




Environmental, economic, and social impacts of precision agricultural technology: Convergences and divergences between theory and practice

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ABSTRACT

Precision agriculture (PA) technologies are widely promoted for their potential to enhance sustainability, efficiency, and resilience in agricultural systems. However, few studies critically assess whether these promises hold in practice, particularly in rural contexts facing infrastructure and resource constraints. The main aim of this paper is to identify environmental, economic, and social (E-E-S) impacts of PA technologies in crop farming, and convergences and divergences between theory and practice. A literature review of E-E-S impacts of PA technologies was combined with an empirical assessment of a multi-robot sensor-based irrigation system deployed on a smallholder farm in the Isles of Scilly, a remote rural island community in the UK. By comparing the expectations documented in the literature with modelled impacts from the case study, this paper identifies areas of convergence and divergence between technological promise and real-world potential in a rural setting. The results reveal several trade-offs between literature expectations and the case study outcomes: although sensor-based irrigation reduced water demand by 23 %, the system's electricity use significantly increased, amplifying carbon emissions; anticipated labour savings were offset by the need for specialized supervision, raising operational costs; and while the literature often highlights community benefits, in practice the social impact remained limited in the case study, with no major changes expected in areas such as worker health and safety or systematic issues like dependency on platforms or agritech providers. This study contributes critical insights for rural social science into the conditions under which PA can support more context-responsive, equitable, and sustainable adoption, highlighting that realizing its full value requires attention not only to technical performance but also to energy trade-offs, cost-effectiveness, and broader societal impacts for smallholder and remote rural communities.

1. Introduction

Smart and connected technologies are transforming modern agriculture and hold considerable promise for enhancing efficiency, productivity, and sustainability, particularly in rural areas (Krampe et al., 2024; Reeves et al., 2025). Precision Agriculture (PA), which integrates tools such as sensors, drones, cameras, and robots, offers practical solutions for enhancing connectivity, improving water and resource management, and increasing productivity (Higgins et al., 2023). By enabling real-time monitoring, data-driven decision-making, and automation, PA helps farmers reduce waste, optimize inputs, and improve yields (Afzal and Bell, 2023; Bongiovanni and Lowenberg-DeBoer, 2004). PA can also enhance working conditions by reducing manual tasks, supporting safer and more informed operations, and making

agricultural knowledge more accessible through digital platforms (Thompson et al., 2019). Furthermore, PA can lower input costs and boost profitability by improving the efficiency of farm operations. Together, these capabilities position PA as a promising pathway for strengthening rural development and increasing long-term agricultural resilience. However, the adoption of PA sometimes faces E-E-S challenges during implementation.

From an environmental standpoint, PA offers significant potential for reducing resource use and minimizing ecological impacts (Balafoutis et al., 2017; Lowenberg-DeBoer & Erickson, 2019; Schimmelpenninck, 2016). Soil moisture sensors, for example, optimize irrigation scheduling and help conserve water (Bondesan et al., 2023; Sariga et al., 2016). Drones can be used for site-specific herbicide application, reducing chemical inputs, saving water, and decreasing labour needs

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(Hiremath et al., 2024). Similarly, robots enhance operational efficiency in tasks such as harvesting and weeding, thereby lowering pesticide use and reducing worker strain (Pal et al., 2024; Gerhards et al., 2022). However, these environmental benefits can be offset by increased energy use, as digital components require continuous power and may place pressure on local energy systems (Khan et al., 2023). This highlights the need for careful integration of renewable energy sources to ensure that environmental gains are not undermined by higher carbon emissions or unsustainable power demands.

From an economic perspective, PA technologies contribute to greater operational efficiency by reducing input use and enabling more targeted interventions. For example, Global Positioning System (GPS)-guided machinery and unmanned aerial vehicle (UAV) mapping facilitate site-specific treatment, lower fertilizer use while maintaining or improving crop yields (Medici et al., 2021). Drone-enabled, variable-rate defoliant application is another example of cost optimization, reducing chemical costs and labour needs. These technologies thus support more cost-effective and sustainable production systems. However, their adoption comes with upfront investments. Establishing the 5G and IoT infrastructure required for PA, for instance, demands significant capital, which is particularly challenging for smaller farms (Walter et al., 2023). Similarly, the use of high-end tools such as UAV LiDAR provides valuable insights but may not be used if there are no clear returns on investment (ROI) (Kiefer et al., 2024). Therefore, for PA to be successfully implemented, there needs to be clear financing models and economic benefits for adoption.

From a social point of view, the adoption of PA technologies shift the role of farmers from manual operators to systems managers, requiring higher levels of digital literacy and technical knowledge (Yaqt and Menezes, 2022). While automation reduces physical labour and improves workflow efficiency, it also raises cognitive demands and necessitates continuous upskilling, thereby changing the identity and expectations of agricultural workers (Pedersen et al., 2020; McGrath et al., 2023). For smallholder farms, however, high costs and digital skill gaps remain key obstacles, risking greater inequity as large farms adopt technology more rapidly (McGrath et al., 2023). At the societal level, digital tools can drive economic diversification and knowledge sharing, yet they also introduce concerns around data ownership, transparency, and decision-making autonomy (Srivetbodee and Igel, 2021; McGrath et al., 2023). Successful deployment of PA requires clear opportunities for empowerment, inclusivity, and better social conditions for rural individuals and communities.

Currently, limited research has explored the integrated E-E-S impacts of PA technologies. Many studies focus on *single* dimensions or *implemented* technologies, leaving significant gaps in understanding how the *multi-dimensional* impact of *new* digital systems will interact with rural ecosystems and communities. In particular, there is little work that (i) compares how impacts are assessed and reported across E-E-S studies, (ii) links these methodological tendencies to the performance of concrete digital architectures such as multi-robot and edge-computing systems, and (iii) examines how these dynamics play out in remote rural smallholder settings.

The main aim of this paper is therefore to identify the E-E-S impacts of PA technologies in crop farming, as well as to examine the convergences and divergences between theory and practice. Specifically, the paper's primary contribution is to rural studies by showing how widely promoted promises of PA are reshaped by the constraints and opportunities of a remote rural island smallholder setting, including infrastructure limits, scale effects, and the practical conditions of technology support and use. To achieve this, we combine the literature review (Section 1) with an empirical case study in the Isles of Scilly (Section 2), followed by a discussion that links review and case findings and a conclusion on the sustainable, context-sensitive adoption of PA in rural regions. In doing so, we draw on PA scholarship and sustainability assessment methods to support a rural social science argument about why "promise versus practice" varies by place and by the characteristics

of rural settings.

2. Literature review

2.1. Literature review methodology

In March 2025, a literature search was run in Scopus and Web of Science. Tailored Boolean queries combined technology terms (e.g., sensor, drone, or robots) with impact-related (i.e., environmental, economic, and social) and sectoral keywords (i.e., crop farming); full strings are provided in [Supplementary Material S1](#). Searches were limited to peer-reviewed journal articles, reviews, and conference papers published in English.

The initial search identified 291 records. After removing seven duplicate entries, 284 records proceeded to title and abstract screening. This phase was supported by ASReview, an open-source active learning tool that prioritizes likely relevant records and helps maintain transparency (van de Schoot et al., 2021). A total of 168 records were excluded for falling outside the review scope using this tool.

Full texts were retrieved for the remaining 112 studies; four articles could not be retrieved, resulting in 112 studies undergoing full assessment, 84 articles were excluded for the following reasons: absence of any form of impact assessment ($n = 73$), mismatch with the technologies of interest ($n = 9$), or misalignment with the agricultural focus ($n = 2$). Illustrative cases include Steiger et al. (2025), which evaluated soil-sensor accuracy without environmental analysis; Karim et al. (2024), which detailed a LiDAR system but omitted economic metrics; and Kumaran et al. (2023), which proposed an IoT pest-control solution yet reported no social outcomes. This resulted in 28 studies that met the inclusion criteria following the systematic screening process.

Backward and forward snowballing yielded 14 additional eligible papers (six environmental and eight social articles). In total, 42 studies met all the inclusion criteria: 23 environmental, seven economic, and 12 social articles (see [Fig. 1](#) for the full PRISMA flow diagram).

To ensure a systematic and comparable synthesis, the 42 included articles were subjected to qualitative coding and structured analysis using ATLAS.ti¹ version 24. A deductive coding approach was employed, with code categories predefined to align with the study's research objectives. Codes were grouped around the three main dimensions (environmental, economic, and social impacts) technology type (e.g., sensors, drones, robotics), the specific assessment method used (e.g., field-level metrics, (social) Life Cycle Assessment (LCA), cost-benefit analysis), and the types of outcomes reported (e.g., input savings, ROI, labour displacement, data ownership, or biodiversity impacts). Within these groups, relevant text passages were systematically coded to extract evidence on outcomes such as input savings, productivity shifts, environmental trade-offs, and labour dynamics. This approach enabled the identification of thematic patterns, methodological gaps, and recurring findings across the literature base, which informed the structure and interpretation of the review results.

2.2. Literature review results

The reviewed literature reveals distinct methodological tendencies across the E-E-S dimensions of PA technologies, with each domain offering complementary insights but also facing specific limitations.

Of the 23 environmental studies, 16 (around 70 %) used partial or field-level assessments focusing on indicators such as GHG emissions, nitrogen use efficiency, pesticide and herbicide reduction, water use and energy balances, mostly in relation to site-specific fertilisation, sensor-based irrigation and UAV spraying (Jovarauskas et al., 2021; Stamatidis et al., 2018; Chen et al., 2020; Han et al., 2021; Hiremath et al.,

¹ ATLAS.ti Scientific Software Development GmbH. (2024). ATLAS.ti (version 24) [Qualitative data analysis software]. <https://atlasti.com>.

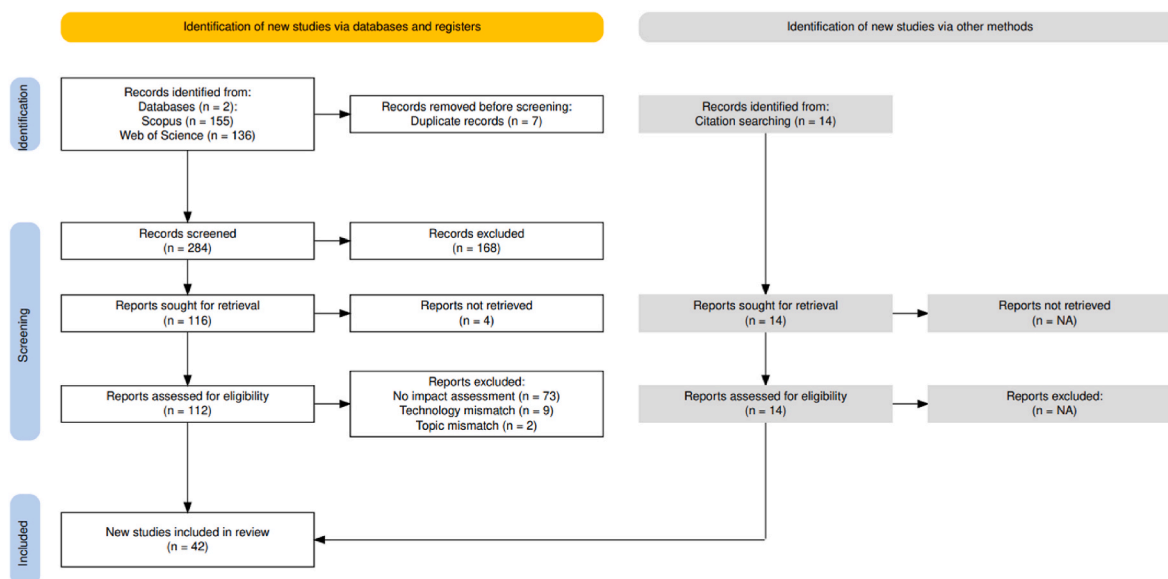


Fig. 1. PRISMA flow diagram of the literature review selection process.

2024; Bondesan et al., 2023; Martelli et al., 2024; Addas et al., 2024; Qaswar et al., 2024; Fu et al., 2024; Zhou et al., 2024; Sariga et al., 2016; Singh et al., 2024). Functional units were usually per hectare, sometimes complemented by yield-based metrics (e.g., kg CO₂-eq per kg product), and toxicity-related impacts were seldom included. Only seven studies (30 %) applied LCA: two full, ISO 14040/44-compliant cradle-to-farm-gate LCAs (Bručienė et al., 2024; Fotia et al., 2021) and five partial LCAs focused on inputs and on-farm operations (Medel-Jiménez et al., 2022, 2024; D'Antonio et al., 2023; Li et al., 2024; Balafoutis et al., 2017). All used area-based functional units, with most also reporting yield-based results, but few explicitly considered complete digital connectivity architectures or system-wide sustainability outcomes.

In the economic literature, five of the seven studies used CBA (Baio et al., 2017; Belayneh et al., 2013; Finco et al., 2022; Qaswar et al., 2024; Zhou et al., 2024), often combined with scenario or sensitivity analysis and partial budgeting (Baio et al., 2017; Finco et al., 2022; Rajmis et al., 2022). The remaining two applied return-on-investment and payback calculations supported by longitudinal cost data (Abdo-Peralta et al., 2024; Belayneh et al., 2013).

Out of the 12 social papers reviewed, four studies (Bacco et al., 2020; Lorek et al., 2024; Mahmoudi et al., 2024; Michaliszyn-Gabryś et al., 2024) applied empirical methods, like expert interviews, questionnaires, and workshops to explore implications of PA technologies for the use phase. The remaining eight studies were non-empirical (Lehmann et al., 2013; van Haaster et al., 2017; Van der Burg et al., 2019; Pedersen et al., 2020; Singh et al., 2024; Ryan et al., 2022; Yaqot and Menezes, 2022; McGrath et al., 2023), relying on literature reviews or conceptual discussion.

2.2.1. Environmental impacts

Across the reviewed studies, PA technologies consistently outperform conventional practices in terms of environmental performance. These systems reduce GHG emissions, improve water and nutrient efficiency, lower pesticide use, and decrease overall energy demand.

2.2.1.1. GHG emissions and climate impact. Reductions in GHG emissions are most prominently reported in studies focused on fertilizer optimization, tractor automation, and improved input targeting. For instance, Medel-Jiménez et al. (2022) modelled a sensor-guided variable-rate nitrogen application in winter wheat, reporting an 8.6 % decrease in climate impact compared to conventional fertilization. Their

later study (Medel-Jiménez et al., 2024) found that proximal sensors offered the highest emission reduction among four precision technologies, achieving a 17 % reduction in emissions. Similarly, a five-year field trial by Jovarauskas et al. (2021) showed a 9.4 % GHG reduction from precision fertilization, while D'Antonio et al. (2023) demonstrated that automatic tractor guidance cut the GHG emissions of weed control operations for each hectare by 27 %. While Balafoutis et al. (2017) found that precision viticulture reduced the product carbon footprint by 25–28.3 %, mainly due to reduced fertilizer use and improved energy efficiency, with results varying by vineyard type and production intensity. Bručienė et al. (2024) demonstrated that robotic sugar beet systems led to lower GHG emissions (27.18 vs. 36.98 kg CO₂-eq t⁻¹) compared to conventional methods.

2.2.1.2. Water use and irrigation efficiency. In the domain of water use, smart irrigation systems yielded consistent improvements in efficiency. For example, Feng et al. (2022) evaluated an IoT-enabled greenhouse system for raising rice seedlings and reported a 47.2 % reduction in water use across the entire growth process. Martelli et al. (2024) applied a machine learning-based irrigation framework in tomato cultivation, achieving up to 32.7 % savings under deficit irrigation conditions. Soil sensor-based irrigation strategies also showed strong results: Bondesan et al. (2023) reported a 26 % reduction in irrigation water use in corn production using soil moisture sensors combined with variable rate irrigation. Addas et al. (2024) demonstrated a 41 % reduction using a real-time AI-powered robotic system. Yang et al. (2020) showed that a UAV-coupled automated irrigation system in rice led to 53.5 % and 21.7 % water savings in two cropping seasons. Hiremath et al. (2024) also recorded substantial water savings using UAV sprayers.

2.2.1.3. Fertilizer and pesticide use reduction. Fertilizer and pesticide optimization emerged as another significant environmental benefit. Stamatiadis et al. (2018) reported a 38 % reduction in nitrogen input in wheat without compromising yields. Jovarauskas et al. (2021) reported a 19 % reduction in nitrogen and improved nitrogen use efficiency (NUE) through sensor-based fertilization. Fu et al. (2024) employed UAV-mounted sensors and a time-series diagnosis approach to dynamically adjust nitrogen application in wheat and rice, aligning topdressing with both agronomic and economic optima in 86 % of cases. Li et al. (2024) showed that an NNI-based strategy reduced nitrogen rates by 42 % and global warming potential by 28.8 %, with no yield penalties. The AI-driven robotic system examined by Addas et al. (2024) further

reduced chemical inputs by 33 % and increased yields by 26 %. [Chen et al. \(2020\)](#) found that a laser-guided intelligent sprayer reduced pesticide use by 30.6 %–58.7 % across various fruit crops. In soybean, [Hiremath et al. \(2024\)](#) also demonstrated a 30 % reduction in herbicide use through drone-based spraying, confirming similar weed control effectiveness. [Mattivi et al. \(2021\)](#) employed UAV and GIS-based weed mapping to restrict herbicide application to just 3.47 % of the total field area.

2.2.1.4. Energy use and operational efficiency. Energy use and operational efficiency improvements were frequently linked to automation and intelligent system design. [D'Antonio et al. \(2023\)](#) showed that automatic tractor guidance increased effective field capacity by 46 %, reduced fuel use by 11.5 %, and decreased energy intensity by 25 %. In olive orchards, [Fotia et al. \(2021\)](#) reported that switching to DSS-based irrigation systems reduced energy use by up to 42.1 %. In broader comparisons, [Medel-Jiménez et al. \(2024\)](#) found that all four evaluated PA technologies (automatic steering, section control, proximal sensors, and prescription maps) reduced environmental impacts per unit of output, including those related to energy use, such as fuel consumption and climate change potential. [Bručienė et al. \(2024\)](#) also reported lower fossil fuel use and energy-related impacts in robotic sugar beet systems compared to conventional ones, with a 19 % lower fossil fuel depletion (213.18 vs. 262.38 MJ), and a 13–22 % decrease across all environmental impact categories assessed.

A consolidated overview of the key environmental outcomes is provided in [Supplementary Material S2](#).

Across the reviewed studies, the environmental literature suggests that PA's sustainability benefits are highly contingent on baseline input intensity and on whether resource savings offset additional energy demand from digital infrastructure. This motivates our empirical focus on use-phase footprints (carbon, energy, water, and biodiversity) when evaluating a multi-robot system in a remote rural setting.

2.2.2. Economic impacts

The reviewed studies demonstrate that PA and edge-enabled farming systems generate tangible economic benefits across diverse crops and geographies by outperforming conventional practices by boosting yields, lowering input and labour costs, improving ROI, and enhancing operational efficiency.

2.2.2.1. Yield gains and profit increases. One of the most consistent findings across studies is a significant increase in yield and profitability. The deployment of edge computing in strawberry greenhouses, as reported by [Abdo-Peralta et al. \(2024\)](#), led to a 15 % yield increase (from 5.0 to 5.75 kg m²), alongside gains in fruit quality and market value. In cotton farming, [Baio et al. \(2017\)](#) documented a 7.9 % rise in operating profit, totaling an additional US\$ 410,000. For potato farming, [Qaswar et al. \(2024\)](#) found that variable rate nitrogen (VR-N) application raised average yield by 1.89 t/ha and increased gross margins by €374.83/ha. Similarly, [Zhou et al. \(2024\)](#) observed an 8.37 % yield increase in maize and a corresponding profit gain of USD 153/ha under variable-rate fertilization (VRF). [Rajmis et al. \(2022\)](#) reported a 25 % improvement in gross margins through site-specific pesticide application.

2.2.2.2. Input cost savings. Reduction in input costs was another key driver of improved economic performance. Fertilizer savings were particularly notable: [Baio et al. \(2017\)](#) reported a 41 % decrease in total fertilizer expenditure, including a dramatic 74 % reduction in urea use and a 94 % drop in potassium chloride. [Zhou et al. \(2024\)](#) recorded a 16.4 % decline in nitrogen application under VRF, resulting in cost savings of USD 37.5/ha. In pesticide management, [Rajmis et al. \(2022\)](#) showed that herbicide and fungicide costs fell by 66 % (€111/ha) and 38 % (€75/ha), respectively, through precision application. [Belayneh et al. \(2013\)](#) quantified irrigation savings at USD 20,288 annually

through sensor-controlled water management.

2.2.2.3. Labor and operational savings. Smart farming technologies also contribute to notable reductions in labour requirements and associated costs. [Belayneh et al. \(2013\)](#) reported a savings of 90 h per year in irrigation management, valued at USD 12,150, due to the use of automated scheduling and monitoring. [Rajmis et al. \(2022\)](#) highlighted the cost advantage of drone-based monitoring, which reduced labour costs to €0.50/ha compared to €2.69/ha for traditional methods. In addition, [Qaswar et al. \(2024\)](#) noted that high-resolution soil scanning, costing only €25 per hectare annually, facilitates long-term precision input planning, thereby improving overall operational efficiency.

2.2.2.4. Return on investment and financial viability. Across the studies, strong ROI was a recurring outcome, demonstrating the financial viability of PA even in capital-constrained contexts. [Abdo-Peralta et al. \(2024\)](#) reported an ROI of 103.03 %, with the entire investment recovered within a single growing season. In the cotton sector, [Baio et al. \(2017\)](#) found that PA shortened the capital recovery period from 11 to 10 months and increased the net present value (NPV) by US\$ 2.72 million. [Belayneh et al. \(2013\)](#) calculated a 37.5 % ROI for sensor-driven irrigation, with payback periods falling below four months under high water pricing scenarios. [Rajmis et al. \(2022\)](#) identified a break-even point at 314 ha/year for site-specific pesticide systems, and found that using external drone services further improved ROI by minimizing upfront investments.

2.2.2.5. Economic trade-offs and threshold conditions. Some studies identified conditional trade-offs and threshold conditions. For example, [Finco et al. \(2022\)](#) highlighted that economic water productivity turned negative (-€0.3/m³) in irrigated plots due to high fixed costs and sub-optimal yield performance, despite irrigation providing yield stability. [Zhou et al. \(2024\)](#) acknowledged that, although the VRF system itself was cost-effective, the initial development and deployment of the nitrogen sensors required a high capital investment. [Qaswar et al. \(2024\)](#) observed diminishing returns when nitrogen was over-applied in low-fertility zones, emphasizing the need for refined zoning and calibration strategies.

A structured summary of the key economic outcomes is provided in [Supplementary Material S3](#).

The reviewed articles indicate that economic viability hinges on how labour and input savings compare with capital, maintenance, and service costs, with outcomes strongly conditioned by scale and crop value. These findings inform our case study cost breakdown, which tests whether the same efficiency mechanisms remain meaningful for a smallholder farm with low baseline resource use.

2.2.3. Social impacts

Social impacts were categorized by stakeholder group, initially following the [UNEP \(2020\)](#) guidelines for Social Life Cycle Assessment (S-LCA) of products and organizations. [UNEP \(2020\)](#) notes that its stakeholder categories are not exhaustive and may be adapted to the goal and scope of the study. In the agricultural technology literature, farmers are consistently distinguished from hired workers due to differences in employment status, decision making authority, and exposure to social impacts. According to the [Hurst et al. \(2007\)](#), waged agricultural workers do not own or rent the land on which they work, nor the tools and equipment they use, they are employed on farms. In these respects, they are a group distinct from farmers. As [UNEP \(2020\)](#) does not explicitly distinguish farmers, they were included alongside workers as a separate stakeholder group to better reflect the empirical literature and improve analytical clarity. The stakeholder category children was excluded, as no references to them were found in the literature. Remaining stakeholder groups are considered conceptually in line with [UNEP \(2020\)](#), though their operationalization varied across studies to

reflect sector- and study-specific contexts.

2.2.3.1. Workers. Digitalization in agriculture through tools such as laser weeders, robots, drones, and data-driven systems has mixed impacts on workers. Benefits include improved occupational health and safety by reducing exposure to hazardous tasks like chemical spraying and repetitive labour (Lorek et al., 2024; Michaliszyn-Gabryś et al., 2024; Pedersen et al., 2020; Singh et al., 2024). However, new risks arise, such as potential eye damage from laser systems, requiring proper safety measures (Lorek et al., 2024). While digital tools boost labour productivity (Singh et al., 2024), concerns about job displacement persist, especially for low-skilled workers lacking access to reskilling (Yaqot and Menezes, 2022) and migrant or seasonal workers by making them more easily replaceable and encouraging stricter immigration policies (Ryan et al., 2022). Mahmoudi et al. (2024), focusing on agricultural robotics and imitation learning, highlight the increasing automation of repetitive tasks, which underscores the urgency of social considerations such as workforce displacement and the need for effective transition strategies. Nonetheless, emerging roles in smart farming and IT services create new employment opportunities (Pedersen et al., 2020). Ryan et al. (2022) highlights that the male-dominated nature of AI and robotics could further reduce women's participation in agricultural jobs, while Bacco et al. (2020) finds no significant change in women's participation in agricultural labour markets. Ongoing labour shortages in agriculture may mitigate negative effects (Lorek et al., 2024).

2.2.3.2. Farmers. Farmers and managers gain improved efficiency, profitability, and resource management from PA technologies such as sensors, drones, and cloud platforms (Bacco et al., 2020; Pedersen et al., 2020). These technologies optimize inputs and increase yields while reducing costs (Yaqot and Menezes, 2022). However, economic risks include high upfront costs and dependence on external providers, disproportionately affecting smaller or less tech-savvy farms (Van der Burg et al., 2019; McGrath et al., 2023). Challenges around data ownership, access, and security raise concerns about power imbalances with large agritech firms (Van der Burg et al., 2019; McGrath et al., 2023). PA adoption requires ICT skills, creating barriers for some farmers, particularly older individuals (Pedersen et al., 2020; McGrath et al., 2023) making them increasingly dependent on technologies expertise (Ryan et al., 2022). Motivation to adopt includes potential work-life balance improvements and operational control, though concerns about accessibility and power dynamics remain (McGrath et al., 2023). Risks related to device malfunction, liability, theft, and damage also affect farmers (Lorek et al., 2024). The increasing automation of agricultural tasks via robotics may widen the gap between large, technologically advanced farms and smaller operations that struggle with adoption (Mahmoudi et al., 2024; Lorek et al., 2024).

2.2.3.3. Local community. PA technologies can enhance public health and living conditions in rural areas by reducing pesticide use and improving air and soil quality (Bacco et al., 2020; Yaqot and Menezes, 2022). They also help address labour shortages by shifting demand toward skilled roles such as technicians and data specialists (Pedersen et al., 2020; Singh et al., 2024). However, these benefits are unevenly distributed. Limited digital infrastructure and affordability constraints exclude some rural populations, contributing to inequality and social polarization (Yaqot and Menezes, 2022).

Automation in agriculture may lead to social disruption in rural communities if displaced workers are not supported through reskilling and social programs, potentially weakening community cohesion (Mahmoudi et al., 2024; McGrath et al., 2023). While digital tools are promoted as inclusive, they often shift power toward agritech firms and fail to address broader social and economic needs (McGrath et al., 2023).

2.2.3.4. Value chain actors. PA technologies generate new opportunities across the value chain, enabling specialized roles in areas such as technical maintenance, agronomic consulting, and data service provision (Pedersen et al., 2020). The development of these technologies typically involves a wide range of stakeholders, including farmers, researchers, agritech companies, and policymakers, fostering multidisciplinary and cross-country collaboration (Pedersen et al., 2020). However, concerns persist regarding power imbalance, as large agritech firms often control data infrastructures and platforms, potentially limiting the agency of farmers and smaller suppliers in both decision-making and value distribution (Van der Burg et al., 2019). The rapid adoption of robotics can reshape employment patterns within the value chain, displacing some roles while creating higher-skilled technical positions, which requires coordinated workforce development efforts (Mahmoudi et al., 2024; Lorek et al., 2024).

2.2.3.5. Consumers. Consumers benefit indirectly from PA through improved food safety, greater traceability, and better alignment with health and environmental standards (Pedersen et al., 2020). Enhanced information systems enabled by PA can strengthen compliance with food safety regulations and provide more transparent supply chains (Pedersen et al., 2020). Michaliszyn-Gabryś et al. (2024) and Lorek et al. (2024) note that the affordability of agricultural products may be affected slightly after the implementation of the new technology. The laser weed control and reduced chemical inputs improve product quality, particularly in conventional farming (Lorek et al., 2024). However, perceived affordability of agricultural products remains unchanged (Michaliszyn-Gabryś et al., 2024; Lorek et al., 2024). Concerns persist around data privacy, digital safety, and broader ethical implications associated with agricultural digitalization (Yaqot and Menezes, 2022). Widespread use of agricultural robots may alter perceptions of food, framing it more as a product of science than nature, and weakening people's emotional and ecological connection to food and farming landscapes (Ryan et al., 2022).

2.2.3.6. Society. PA advances societal goals like sustainable development, environmental protection, and rural revitalization by enhancing resource efficiency and transparency (Pedersen et al., 2020; Singh et al., 2024). Innovative weed control technologies reduce chemical residues on crops and lower risks to pollinators and birds, supporting biodiversity and long-term environmental health (Lorek et al., 2024). PA tools such as UAVs improve crop yields to meet rising food demand (Yaqot and Menezes, 2022). However, societal concerns about technology-driven polarization reflect fears amplified by media (Yaqot and Menezes, 2022). The widespread deployment of agricultural robotics necessitates robust governance frameworks to address ethical challenges, including labour displacement, data governance, and equitable access to technology. These measures are essential to prevent the exacerbation of social inequalities as automation becomes more embedded in agricultural systems (Mahmoudi et al., 2024; McGrath et al., 2023). Food security effects are generally modest, with weed removal technologies slightly improving production quality and quantity, while some digital platforms have no measurable impact (Bacco et al., 2020). Laser weed control positively affects product safety and environmental quality (Michaliszyn-Gabryś et al., 2024).

2.2.4. Summary literature review

Across these strands, most studies treat E-E-S effects separately and rarely integrate them into a single assessment framework, which makes it challenging to characterize trade-offs and synergies or to judge the overall sustainability performance of PA technologies (see [Supplementary Material S4](#)). These methodological tendencies point to three main gaps: limited integrated E-E-S assessments, underrepresentation of smallholder and low-infrastructure settings, and a lack of forward-looking analyses that connect emerging digital architectures (e.g.,

multi-robot and edge-computing systems) to multi-dimensional impacts. The combined systematic review and empirical case study in this paper directly address these gaps by applying a common impact framework across all three dimensions and by focusing on a rural, smallholder context where many of these limitations are most pronounced.

3. Empirical research

3.1. Empirical research methodology

The second part of our research assessed the potential E-E-S impacts of implementing PA technologies in the case study of the Isles of Scilly, UK. The Isles of Scilly case integrates ground robot equipped with soil moisture sensors, RGB cameras, and a 5G Wi-Fi router mounted on a drone to enable real-time monitoring of soil, crop, and weather conditions, with edge data pre-processing, and a cloud-based dashboard. By improving water management, reducing reliance on heavy machinery, and extending connectivity across the island, the system aims to enhance sustainability in farm operations. The empirical component adopts a single-case, mixed-methods design with an applied, problem-oriented approach. Rather than seeking statistical representativeness, the case is used to explore how a specific digital architecture may affect E-E-S outcomes in a remote rural setting and to generate analytically generalisable insights. Accordingly, participant selection was purposive and bounded to the small set of actors (only five people) directly involved in the pilot, prioritising information-rich roles over sample size for statistical inference (Palinkas et al., 2015). Evidence is triangulated across surveys, follow-up correspondence, and publicly available materials to strengthen credibility.

As the technologies were not yet implemented, the assessment uses a two-step, forward-looking approach across the E-E-S dimensions. The baseline evaluates current conditions using farm data, stakeholder input, and assumptions from literature and technical specifications (see sections 1.3.1-1.5.1). The comparative scenario explores potential changes from adopting PA technologies, based on the farmer's expectations and supporting assumptions, allowing structured analysis of present and anticipated impacts. Combining a baseline of current practices with scenario-based projections to capture existing conditions and anticipated outcomes.

For this assessment, a time-based functional unit² was chosen to reflect the operational nature of these technologies in the use phase. However, the functional unit is only used for the environmental and economic part of the assessment and not for the social part.³ The social impact is assessed at the whole-farm level, as it involves complex, context-dependent factors that cannot be clearly quantified or linked to specific time-based units.

All three impact assessments were implemented to gather insights about levels 1 and 2 of the life cycle of the PA technologies, as seen in Fig. 2. The assessment framework distinguishes between impacts from (i) producing connectivity and device infrastructure (Level 0), (ii) operating connectivity and edge technologies (Level 1), (iii) the services

² The functional unit serves as an essential assessment foundation, providing a standardized metric to ensure fair and consistent comparisons between systems or scenarios.

³ This is because in social impact assessments, the impacts, such as changes in labour conditions, access to technology, or effects on community well-being, are often influenced by qualitative factors and context-specific conditions that may not directly correlate with a time-based unit. For instance, the social impact of 1 h of technology use can vary significantly depending on the region, demographic group affected, and service type. Unlike environmental and economic metrics, which are often quantifiable and time-dependent, social outcomes tend to be more diffuse and complex to measure uniformly across contexts. Thus, while the functional unit works well for assessing environmental and economic impacts, it may not fully capture the breadth or complexity of social impacts.

they enable in context (Level 2), and (iv) end-of-life processes (Level 0, grave phase: disassembly, waste management, and recycling). This study focuses on Level 1 and Level 2 impacts, which are most relevant to the on-farm use phase of the multi-robot system, while Level 0 and end-of-life impacts are acknowledged but remain outside the empirical and geographic scope of the case study.

3.1.1. Materiality assessment and data collection

A materiality assessment is a selection process used to identify topics of greatest relevance due to their potential impact on stakeholders. Material issues are those that reflect the organization's significant impacts or are likely to substantively influence stakeholder decisions (UNEP, 2020). Such an assessment helps determine the most relevant impact subcategories, ensuring that the study remains focused, manageable, and meaningful, and that the identified aspects are likely to significantly influence conclusions and related decisions (ISO 14075:2024). For the present study, a materiality assessment was conducted to identify the most relevant topics related to precision agriculture technology adoption in rural contexts, using a combined top-down and bottom-up approach, as recommended by Kruse et al. (2009).

Firstly, in the top-down step, experts pre-selected impact (sub)categories for the environmental, economic and social dimensions. For the environmental and economic dimensions, the review of LCA and CBA studies was used to compile a broad list of commonly assessed impact categories, including carbon and energy footprints, water use, nutrient-related impacts (e.g., nitrogen use and losses), pesticide use and associated toxicity, biodiversity impacts, operational costs, and avoided costs or benefits. For the pre-selection of the social topics, the UNEP S-LCA guidelines (2020) provided a structured framework across key stakeholder groups. The stakeholder groups 'workers', 'local community', and 'society', along with their 27 associated impact subcategories (Supplementary Material S5), were deemed most relevant to the PA technology use phase.⁴

Secondly, for the bottom-up part, a survey (Supplementary Material S6) was sent out to six stakeholders who are knowledgeable about the case study (one of the six is part of the UK case study itself) to prioritize the pre-selected impact subcategories for PA technologies in the rural context across the three dimensions (E-E-S). For the environmental and economic dimensions, this meant identifying the impact categories where stakeholders expected PA to have the most substantial effect in the Isles of Scilly context, see Table 1. With regards to the social topics, the case study leaders ranked the 27 impact subcategories on a five-point scale from extremely not important to extremely important. This resulted in the identification of the top five most relevant impact subcategories, as presented in Table 1. This materiality assessment is case-specific, reflecting the stakeholders' perspectives in the UK context and not necessarily representative of PA adoption more broadly.

A second survey (Supplementary Material S7) targeted the two farmers working on the case study and collected both baseline data for 2023 and expectations for post-implementation changes. These two interviewees were selected purposively as key informants because they are the primary farm-level users and decision-makers for the pilot, and because the total number of actors directly involved in system operation is small (five people). Additional information was gathered through follow-up correspondence with the participating farmer to clarify technical and operational details. Publicly available information, including an earlier interview and content from the farm's website, was used to

⁴ It is important to note that this study does not constitute a full S-LCA. As the technology has not yet been implemented or adopted, no primary data on its use were available; the baseline was assessed more quantitatively, while anticipated future changes were explored qualitatively within a single, limited system boundary. The methodology was therefore adapted to provide an exploratory and indicative assessment, rather than a fully developed (prospective) S-LCA.

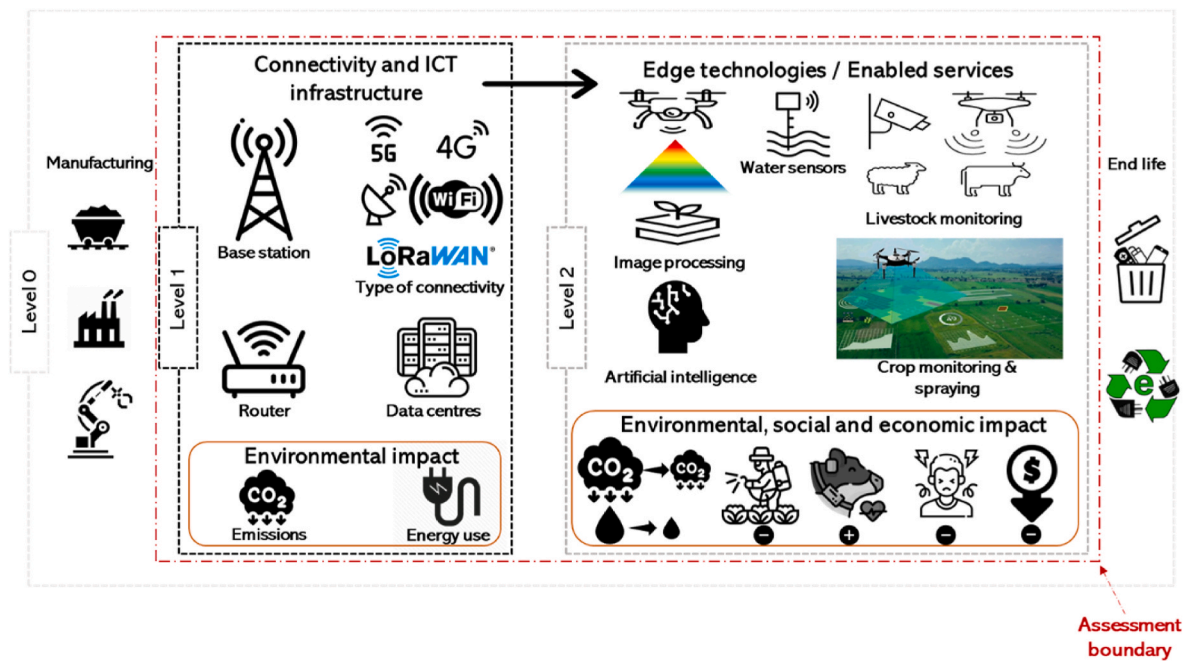


Fig. 2. System boundary for assessing the use-phase impacts of PA technologies.

Table 1
Environmental, economic, and social impact categories.

Environmental impact categories	Economic impact categories	Social impact subcategories
Carbon footprint (CFP)	Operational costs	Occupational health and safety
Energy footprint (EFP)	Avoided costs (benefits)	Safe and healthy living conditions
Water footprint (WFP)		Community engagement
Biodiversity footprint (BFP)		Technology development
Impact on human health		Contribution to economic development

contextualize and cross-check reported practices. Given the bounded nature of the case, the relevant population is inherently small, and the empirical component is designed for analytic generalisation: the aim is to use triangulated evidence from core actors to generate insights that may transfer to comparable remote rural settings, rather than to estimate population parameters (Yin, 2018). Credibility is strengthened through triangulation across surveys, follow-up correspondence, and publicly available materials, and by reporting assumptions and data sources transparently.

3.1.2. Environmental impact assessment

The environmental assessment focused on the operational (use) phase of the monitoring systems and aimed to evaluate the key sustainability performance of innovative technologies compared to conventional practices. The analysis concentrated on four core indicators: CFP, EFP, WFP, and BFP, with an estimate of potential impacts on human health.

This footprint-based approach quantifies environmental pressures resulting from electricity consumption, water use for irrigation, and associated emissions. These indicators are grounded in sustainability frameworks that link human activity to planetary boundaries and biodiversity loss (Fang et al., 2015).

The CFP quantifies GHG emissions from electricity use based on country-specific emission factors derived from national energy mixes (IEA, 2023) and IPCC (2006) guidelines, and its contribution to

biodiversity loss is characterised using LC-IMPACT (Verones et al., 2020). The EFP represents the electricity required for irrigation, calculated from the mechanical energy needed to lift water and corrected for pump efficiency following Sobhani et al. (2012) and de Souza et al. (2021). The WFP reflects the volume of pumped water and its associated water-stress impacts on biodiversity, again using LC-IMPACT characterisation factors. The BFP aggregates climate- and water-related biodiversity impacts into a single indicator expressed as the potentially disappearing fraction of species (PDF). Human health impacts are derived from the CFP by applying damage factors from De Schryver et al. (2009) and LC-IMPACT. Full equations and parameter values are provided in Supplementary Material S8.

To ensure consistency across scenarios, the assessment applied a fixed set of assumptions and environmental characterization factors (Supplementary Material S9). When direct measurements were unavailable, the analysis relied on expert judgment and peer-reviewed literature. This approach was especially important for estimating energy requirements for water pumping and expected water savings from sensor-guided irrigation.

In the baseline scenario, irrigation is minimal due to high reliance on rainfall, except in polytunnels, where approximately 10 m³ of water is used per month. Rainwater is collected, stored, and pumped to a head tank for drip irrigation. Based on the farmer's input, irrigation occurs once per week for 1.4 h, with a pump head of 10 m and an efficiency of 60 %. Energy demand for water pumping was calculated accordingly.

3.1.3. Economic impact assessment

The economic impact assessment focused exclusively on the operational (use) phase of the monitoring systems. The approach draws on established CBA practices in irrigation system evaluations (Lorenzo López and Expósito, 2025), while also integrating environmental cost components such as carbon pricing. These elements reflect broader valuation strategies for water use and emissions applied in energy and agricultural systems (Borrego-Marín and Berbel, 2019; World Bank, 2024). The assessment compares the operational costs of deploying innovative versus traditional irrigation monitoring systems with their potential economic benefits, offering insights into cost-effectiveness and resource efficiency.

The assessment covers four cost pillars: (i) energy consumption,

valued at current fuel or electricity market prices; (ii) labour, calculated from hourly wages for operation and maintenance; (iii) capital, amortized each component's service life; and (iv) the cost of carbon by applying the prevailing market price of emissions permits to the system's carbon footprint. Offsetting these outlays are avoided costs arising from lower water and energy use, reduced labour needs, and decreased agrochemical inputs thanks to precision monitoring.

As for the environmental assessment data, cost data were collected through two survey rounds and follow-up correspondence with the farmer and the technology supplier. In cases where data were missing, market quotations and recent official statistics were used to fill gaps. Capital costs were annualized and expressed as monthly values for comparability.

No discounting was applied, as the evaluation considers monthly cash flows within a short (1-year) appraisal horizon. The total operational cost was calculated using Sup. Eq. (9) (Supplementary Material S10), and the monetary cost of carbon using Sup. Eq. (10) (Supplementary Material S10).

Key economic parameters are summarized in Supplementary Material S11.

3.1.4. Social impact assessment

Performance indicators were developed for each of the selected impact subcategories based on UNEP (2020), the Global Farm Metric (GFM) (Kipling et al., 2023), and the Sustainability Assessment of Food and Agriculture Systems (SAFA) (FAO, 2014). These indicators provide measurable and context relevant metrics to evaluate the social performance of PA technologies, ensuring the assessment focuses on the most material issues for this case study.

A reference scale approach was used to allow a comparison of the baseline data to a reference, with each position on the scale being a performance reference point, assigned a score ranging from -2 to $+2$ (Goedkoop et al., 2020), as presented in Supplementary Material S12. The reference scale follows a stepwise logic, starting at the -2 level. Each level is assessed in order by checking whether the statement is 'true' or 'false' until a level is reached where the statement can no longer be confirmed as 'true' (Goedkoop et al., 2020). A separate reference scale was created, based on Harmens et al. (2022) for each of the selected impact subcategories, see Supplementary Material S13.

For the comparative scenario, a qualitative approach was used by directly asking the farmer how they expect adopting the technology would affect their current operations across the impact subcategories. Since no primary or secondary data on actual technology implementation was available, the farmer's own expectations served as the basis for assessing potential changes relative to the baseline.

3.2. Empirical research results

3.2.1. Environmental impact assessment

3.2.1.1. Baseline scenario: current irrigation system. The baseline assessment represents the environmental performance of the farm without any sensor or robotics technology for irrigation monitoring. The calculated energy demand is approximately 0.0035 kWh per month. Applying the UK's 2024 electricity emission factor (0.207 kg CO₂-eq/kWh), this results in a carbon footprint of 0.0007 kg CO₂-eq/month (see Table 2).

The biodiversity impact of the carbon emissions alone is approximately 1.44×10^{-17} PDF-year/month, and the corresponding human health impact is around 8.75×10^{-9} DALY/month. The 10 m³/month of pumped water contributes 2.68×10^{-14} PDF-year/month, based on the UK's regional water stress characterization factor. No human health impact is attributed to water use, consistent with the LC-IMPACT guidance for low water-stress regions.

Table 2

Comparative environmental impacts of baseline vs. multi-robot system (monthly values and change vs baseline).

Indicator group	Indicator (unit)	Baseline System	Multi-Robot System	Change (multi-robot system vs baseline)
CO ₂ -related impact	Carbon footprint (kg CO ₂ -eq/month)	0.0007	1.051	1500 × higher
	Biodiversity impact-CO ₂ (PDF-year/month)	1.44×10^{-17}	2.15×10^{-14}	1500 × higher
Water-related impact	Water footprint (m ³ /month)	10.00	7.71	23 % lower
	Biodiversity impact - water (PDF-year/month)	2.68×10^{-14}	2.07×10^{-14}	23 % lower
Overall impact	Biodiversity footprint - aggregated (PDF-year/month)	2.68×10^{-14}	4.22×10^{-14}	57 % higher
	Human health impact (DALY/month)	8.75×10^{-9}	1.31×10^{-5}	1500 × higher

3.2.1.2. Comparative scenario: UK case study with multi-robot system.

The comparative scenario evaluates the environmental impact of implementing a sensor-based monitoring system operated by a multi-robot platform. The system includes a LoRa gateway, 20 soil moisture sensors, and a Jetson Orin NX processing unit. Based on technical specifications and expert input, the combined electricity use is 0.0253 kWh/hour. With an estimated 50 monitoring hours per week, monthly energy consumption reaches 5.06 kWh (see Supplementary Material 14 for energy consumption per component).

Sensor-based monitoring has been shown to reduce water consumption by an average of 22.9 % without yield losses (Tüzel et al., 2023). Applying this efficiency gain to the UK case study, irrigation demand drops from 10 m³/month to 7.71 m³/month. This slightly lowers the pumping energy footprint to 0.0028 kWh/month, though the robot system's demand dominates the total energy use. The values used in both scenarios are detailed in Table 2.

The associated CFP increases to 1.051 kg CO₂-eq/month. The biodiversity impact from CO₂ emissions rises to 2.15×10^{-14} PDF-year/month, while the impact from water use slightly decreases to 2.07×10^{-14} PDF-year/month. The aggregated BFP reaches 4.22×10^{-14} PDF-year/month. The corresponding human health impact is approximately 1.31×10^{-5} DALY/month.

3.2.1.3. Interpretation. The analysis reveals a clear environmental trade-off. On one hand, the introduction of the multi-robot system improves water use efficiency, resulting in a nearly one-quarter reduction in irrigation demand and a corresponding decrease in ecosystem pressure from freshwater abstraction. On the other hand, energy requirements rise sharply due to the continuous operation of digital components, more than offsetting the savings in pumping electricity. The carbon footprint increases from 0.0007 kg to 1.051 kg CO₂-eq/month.

Biodiversity impacts reflect this trade-off: while water-related pressure slightly decreases, climate-related effects dominate, nearly doubling the overall biodiversity footprint. Likewise, the human health impact increases significantly due to higher energy consumption. Although the improved irrigation management brings operational advantages, its environmental benefits depend heavily on the electricity mix. Without a shift to renewable energy, the net impact of digitalization may outweigh its benefits in terms of water conservation.

These findings underscore the importance of energy-efficient system design and clean power integration when scaling sensor-based monitoring solutions in agriculture. Next to that, it is also important to note that the UK case study represents a small-scale operation with relatively

low baseline water and energy use. At this scale, the environmental return on deploying a multi-robot system remains limited. However, if the same system was deployed in larger farms with higher irrigation demand, the same 22.9 % water saving could translate into much greater absolute reductions in water use and associated environmental burdens, potentially tipping the balance in favour of overall sustainability benefits.

3.2.2. Economic impact assessment

From an economic perspective, two types of effects were considered. *Direct* effects capture monetary items that change the farm's monthly balance sheet, namely, energy, labour, capital depreciation, and the carbon cost associated with grid electricity. *Indirect* effects, such as improved working conditions, higher safety, and faster decision-making, are acknowledged qualitatively but not monetized in this context.

3.2.2.1. Baseline and comparative scenario inputs. The baseline scenario relies on manual irrigation monitoring, using stationary sensors and minimal ICT infrastructure. In contrast, the comparative scenario involves a multi-robot system composed of a drone, a four-wheeled ground robot, and LoRa WAN-connected sensors. This system enables more frequent and automated data collection, reducing the farmer's time investment. Capital and operational differences between the two setups are summarized in Table 3. Details on the capital components and their depreciation assumptions are provided in Supplementary Material S15.

3.2.2.2. Cost breakdown and interpretation. The comparative analysis reveals a clear trade-off between labour intensity and capital intensity in the transition to the multi-robot system. In the baseline system, labour costs account for nearly half of the monthly expenditures, as sensor readings must be collected manually. Conversely, the multi-robot system substantially reduces human effort, cutting labour costs by nearly €150 per month, thanks to automation and remote monitoring capabilities.

However, these labour savings come with a marked increase in capital expenditure. The multi-robot system's components (drone, robot, cameras, and communication infrastructure) require a higher upfront investment. When amortized over their service life, these costs result in an additional €192 per month in capital depreciation compared to the baseline, increasing the total capital cost from €204 to €396.

Electricity and carbon costs remain a minor share of total monthly expenses in both scenarios. Despite the longer runtime of the robotic system (approximately 200 h per month for its ICT setup), overall energy use remains low due to the efficiency of its components. Carbon costs, derived from the EU Emissions Trading System, are negligible.

From a monthly cost perspective, the multi-robot system is about €45 more expensive than the manual approach. Whether this additional expense is justified depends on the value attributed to non-monetized

Table 3
Monthly resource use and capital costs for baseline and multi-robot system, including change vs baseline.

Item group	Item (unit)	Baseline system	Multi-robot system	Change (multi-robot system vs baseline)
Electricity and carbon	Electricity use (pump and ICT) (kWh)	0.0035	5.06	1446 × higher
	Electricity cost (€)	0.001	1.42	1420 × higher
	Carbon cost (€)	0.00005	0.068	1360 × higher
Labour	Labour hours (h)	5	1	80 % lower
	Labour cost (€)	200	52	74 % lower
Capital and total costs	Capital depreciation (€)	204	396	94 % higher
	Total cost (€)	404	449	11 % higher

benefits such as yield protection through faster anomaly detection, richer decision-support data, and intangible gains in worker safety and convenience. In seasonal or high-value crop systems, the improved information flow and reduced manual labour might offset the higher capital costs. Moreover, in labour-constrained regions, automation may present a more scalable and resilient irrigation management option. On larger farms, where baseline irrigation volumes and labour inputs are greater, the same 23 % water saving and 80 % labour reduction would translate into far larger absolute savings, making the business case more compelling. Future work should therefore trial the system at commercial scale and explore cooperative financing or service-provider models that spread capital costs across multiple growers or seasons.

3.2.3. Social impact assessment

3.2.3.1. Baseline scenario: current irrigation system. In the baseline scenario the social impact of the farm without any sensor or robotics technology for irrigation monitoring is assessed using the reference scale method for the top five most relevant impact subcategories.

The UK case study scored a 0 for occupational health and safety. While no accidents or injuries were reported and basic safety protocols are in place, including a health and safety plan and worker training, the farm lacks a formal system for proactively identifying risks or improving safety over time. This reactive approach means they meet minimum standards but do not actively work to enhance safety culture or prevent future issues.

The farm scored a +1 for safe and healthy living conditions, as no health or safety incidents were reported and it maintains a safe work environment while being attentive to the health needs of the surrounding community. The farm also supports local well-being by producing nutritious, locally grown food. These efforts contribute positively to community health, though the farm's impact remains limited to operational activities and could be strengthened through more formal community health initiatives.

For technology development the farm scored a 0. Although the farm participates in external research projects, it does not actively develop or implement new technologies on-site. This passive role means the farm benefits from innovation indirectly but does not contribute to advancing or applying technologies itself. As a result, its impact on technology development remains neutral.

The farm scored a 0 for contribution to economic development. This is because they provide limited economic benefits through the employment of one worker and local sourcing of supplies, but does not engage in broader initiatives that drive regional growth, such as partnerships or innovation investments. Without these efforts, the farm's role in local economic development remains minimal.

For community engagement, the farm scored a +1. The farm supports the local area by providing vegetables, maintaining the landscape, and offering land access. Communication with the community occurs through social media and monthly meetings. While these efforts build local ties, the lack of formal engagement structures limits their potential for deeper impact.

3.2.3.2. Comparative scenario: UK case study with multi-robot system. In the comparative scenario, the UK case study anticipates no change in occupational health and safety, as daily tasks and safety conditions are expected to remain largely unchanged. Similarly, they do not foresee any change in their overall contribution to economic development or their involvement in technology development, which continues to be limited to participation in external research initiatives. However, they expect a modest effect on safe and healthy living conditions due to potential noise generated by components such as the drone. Finally, they anticipate a positive effect on community engagement, as the introduction of PA technologies may foster increased interaction through shared data, participation in pilot activities, and communication.

4. Discussion

This section integrates insights from the systematic review and the case study to examine how the widely reported promises of PA align with their anticipated performance in practice. Building directly on the methodological tendencies and impact patterns identified in the literature review, it explores where E-E-S expectations surrounding PA technologies align with or diverge from the observed or modelled effects of deploying PA in practice (e.g., a sensor-guided multi-robot irrigation system in the Isles of Scilly), with a specific focus on a remote rural, smallholder island context. Framed as a contribution to rural studies, this comparison shows how place-based constraints and enabling conditions in a remote rural setting reshape what PA can realistically deliver. The discussion highlights the contextual factors that explain convergence and divergence between promise and practice and outlines what these findings imply for the wider roll-out of PA in rural settings.

4.1. Environmental expectations from literature vs. in practice

The literature consistently reports that PA lowers input-related impacts, particularly GHG emissions, water abstraction, and agrochemical leaching (Medel-Jiménez et al., 2024; Bondesan et al., 2023). The case study results partly confirm this narrative: introducing sensor-based scheduling reduced irrigation demand by 23 %, cutting the water-stress-related biodiversity impact from 2.68×10^{-14} to 2.07×10^{-14} PDF.year/month. Yet, because the baseline farm already relies largely on rainfall, the absolute saving of 2.3 m³/month is modest compared with the larger reductions in the literature, often reported in experimental or high-input systems.

In addition, operating the multi-robot system in the case study raised monthly electricity use from 0.0035 kWh to 5.06 kWh, lifting the carbon footprint from 0.0007 kg to 1.051 kg CO₂-eq. The resulting climate-related biodiversity impact rose by three orders of magnitude, echoing concerns in the LCA literature that digitalization can shift burdens from water to energy usage when the power mix is fossil-intensive (Khan et al., 2023), especially in rural regions with limited access to low-carbon energy. This pattern is increasingly noted across LCA-informed studies, where the environmental gains from reduced inputs may be counteracted by upstream or operational energy use.

The comparison between the case study and systematic review highlights a scale-dependent effect that conditions the outcomes of PA technology. On large commercial farms with higher baseline water abstraction or labour intensity, the same percentage savings in inputs can translate into substantial absolute reductions, sufficient to offset the additional energy demand and capital costs of ICT-enabled systems. In low-input, rainfed settings such as the Isles of Scilly farm, marginal gains may be insufficient to justify higher electricity use or equipment costs unless the system is powered by low-carbon energy. This reinforces calls in the LCA literature to integrate PA deployment with decentralised renewable energy solutions (Fotia et al., 2021) and to match technological design with the energy and financial realities of end users, particularly those in rural and remote communities.

These findings highlight that environmental expectations from the literature only translate into practice when PA designs are explicitly aligned with local energy systems, baseline practices, and farm scale, and when trade-offs between different impact categories are made transparent.

4.2. Economic expectations from literature vs. in practice

The economic literature reviewed frequently point to attractive returns once input savings and yield gains accumulate over multiple seasons (Abdo-Peralta et al., 2024; Baio et al., 2017). In the one-year horizon analysis of the case study, total monthly expenditure would increase by €45 with the PA technology adoption despite a 74 % fall in labour costs. The main driver is the steep rise in capital depreciation

(from €204 to €396/month) required to finance the PA technologies. This short-term cost increase aligns with findings in the literature, which often note that initial investments in PA technologies can outweigh early savings, particularly in small-scale or less capital-intensive systems (Baio et al., 2017).

In the case study, the economic balance was shaped almost entirely by the trade-off between reduced labour costs and increased capital requirements associated with the adoption of PA technology. On small organic farms (such as the case study), where manual tasks are already relatively modest and financial margins are tight, this balance becomes particularly fragile. This diverges from much of the literature, which often emphasizes labour savings and input efficiency as key economic advantages of PA (Bondesan et al., 2023; Medel-Jiménez et al., 2024). However, these studies typically focus on larger or more intensively managed farms, where scale economies make capital investments more viable. In contrast, the case study shows that unless intangible benefits, such as yield protection, improved marketability, or compliance gains, can be monetized, PA technologies may remain economically unfeasible for smallholders.

The modest scale of the case study also plays a role in shaping its outcomes. On small farms like the one in the Isles of Scilly, baseline irrigation and labour demands are already low, which limits the absolute resource savings that precision technologies can deliver. Consequently, the 23 % reduction in irrigation demand achieved through sensor-guided scheduling translates into only marginal environmental and economic gains. This observation aligns with Belayneh et al. (2013), who observed that while sensor-controlled irrigation reduced water use by over 60 %, the ROI remained modest due to low baseline costs and minimal differences in plant quality. This reflects broader findings from Baio et al. (2017), who showed that the financial returns from PA techniques on cotton became more favourable when scaled to larger farms, with profitability improving despite high initial investments in equipment. In water-scarce or regulated regions, precision technologies become particularly valuable. Finco et al. (2022) also noted that irrigation monitoring tools support viticulture in drought-prone areas by ensuring water-use efficiency.

In combination, the review and case study therefore suggest that positive economic expectations for PA are conditional on scale, crop value, and water or labour pricing, and may not straightforwardly apply to small, low-input farms in remote rural areas, such as the Isles of Scilly case.

4.3. Social expectations from literature vs. in practice

The literature on PA technologies highlights a wide range of social impacts across stakeholder groups, and several of these are reflected in the case study. In the areas of health and safety effects on the public and community engagement, there is a convergence between what is anticipated in theory and what is seen in practice. PA technologies can have environmental impacts, i.e. reduced water use and increased energy consumption for this case study, which according to literature can affect public health and living conditions (Bacco et al., 2020; Yaqot and Menezes, 2022) or affect resource efficiency and transparency (Pedersen et al., 2020; Singh et al., 2024). Next to that, the adoption of PA in the case study supports local engagement by enabling the farm to share updates and communicate changes through channels such as social media and open farm days. These efforts aim to keep local residents informed and involved, reflecting literature that highlights a positive link between PA adoption and increased community interaction (Pedersen et al., 2020). More broadly, research on digital and automated agriculture shows that such technologies can foster interaction, strengthen social networks, and encourage participation in rural communities (Carolan, 2020; Gardezi and Stock, 2021; Rotz et al., 2019; Legun and Burch, 2021). At the same time, responsible digital agri-technology practices emphasize the importance of aligning adoption with local social and ethical considerations, ensuring that

innovations genuinely support community engagement and address local needs (Jakku et al., 2022).

At the same time, several key issues raised in the literature are not visible in the case study or vice versa, indicating a divergence. Regarding health and safety, the case study expects no significant change in occupational health and safety. However, literature on similar automation technologies suggests potential benefits such as reduced physical strain and fewer repetitive tasks, which can improve working conditions (Lorek et al., 2024; Michaliszyn-Gabryś et al., 2024; Pedersen et al., 2020; Singh et al., 2024). Other PA-related risks, like eye damage from laser systems or mental fatigue from complex interfaces, are linked to different technologies and not relevant here. This divergence between the impact of PA technologies in literature and in the case study likely stems from the anticipatory nature of the assessment, as the farm had not yet implemented the technology and may therefore under/overestimate both risks and benefits. Next to that, the limitation of expectation-based self-assessment is highlighted and suggests that realized occupational health and safety effects may only become visible through follow-up once adoption occurs. On the other hand, the case study expects an impact on safe and healthy living conditions because of potential noise from the drones, which was not mentioned in the reviewed literature. Broader structural impacts from PA technology, discussed in the article's literature review as well as in the broader literature outside of the literature review, do receive little attention in the case study. For example, job loss for low-skilled workers, shifts in labour roles, and growing demand for digital and data skills are widely cited in the article's literature review (Yaqot and Menezes, 2022; Pedersen et al., 2020) and are also highlighted in the broader literature (Rotz et al., 2019; Legun and Burch, 2021). Additionally, broader sector-wide concerns such as dependency on agritech providers (Pedersen et al., 2020), platform dependency (Yaqot and Menezes, 2022), limited control over data (Pedersen et al., 2020), changing the consumer's perception of food (Ryan et al., 2022), and unequal value distribution across the supply chain (Yaqot and Menezes, 2022) are widely discussed in the literature but did not appear in the case study. Similar issues are also discussed in the broader literature, which shows that dependencies on technological infrastructures, control over data, and algorithmic governance can affect farm management, agency, and social identities (Rotz et al., 2019; Legun and Burch, 2021; Gardezi and Stock, 2021; Carolan, 2020; Fraser, 2021; Higgins et al., 2023; Caffaro et al., 2020). These dynamics may create complex governance and ethical challenges requiring reflexive decision-making and inclusion of multiple stakeholders (Jakku et al., 2022). These studies emphasize that decisions influenced by digital platforms and data governance arrangements can shape trust, power relations, and the negotiation of expertise in agricultural communities. These impacts, identified in the literature review as well as the broader rural studies literature, did not emerge in the case study, likely because the farm was in an early deployment phase, focusing on immediate operational and community-level effects, and the empirical assessment covered only five impact subcategories, limiting visibility of wider sectoral or structural consequences. This illustrates how many social impacts unfold at higher system levels, while individual case studies with limited scope risk overlooking broader or indirect effects.

This comparison between the case study and the (broader) literature highlights how social impacts depend strongly on context: they converge on immediate issues like public health and safety and community engagement, but they diverge on structural questions around labour markets, data governance, technological infrastructure and power relations. This underscores the value of combining system-level perspectives from the literature with granular, farm- and community-level evidence, so that debates about the social implications of PA are grounded in the realities of specific rural areas settings.

4.4. Reflections on assessment scope, limitations, and broader implications

This study reflects typical constraints of early-stage assessments of emerging technologies, particularly in rural settings. The analysis focused intentionally on on-farm operations, aligning with our aim to evaluate the direct E-E-S effects most relevant to farmers and rural stakeholders. While the literature on the environmental evidence base for PA is relatively mature, studies on economic and social impacts remain limited. Despite this, it is important to include these dimensions in impact assessments, as considering economic and social impacts alongside environmental impacts provides a broader perspective, helps identify potential trade-offs, and ensures that key aspects of sustainability are not overlooked. Integrating these underexplored areas allows for a more comprehensive understanding of how PA may affect rural agricultural systems. Further empirical research is needed to build a more complete picture of the economic and social impacts and to support robust, evidence-based comparisons across all sustainability dimensions. The small number of survey participants is a direct consequence of the bounded nature of the case, where only a handful of actors are directly involved in the design and operation of the system. This limits opportunities for statistical inference, but is consistent with an in-depth single-case design; our intention is to provide analytically transferable insights for similar rural settings, rather than claims of broad representativeness. By centring a remote island smallholder farm, this study adds empirical evidence from a type of rural setting that is largely absent from existing impact assessments of PA.

From an LCA perspective, our footprint-based use-phase assessment sits between the approaches identified in the literature review. Only a small number of studies applied full, ISO-compliant cradle-to-farm-gate LCAs with multiple midpoint impact categories (Bručienė et al., 2024; Fotia et al., 2021), while most relied on partial LCAs or field-level indicators focused on specific inputs or operations (Medel-Jiménez et al., 2022, 2024; D'Antonio et al., 2023; Li et al., 2024; Balafoutis et al., 2017). In contrast, we restrict the system boundary to the operational phase of a concrete digital architecture (a multi-robot, sensor-based irrigation system), but broaden the indicator set to link energy and water use to biodiversity and human health. This complements existing LCAs by providing a detailed view of use-phase trade-offs for digital technologies in a rural setting, while highlighting the need for future work to embed such systems within full cradle-to-grave assessments.

Broader life-cycle stages, including upstream production and end-of-life phases of digital infrastructure, were not included, as they lie beyond the empirical reach of this single-farm assessment. While the study is based on a single farm, this reflects the unique geographical and logistical constraints of implementing and monitoring PA technologies in practice. Furthermore, the one-year time horizon captures immediate impacts but does not reflect potential longer-term benefits, such as yield improvements, learning curves for the technology, or equipment amortization over time. In addition, energy use for the conventional system and expected water savings for the multi-robot system were partly based on expert judgement and greenhouse trials rather than direct local measurements. Similarly, water-saving estimates were derived from controlled greenhouse trials (Tüzel et al., 2023), which were chosen due to the lack of comparable field data for this specific sensor-guided multi-robot configuration. Future work should aim to address these aspects through longer-term, multi-site studies and expanded system boundaries.

Despite these constraints, the combined review and case study offer valuable insights into short-to medium-term outcomes of PA adoption in a rural, smallholder context. While many reviewed studies similarly adopt field-level perspectives (Jovarauskas et al., 2021; Stamatiadis et al., 2018; Chen et al., 2020; Han et al., 2021; Hiremath et al., 2024; Bondesan et al., 2023; Martelli et al., 2024; Addas et al., 2024; Qaswar et al., 2024; Fu et al., 2024; Zhou et al., 2024; Sariga et al., 2016; Singh et al., 2024), they still enable targeted interventions and adaptive

decision-making. Such approaches also lend themselves to flexible evaluation frameworks that move beyond carbon-centric indicators to include pressures on biodiversity, water systems, and farm resilience, and how they can be explicitly linked to social and economic considerations.

For researchers, this work highlights the importance of embedding PA assessments within broader system boundaries and longer timeframes. Future studies should incorporate full cradle-to-grave LCA assessments to explore upstream and downstream effects of automation, while also applying social impact methodologies that address data governance, autonomy, and rural livelihoods. Overall, while PA holds clear potential for sustainable intensification, its benefits will materialize most reliably when deployed through integrated strategies that explicitly consider energy sourcing, financing structures, and knowledge accessibility in the kinds of rural settings where these technologies are promoted, including remote islands and other hard-to-reach rural areas. For policymakers, this implies prioritising support schemes that link PA deployment to low-carbon energy and accessible finance in rural areas; for farmers, it underscores the importance of assessing technologies not only on input savings but also on capital and energy commitments; and for technology developers, it points to the need for low-energy, modular systems with clear service arrangements that are tailored to small, remote farms.

5. Conclusion

This study combined a literature review of PA technologies with an empirical assessment of a sensor-guided multi-robot irrigation system on a smallholder farm in the Isles of Scilly, in order to identify convergence and divergence on E-E-S impacts of PA technologies in crop farming. This paper evaluated the extent to which expected E-E-S benefits of PA materialize in practice, using the Isles of Scilly case study. Through this multi-dimensional impact assessment, the study provides insight into both the convergences and divergences concerning the E-E-S impacts of PA technologies between the literature and a particular contextual case study, realizing the outcomes of PA technologies.

The results point to a complex trade-off structure. On the environmental front, the case study achieved a notable reduction in water use, nearly 25 %, aligning with the promise of resource efficiency, through improved irrigation scheduling, leading to a modest reduction in water-stress-related biodiversity pressure. However, this benefit was offset by a substantial rise in electricity consumption and associated carbon emissions, which became the dominant contributor to environmental burden when deploying PA technologies. This divergence (Isles of Scilly context) illustrates a key challenge in PA adoption: targeted efficiencies at the input level may not translate into net-positive outcomes when energy use is high and the electricity mix remains carbon-intensive, which is a common condition in many rural areas.

In an economic sense, the PA technology reduced labour costs by nearly 75 %, reflecting anticipated operational efficiencies. Yet, this benefit came at the cost of increased capital depreciation, resulting in an overall rise in total monthly expenditures. These findings mirror the literature's emphasis on economic restructuring in PA adoption but point to the difficulty of realizing net gains in marginal or smallholder systems without scalable mechanisms or collective investment models. The convergence lies in the shift from labour to capital intensity; the divergence emerges in how this shift affects viability in different farming contexts, especially for small farms in remote rural regions.

Social outcomes in the case study showed partial alignment with expectations from literature. Stakeholders reported a potential noise impact from drones and connectivity equipment, which was identified as a concern affecting safe and healthy living conditions in the local community. No substantial impacts were expected for occupational health and safety and labour dynamics. However, based on the outcomes of the environmental and economic impacts, some indirect effects may emerge, for example on the working conditions or the profitability. The

literature highlights that PA can enhance occupational safety and efficiency but also requires workers to develop new skills and manage added mental and physical demands. Balancing these positive and negative effects is essential to ensure that social and economic benefits support overall quality of life. These results reinforce that social outcomes depend not only on the technology itself but also on the local context, size of the farm, and accompanying practices, such as training, which take on particular importance in rural settings with limited support infrastructure.

In summary, this study underscores that the impacts of PA technologies are highly context-specific and that the realization of promised benefits depends on their interaction with local environmental conditions, economic constraints, and social infrastructures. Although the environmental evidence base for PA is more developed than the social and economic literature, our findings show that omitting these latter dimensions would obscure key constraints and enablers for adoption in rural areas, so documenting where evidence is still thin is itself an important contribution to a more balanced assessment of smart agriculture. By explicitly comparing literature-based expectations with empirical findings, the paper strengthens rural social science accounts of PA by showing how "promise versus practice" is shaped by constraints and enabling conditions in a remote rural setting. The multi-dimensional assessment approach is used here as a tool to make these place-based trade-offs visible across environmental, economic, and social dimensions. A key contribution is to provide detailed evidence from a remote rural island farm, offering insights that are often missing from impact assessments focused on larger or more accessible regions. These insights emphasize the need for more integrated, system-level evaluations and participatory implementation strategies to ensure that digital innovations in agriculture contribute meaningfully to sustainability and rural development. Future work should prioritize longer-term, multi-site trials; system-wide life cycle assessments; and participatory approaches that embed digital tools within the broader landscape of rural development and climate resilience, with particular attention to the constraints and opportunities that characterize rural areas. Practically, this means that policymakers should design incentives and regulations that reward integrated E-E-S performance in rural PA projects; farmers should approach PA adoption by weighing labour savings against capital and energy costs in their specific context; and technology developers should co-design solutions with rural users, focusing on robustness, low energy demand, and transparent long-term service provision.

CRedit authorship contribution statement

Annabel Oosterwijk: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hatem Chouchane:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mark Ryan:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Katrine Soma:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jrurstud.2026.104007>.

Data availability

The data that has been used is confidential.

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