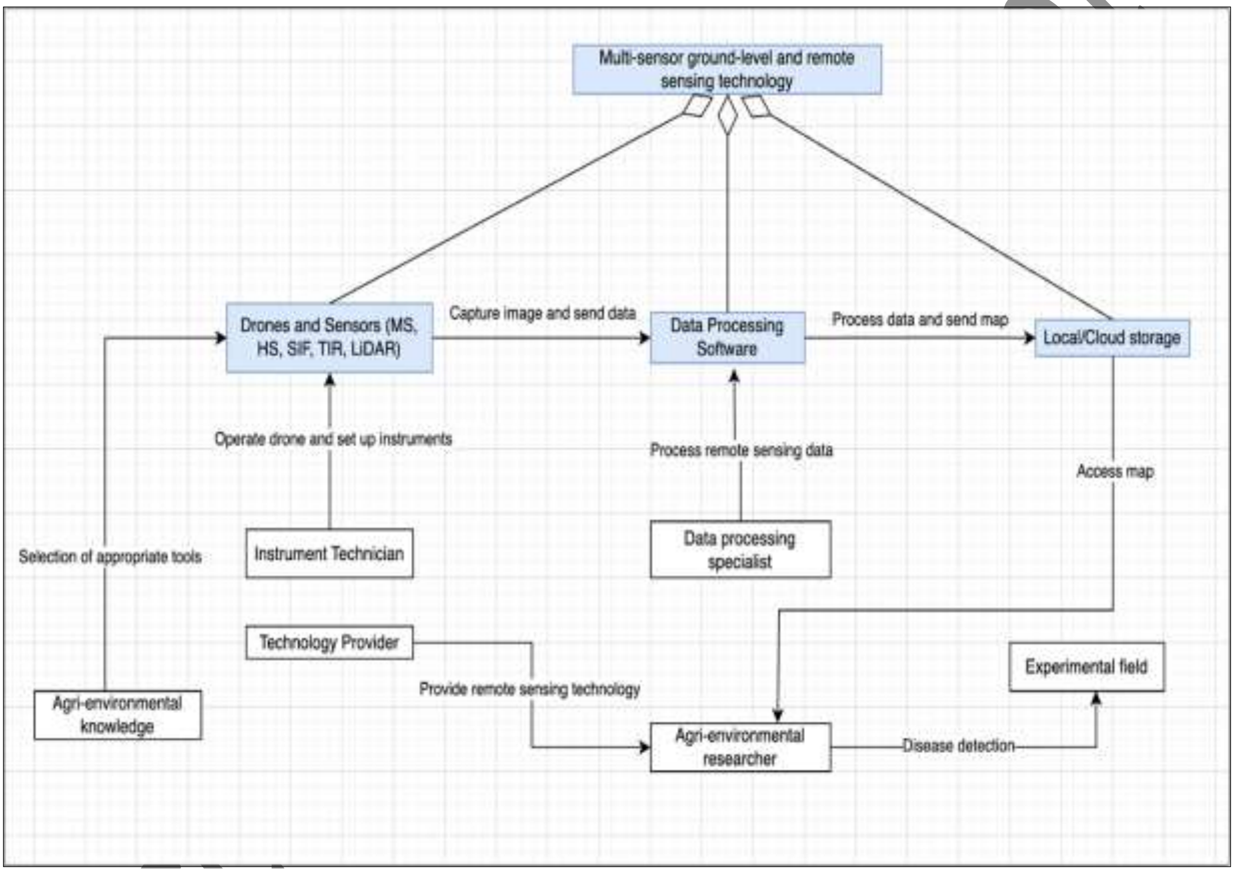

Figure 2: Interactions between system entities with the multi-sensor approach

Overall, by aligning their individual goals, the actors collaborated to advance their collective objective: developing an effective, early crop disease detection system. In this case, this alignment occurred at multiple stages along the digital value chain:

- Initial Phase (Technology-Knowledge Alignment): Here, the researchers aligned their scientific goals with the technical capabilities of drones and sensors. This is the exact interface where the 'social' met the 'cyber'.

- Execution phase (Operational Alignment): In this phase, the technician aligned the equipment supplied by the technology provider with the physical reality of the field.
- Processing phase (Technical and Cognitive Alignment): Here, collaboration happened among the data processing specialist, the processing software, and the cloud storage. This is where computing power (resource) is aligned with human skill to create a digital asset: the disease incidence map.
- Final Phase (Action Alignment): In this stage, the researcher used the disease map to intervene in the experimental field. At this point, the multi-sensor approach successfully achieved early disease detection.

4.1.2 Process Diagrams - Process Before (AS-IS) & Process After (TO-BE)

The 'process before' diagram models the sequence of activities conducted without digital technology, as shown in Figure 3. In this scenario, the researcher monitors the field manually for visual disease symptoms, relying on personal expert knowledge and traditional analysis for identification. If no symptoms are detected, routine monitoring continues. However, researchers cannot always identify symptoms immediately when they appear. Continuous manual field monitoring is rarely feasible, and even with daily inspections, early symptoms can easily be overlooked. Delays in identification caused by human error allow disease to spread unchecked. In real-world scenarios, this frequently leads to severe plant damage, increased chemical use, and significant crop loss.

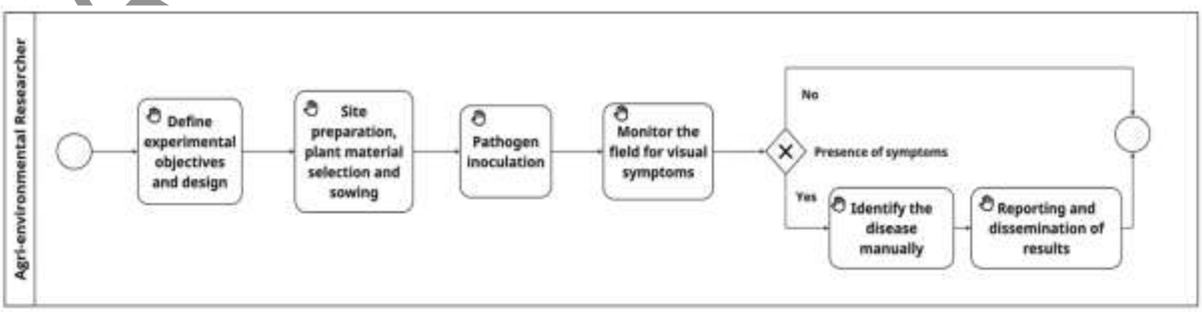

Figure 3: Process before the introduction of multi-sensor approach

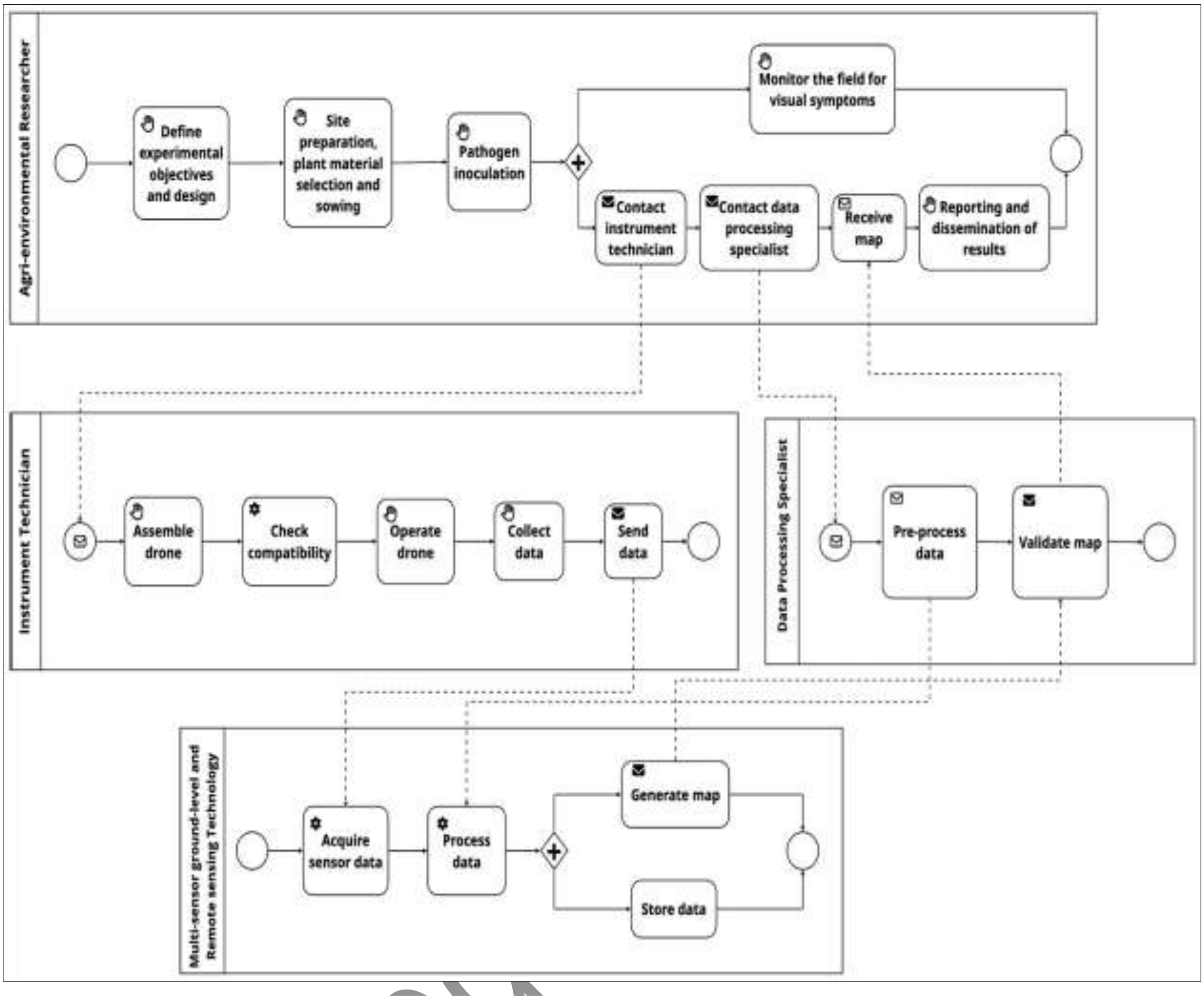

Figure 4: Process after the introduction of multi-sensor approach

The multi-sensor approach changed the current setup by adjusting both when and how information became available, as shown in Figure 4. By employing early sensor-based monitoring, physiological stress indicators linked to disease development were detected before any visible symptoms appeared. This proactive insight influences decision-making and redistributes effort throughout the monitoring process. In this case, data collection and analysis were incorporated earlier in the workflow, thereby modifying key decision points. Traditional manual observation was partially substituted with digital monitoring, while new roles emerged to handle data processing and interpretation. At a farm level, these adjustments introduce new costs, including investments in equipment, data services, and training.

Further, the introduction of this technology did not replace the researchers' conventional activities; rather, it restructured the system by incorporating new actors, resources and practices into the research process. While these additional configurations inevitably generated new costs, they also introduced significant benefits, including a reduction in human error and enhanced precision in disease detection. Overall, by enabling timely and more reliable identification of crop health issues, the technology demonstrated the potential to improve decision-making processes and contribute to more resilient agroecological management.

4.1.3 Process Overlap diagram

The process overlap diagram in Figure 5 represent the system's actors, resources, and activities using a distinct colour-coded framework:

- Green: Represent activities that remained unchanged during the process.
- Blue: Denote newly introduced activities with the technology.
- Red: Indicate activities removed as a consequence of this transition.

In this case, no resources or actors were eliminated. However, substituting traditional disease identification with technology-enabled detection introduced new actors, resources, and activities. Moreover, the role of the researcher became less central, because tasks were redistributed to newly introduced entities including the technician, the data processing specialist, and the technology itself. Consequently, while the researcher's role was reduced in terms of workload, the overall capability to detect diseases was significantly enhanced, as the system successfully identified threats before visible symptoms appeared.

One key transformation concerns the intervention timing. Earlier disease detection facilitates action when disease pressure is still low, influencing both the intensity and frequency of treatments. This shift directly affects input use, labour planning, and operational flexibility. In some cases, early information supports the decision not to intervene, thereby avoiding unnecessary treatments and costs. Importantly, these benefits arise not from guaranteed yield gains, but from expanding the decision options available to farmers.

Another key transformation concerns how monitoring activities are structured. In the AS-IS approach, monitoring was often labour-intensive and limited in scope, relying on field visits that only covered portions of the cultivated area at any given time. In the experimental TO-BE model, monitoring became more continuous, driven by digital tools. This shift changed the distribution of labour, moving effort away from repetitive manual work towards tasks such as data analysis and coordination. Consequently, the necessary skills and underlying cost structures had to adapt, with subsequent effects on workforce organisation and demand for specialised expertise. A summary of how workflow changes correspond to different implications is presented in Table S2 (see supplementary material).

The impacts of this transformation emerged primarily at the points where the blue elements are located in Figure 5. These newly introduced components incurred new costs, including the hiring of specialised personnel, capital investments in infrastructure, and software subscriptions. However, these expenses can be balanced by the technology's capacity to reduce chemical inputs and their associated costs, while simultaneously improving both the quantity and quality of produce. Beyond the farm-level, these benefits contribute to broader societal and environmental goals. Because these broader impacts are not immediately visible and are typically generated over long-term, they are not explicitly represented in this study.

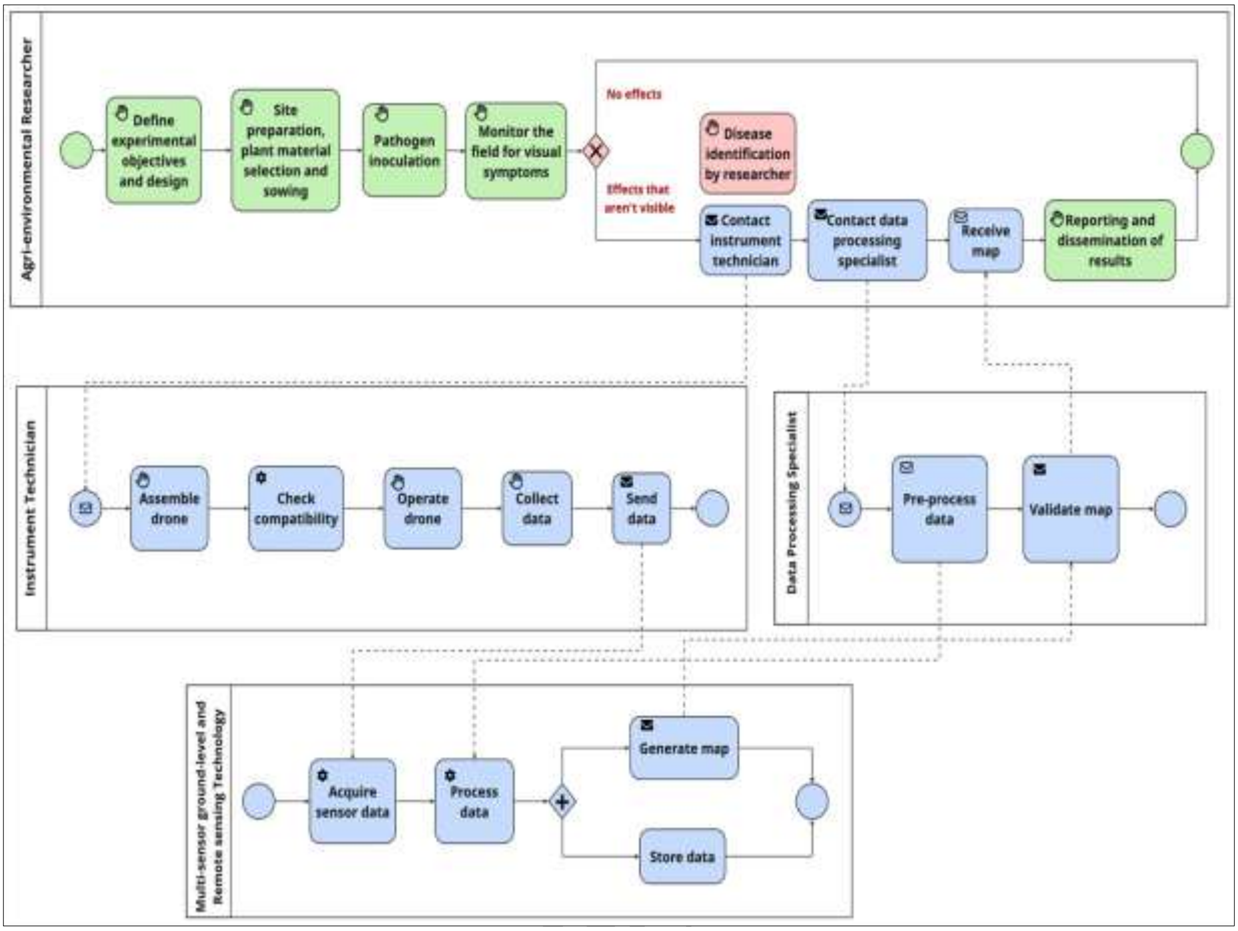

Figure 5: Process overlap diagram representing the added (blue), removed (red) and retained (green) activities

4.2 Impact assessment of multi-sensor approach

4.2.1 Illustration of Costs-Benefit drivers

In the process diagrams, physical components such as tools and digital infrastructure were implicitly included within operational tasks like 'acquire sensor data' or 'process data'. However, these elements were not visually distinguished. In contrast, the CB map explicitly highlights the specific physical components that generate cost and benefits, as shown in Figure 6. These components include new actors, such as the instrument technician and the data processing specialist, alongside dedicated software and hardware tools. In addition, because this workflow functions independently of observable field symptoms, it substantially shortens the time required for disease detection, enabling more timely and accurate interventions.

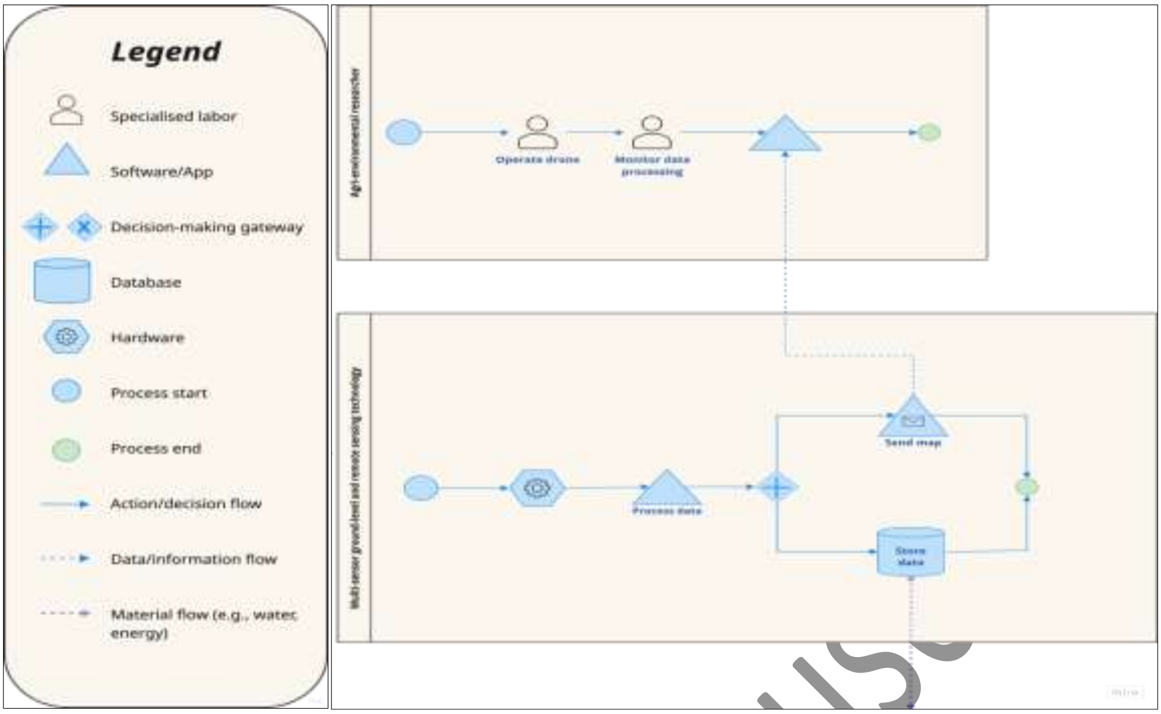

Figure 6: Transformation of Process map to Cost-benefit map with standardised notations

4.2.2 Cost-Benefit Evaluation

Using the cost-benefit checklist as a reference (see Figure S1 in supplementary material), the costs and benefits of the multi-sensor approach were identified and validated with the key stakeholders.

4.2.2.1 Cost Components of the Technology

The major costs associated with the multi-sensor approach include the operational expenses, training and human capital costs, coordination and integration costs, transition costs, governance and compliance costs, and risk and uncertainty costs. These are spread across the three temporal phases (S, I and O). The initial stages (S) incurred high upfront costs, including capital infrastructure investments (see Table S3 in supplementary material), human capital development, and transaction fees. Because these costs emerged within an experimental setting, typically during a technology development phase, where the environment is restricted and institutional funding absorbs most financial expenditures, assigning precise numerical values at this stage is not feasible. Instead, this assessment serves as an indicative representation of the types of costs that emerge during multi-sensor remote sensing development. These potential costs highlight important considerations for future scaling. Specifically, they may substantially influence adoption decisions, financial viability, and overall system sustainability as the technology transitions from controlled research environments to real-world agricultural contexts.

4.2.2.2 Implications at the SES level

The principal benefit of this technology is its capacity for precise, early plant disease detection. Mirroring this, the empirical benefits observed during the experiment focused primarily on enhanced decision-making, operational efficiency, and early detection. At the system level, the multi-sensor approach supports resilience, improves transparency, and enables more accurate monitoring. These capabilities can lower transaction costs and strengthen the collective capacity to manage disease outbreaks. When scaled to the farm and regional level, these benefits translate into lower environmental externalities, improved traceability, and more sustainable resource allocation.

Economic benefits: At the process level, the multi-sensor approach reduces the resources required to control crop diseases, thereby lowering associated costs and increasing net business profits. Consequently, this leads to enhanced production and improved product quality. Further, early identification minimises the time, costs, and energy traditionally associated with manual labour. Through data-driven decision making and optimised management, overall agricultural efficiency is significantly improved. Moreover, workforce productivity increases as the workload can be lightened by the automation of symptom monitoring.

At the SES level, collaboration among system stakeholders facilitated successful technology implementation and reciprocally, the technology itself strengthened this collaboration (as detailed in section 4.1.1), thereby improving accessibility to resources, markets, information, and innovation. These benefits are primarily realised during the implementation and operation phases of the technology, as streamlined processes eliminates operational inefficiencies and allow long-term productivity gains to materialise.

Environmental benefits: At the ecological level, reduced chemical application and the subsequent decrease in chemical drift minimise environmental disturbances, thereby supporting biodiversity conservation and ecological balance. Moreover, this approach mitigates the negative environmental externalities typically associated with conventional spraying regimes. By enhancing resource-use efficiency, the technology promotes a transition towards more sustainable practices, while strengthening the overall robustness of the system. These broader environmental benefits are expected to be realised over the long-term, particularly during the operation phase, when the continuous deployment of the technology drives large-scale reductions in chemical inputs.

Social benefits: At the social level, this approach improves labour conditions, specifically regarding worker health and safety by significantly lowering chemical exposure. Through enhanced collaboration, the multi-sensor approach promotes knowledge sharing and transfer, thereby opening the system to new innovations. Further, by contributing to environmental protection, the technology enables farmers to operate in an ethically responsible manner. At the SES level, it promotes the production of safer, higher-quality food along the supply chain. These benefits are typically realised during the implementation and operation phases of the technology.

Overall, most costs occur during setup and implementation, while benefits are typically realised later during long-term operation. Therefore, these benefits are not immediately visible or easily quantifiable. Nevertheless, as the technology is adopted and deployed over time, these advantages will gradually materialise.

In addition, the CBA framework deepens the understanding of how impacts are distributed across different stakeholder groups. This analysis was informed by interview data, project documentation, and observations collected during the study. Where the technology has not yet been deployed at scale, such as in case of farmers, the implications represent anticipated outcomes based on stakeholder perspectives and empirical evidence from the literature (see Table S4 in supplementary material). According to the analysis, although the development and operational stakeholders carry most of the technical and operational costs, farmers will bear substantial financial responsibilities. However, they also stand to gain significant benefits through improved disease detection and management. To align these dynamics, a balanced approach combining targeted subsidies, collaborative frameworks, and shared data access can help distribute responsibilities equitably.

5. DISCUSSION

Introducing the multi-sensor approach into the researchers' disease monitoring routines transformed the system from a socio-physical system to an SCPS (Rijswijk et al., 2021). This transition altered the roles of researchers; introduced new actors, artefacts, and routines, and triggered innovation processes such as the development of a more efficient detection system. Collectively, these changes transformed the conditions required to operate the SCPS. The transformed system necessitated new skills, knowledge, and investments while simultaneously generating impacts at the broader SES level. Within this framework, 'impacts' refer to the direct and indirect implications of digital transformation on the SCPS elements (entities, relationships, and activities), alongside its evolving needs and expectations (Metta et al., 2022).

To elaborate, the developed technology holds significant potential for ensuring early disease detection at the process level, as it combines sensors capable of collecting data across diverse crop characteristics (Centorame et al., 2024; Ishimwe et al., 2014; Khanal et al., 2017; Ndlovu et al., 2024; Wiersma & Landgrebe, 1980; Yadav et al., 2024). Specifically, hyperspectral sensors can identify specific diseases by capturing many narrow spectral bands (Adão et al., 2017; Mahlein et al., 2012). This capability minimises yield losses and reduces reliance on chemical treatments within individual SCPS units, ultimately impacting the SES level (Calderone et al., 2025; Chen et al., 2020; Gheorghe et al., 2024; Nguyen et al., 2025; Rahman et al., 2021). However, the structural conditions needed to operationalise this transformed SCPS may introduce new challenges and broader systemic issues across different levels if left unaddressed.

5.1 Economic, Environmental and Social Implications

The multi-sensor approach can contribute to improved economic returns by reducing yield losses and enhancing resource-use-efficiency; however, acquiring and processing high-resolution spectral data remains capital-intensive and complex (Mammarella et al., 2022). This complexity stems from the high-end infrastructure requirements observed in the current case study (see Table S1). Huge capital and management costs render the technology unaffordable, particularly for smallholder farmers (Ndlovu et al., 2024; Nhamo et al., 2020). In addition, operating these systems requires specialised expertise that farmers often lack - a common barrier to technology adoption (Pathak et al., 2019). This creates additional costs associated with recruiting personnel who possess the necessary expertise and certifications (European Commission, 2025; Trendov et al., 2019; Yu et al., 2025). For example, if a specialist lacks the training needed to interpret multi-sensor data, the transaction costs in terms of time and labour increase dramatically.

In addition, because multi-sensor systems are data-intensive, they require robust infrastructure, extensive computational resources for data processing, and significant power and time commitments (Anam et al., 2024; Mammarella et al., 2022; Yacoob et al., 2024; Zhang & Zhu, 2023). Securing the availability and accessibility of such infrastructure, however, often presents a significant challenge. Although the findings from this experimental context are qualitative, they closely align with previous literature highlighting the huge costs associated with integrating digital technology into agriculture (Anam et al., 2024; Knierim et al., 2018; Mammarella et al., 2022; Rahman et al., 2021; Rejeb et al., 2022; Yacoob et al., 2024; Yu et al., 2025; Zhang & Zhu, 2023).

Regarding the environment, early disease detection and targeted mitigation reduce agrochemical use and its associated environmental drift (Calderone et al., 2025), thereby supporting ecological balance (Mclaughlan & Brandli, 2013). Within this experimental context, disease detection efficiency was significantly improved, demonstrating that technological integration enhances agricultural efficiency through data-driven decision-making (Saiz-Rubio & Rovira-Más, 2020). Furthermore, it boosts labour productivity by reducing human error, improves overall working conditions (Hansen et al., 2022; Shepherd et al., 2020), and contribute to increased competitiveness (European Commission, 2025).

At the SES level, food standards, particularly regarding food safety are enhanced through reduced chemical use, while safer labour conditions foster the development of an ethically responsible system (Rahman et al., 2021). As evident from this case study, adopting a multi-sensor approach fosters collaboration among stakeholders, enhances knowledge exchange, and supports the formation of a dynamic innovation ecosystem.

5.2 Political and Institutional Implications

The high upfront costs of this approach risk widening the digital divide (Arion et al., 2024; Selwyn, 2004) and further marginalising resource-limited farmers, a pressing concern for policy-makers (Shepherd et al., 2020). In addition, uneven technology access and inadequate regulatory frameworks can exacerbate systemic dependencies, alter power dynamics (Chancellor et al., 2020) and displace traditional labour (Carolan, 2020; Prause, 2021). At the farm level, this can result in a loss of both traditional experiential knowledge (Ingram & Maye, 2020; Moschitz & Stolze, 2018; Mute Schimpf et al., 2023) and decision-making autonomy (Nuthall & Old, 2018).

At a farm level, digitalisation redistributes power through data governance: specifically, actors who control data storage, analytics and software updates acquire disproportionate influence over decision-making, thereby altering traditional power structures (Arora & Glover, 2017; Foley, 2004). This shift represents a critical issue and remains a priority research question within digital agriculture literature (Ingram et al., 2022). Understanding these implications is essential for ensuring that digital innovation fosters inclusive and responsible development, rather than reinforcing existing inequalities or dependencies. Because this technology has not yet been deployed outside controlled environments, these socio-political implications are not yet visible. However, once the technology scales to the farm level, such factors will substantially affect overall system sustainability if left unaddressed.

At the institutional level, a lack of interoperability frequently hinders technology integration (Abbasi et al., 2022; Aydin & Aydin, 2020; European Commission, 2025), as harmonising and integrating new technology with existing equipment or software presents a significant challenge (Degieter et al., 2023). In this specific case, the experiment utilised data processing software supplied by the drone manufacturer (DJI), which rendered the users reliant on the company for software updates. This reliance creates an enforced dependence on the technology provider (Martens & Zscheischler, 2022) and highlights the systemic risks associated with technological dependency and vendor lock-in, where long-term reliance on proprietary platforms can undermine operational autonomy and inflate costs.

At a farm level, this dynamic mirrors the widely perceived risk of becoming overly dependent on technical experts (Ajena et al., 2022; Milian Gómez & Byttebier, 2025; Moschitz & Stolze, 2018). Furthermore, the data protection concerns raised in this study highlight barriers that can prevent transparent data sharing among stakeholders (Hansen et al., 2023; Paudel et al., 2025). Therefore, a key recommendation is to develop robust frameworks capable of addressing data privacy and security concerns to foster trust and encourage wider technology adoption (McCarthy et al., 2023).

Finally, a critical issue within this experimental context is the lack of end-user involvement in the technology development process. Research initiatives frequently exclude farmers during the design and development stages, which complicates subsequent scaling efforts and diminishes the technology's practical applicability. Therefore, approaches such as 'user-centred design' or 'living labs' must be promoted to anticipate systemic risks, thereby ensuring inclusive, context-specific technology development and integration.

5.3 Way Forward & Limitations

In summary, the impacts identified in this study are consistent with the existing literature, reinforcing the validity of these findings. This alignment indicates that recurring cost categories - operating expenses, human capital requirements, data management, and transaction costs remain critical determinants in technology adoption. Nevertheless, targeted strategies can mitigate these high adoption costs. One approach is to involve technological specialists and innovative enterprises to offer affordable models where initial investments are shared among multiple farms (United Nations Development Program (UNDP), 2021) or managed through community-based ownership structures (Nhamo et al., 2020) that distribute costs more equitably.

Furthermore, collaboration among diverse stakeholders is crucial for establishing ethical frameworks and regulations that ensure responsible technology use (Anam et al., 2024). From a technical perspective, specialists must design systems that are simpler, more user-friendly, and adaptable to varied farming contexts (Zhang & Zhu, 2023). Simultaneously, end-users and farmers require adequate training to operate these technologies effectively, thereby supporting long-term adoption (Yacoob et al., 2024).

Methodologically, experimental setups may not fully capture real-world variability, potentially affecting the generalisability of the findings. Consequently, the results of this study are primarily applicable to experimental fields and research centres. However, this experimental-level analysis successfully anticipated potential risks and benefits, thereby easing the technology's future transition to commercial farm use.

Another major limitation concerns the quantification of the costs and benefits associated with the multi-sensor approach. While traditional CBA frameworks typically extend to the monetary quantification, this study focuses primarily on the qualitative and process-based phases of the BPM-CBA framework. The main aim is to identify the operational changes, potential impacts, risks, and trade-offs associated with technology integration, rather than establishing a full monetary valuation. This choice rooted in the experimental, publicly funded nature of the technology development process, where major capital expenditures are subsidised and do not yet reflect real market conditions.

6. CONCLUSION

In this study, a novel multi-sensor approach was assessed across economic, social, environmental, governance, and technical domains. Adopting a sustainable digitalisation framework and a tailored methodology (BPM-CBA), the operational context was mapped and the associated costs and benefits were identified through user interviews guided by a structured cost–benefit framework. The results demonstrated that feasibility depends not only on hardware and operational costs, but also on integration risks, coordination strategies, regulatory pressures, and distribution of intangible benefits. Further, the multi-sensor approach enables disease detection at the pre-symptomatic stage, thereby establishing the necessary conditions for early intervention. This approach lowers reliance on agrochemicals, reduces input costs, and improves resource-use efficiency, while minimising environmental impacts and supporting ecological balance. Moreover, by providing real-time data, it strengthens food system resilience, reduces farmers' workloads, supports data-driven decision making and promotes stakeholder collaboration.

However, advanced agricultural technologies presents significant challenges that must be addressed before widespread farm-level implementation. The primary limitations relate to infrastructure acquisition and maintenance, operational coordination, complex data management, and secure data sharing. Furthermore, recruiting skilled personnel for specialised tasks escalates operational costs. Analysing the distribution of impacts among stakeholders highlights key equity concerns and underscores the importance of collaboration among diverse actors. Finally, the temporal asymmetry of these factors demonstrates that implementation costs are immediate, whereas the benefits typically accrue over the long-term.

In conclusion, while technological integration in agriculture entails significant financial, technical and regulatory challenges, coordinated stakeholder collaboration and targeted policy frameworks can effectively mitigate these barriers. Implementing these strategies is crucial for achieving sustainable digitalisation. Further, it is recommended to examine these multidimensional impacts within other contexts to develop a comprehensive understanding of sustainable technology integration.

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