

Review

The Economics of Precision Agriculture (PA) and Resource Efficiency: Digital Technologies for Sustainable and Profitable Farming

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Abstract

Precision agriculture (PA) has emerged as a transformative approach for improving agricultural productivity, resource-use efficiency, and environmental sustainability through the integration of digital technologies, including Global Positioning Systems (GPSs), Geographic Information Systems (GISs), remote sensing, the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and autonomous systems. Although previous reviews have primarily emphasized technological innovation, adoption trends, or environmental outcomes, they have provided limited synthesis of the economic mechanisms linking technology adoption, resource allocation, production efficiency, investment performance, and long-term sustainability. A structured narrative–systematic review was conducted using peer-reviewed research retrieved from Scopus, Web of Science, and Google Scholar, covering studies published between 2004 and 2026. An integrated analytical framework combining technology adoption theory, resource economics, and production-efficiency models was employed to explain how digital technologies generate economic value while identifying methodological limitations, geographical bias, unresolved research questions, and future research priorities. The review demonstrates that GPS-guided machinery, variable-rate technologies, smart irrigation systems, AI-driven decision-support tools, and integrated digital platforms improve water- and nutrient-use efficiency, labor productivity, production efficiency, and farm profitability. However, economic performance remains highly context-dependent, varying according to farm size, crop type, climatic conditions, institutional support, digital infrastructure, resource scarcity, and policy environments. Methodological inconsistencies in return on investment (ROI), net present value (NPV), lifecycle costing, ecosystem-service valuation, and environmental externality assessment reduce comparability among studies and complicate evidence-based policy-making. The review further identifies a pronounced geographical concentration of evidence in North America, Europe, and Australia, with comparatively limited understanding of PA economics in China, India, Brazil, Sub-Saharan Africa, and Southeast Asia. Persistent challenges include high capital costs, unequal access among smallholder farmers, data governance concerns, interoperability limitations, uncertainty in long-term investment performance, and limited integration of agricultural insurance, climate-risk management, and digital finance. By integrating economic theory, methodological comparison, geographical analysis, sustainability valuation, and policy perspectives within a unified conceptual framework, this review highlights the need for standardized economic evaluation methodologies, broader geographical representation, and interdisciplinary research to support evidence-based policy and the sustainable digital transformation of global agriculture.



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1. Introduction

Global agriculture faces the unprecedented challenge of simultaneously increasing food production, improving resource-use efficiency, and reducing environmental degradation under accelerating climate change, population growth, and resource scarcity. Rising demand for food, increasing pressure on freshwater resources, land degradation, volatile energy and fertilizer prices, labor shortages, and greater climatic variability have intensified the need for agricultural systems capable of producing more with fewer inputs while maintaining long-term environmental sustainability [1,2]. In response to these challenges, PA has emerged as a transformative production paradigm that integrates advanced digital technologies including GPS, GISs, remote sensing, unmanned aerial vehicles (UAVs), the IoT, AI, ML, robotics, and autonomous systems to support site-specific management and data-driven decision-making [3–8]. These technologies enable producers to optimize the spatial and temporal allocation of water, fertilizers, pesticides, energy, and labor, thereby improving production efficiency, reducing environmental externalities, and enhancing farm profitability.

Growing recognition of PA has stimulated an expanding body of interdisciplinary research spanning agricultural engineering, environmental science, computer science, resource economics, and sustainability studies. Previous reviews have comprehensively documented technological developments, adoption trends, digital innovations, and environmental benefits associated with PA [4,8–20]. However, these reviews have largely emphasized technological performance and adoption patterns while providing comparatively limited synthesis of the economic mechanisms through which digital technologies create value under different resource, institutional, and market conditions. Economic outcomes are frequently reported as isolated indicators, such as yield improvement, water savings, fertilizer reduction, or return on investment (ROI), without integrating these outcomes into a coherent analytical framework that explains how technology adoption, resource allocation, production efficiency, and policy environments collectively determine long-term economic performance.

Another important limitation of the existing literature concerns the methodological diversity used to evaluate economic performance. Current studies employ a wide range of valuation approaches, including ROI, net present value (NPV), internal rate of return (IRR), partial budgeting, cost-benefit analysis (CBA), lifecycle costing, ecosystem-service valuation, shadow pricing, and avoided-cost methods [21,22]. While each methodology provides valuable insights into specific dimensions of investment performance, differences in analytical assumptions, planning horizons, treatment of uncertainty, discount rates, and environmental valuation substantially reduce comparability among studies and complicate the translation of research findings into agricultural policy and investment decisions. Consequently, the absence of standardized evaluation frameworks remains a significant barrier to evidence synthesis and policy development.

The geographical distribution of existing evidence also presents an important research limitation. Most empirical economic studies originate from North America, Europe, and Australia, where agricultural production is characterized by relatively large commercial farms, advanced mechanization, mature digital infrastructure, and sustained public investment in agricultural innovation [13,20]. Although these regions have substantially advanced the development of PA economics, comparatively limited empirical evidence is

available from emerging agricultural economies such as China, India, Brazil, Sub-Saharan Africa, and Southeast Asia, where agricultural production is dominated by smallholder farmers operating under different institutional, financial, technological, and climatic conditions [13,14]. This geographical concentration has influenced the evolution of PA economic theory by emphasizing capital-intensive production systems while underrepresenting co-operative ownership models, digital service platforms, and institutional innovations that may be more appropriate for resource-constrained agricultural systems.

Furthermore, several rapidly evolving areas remain insufficiently integrated into existing economic reviews. Recent advances in AI-driven decision-support systems, digital twins, autonomous agricultural machinery, robotics, climate-risk assessment, agricultural insurance, carbon markets, ecosystem-service payments, and sustainable agricultural finance have expanded the scope of PA beyond traditional resource optimization [10,21,22]. However, these emerging technologies and institutional mechanisms are typically examined independently rather than within a unified economic framework capable of explaining their interactions with farm profitability, investment risk, environmental sustainability, and public policy. Consequently, important questions remain regarding the long-term economic resilience of digital agriculture, the valuation of environmental externalities, and the role of policy interventions in supporting equitable technology adoption.

To address these limitations, this review develops an integrated analytical framework that combines technology adoption theory, resource economics, and production-efficiency models to explain the economic pathways through which PA technologies generate value across multiple analytical scales. Unlike previous technology-oriented syntheses, this review systematically compares alternative economic valuation methodologies, critically examines the structural causes and implications of geographical research bias, evaluates the policy relevance of different economic assessment approaches, and synthesizes emerging evidence relating to agricultural insurance, climate-risk management, digital twins, autonomous agricultural systems, and sustainable finance. The review further distinguishes areas of established scientific consensus from methodological uncertainty, unresolved research questions, and future research priorities, thereby providing a comprehensive knowledge map of contemporary PA economics.

Accordingly, the objectives of this review are to (i) synthesize the theoretical foundations linking technology adoption, resource economics, and production efficiency; (ii) evaluate the economic performance of major PA technologies across diverse agricultural systems; (iii) compare methodological approaches used to assess profitability, investment performance, and sustainability outcomes; (iv) examine the influence of geographical, institutional, and policy contexts on technology adoption and economic performance; (v) assess the emerging roles of digital agriculture in climate-risk management, agricultural insurance, and environmental valuation; and (vi) identify critical knowledge gaps and future research priorities that can support evidence-based policy and sustainable digital transformation within global agricultural systems. By integrating technological innovation, economic theory, methodological evaluation, geographical perspectives, and policy analysis within a unified conceptual framework, this review advances current understanding of PA economics beyond existing reviews and provides a stronger scientific foundation for future research, investment planning, and sustainable agricultural development.

2. Review Methodology

2.1. Review Design

This study utilized a structured narrative–systematic review to synthesize current evidence on the economics of PA. This approach combined systematic literature identification and screening with qualitative and quantitative synthesis to evaluate the economic, envi-

ronmental, and technological dimensions of PA adoption. A conventional meta-analysis was impractical due to the substantial methodological heterogeneity across the multidisciplinary literature, which includes agricultural economics, digital agriculture, environmental management, engineering, data science, and sustainability studies [23,24]. Keyword co-occurrence and co-authorship network maps (Figure 1a,b) were generated using VOSviewer software (version 1.6.21), applying the full counting method for co-occurrence analysis and the association strength normalization technique for network clustering. The review focused on evaluating the economic performance of PA technologies such as GPS, GISs, VRT, remote sensing, UAVs, IoT systems, AI, ML, decision-support systems, autonomous agricultural machinery, and digital twin technologies. Particular attention was paid to profitability, ROI, NPV, resource-use efficiency, sustainability outcomes, and adoption barriers.

2.2. Literature Search Strategy

Peer-reviewed research published since January 2004 was collected from Scopus, Web of Science Core Collection, and Google Scholar between January and March 2026, with the 2004 starting point reflecting the emergence of modern PA technologies following the adoption of GPS-guided machinery, and the search strategy employed keywords focused on PA, digital technologies, economic performance, sustainability, and resource-use efficiency across various search strings including “PA” AND economics, “precision farming” AND profitability, “digital agriculture” AND economic performance, “PA” AND ROI, “variable rate technology” AND economic benefits, “smart irrigation” AND water-use efficiency (WUE), “AI” AND agriculture economics, “IoT” AND PA, “remote sensing” AND farm profitability, “PA” AND sustainability valuation, “digital twins” AND agriculture, and “autonomous farming systems” AND economic analysis, with additional studies identified through backward and forward citation tracking of highly cited review articles and seminal publications.

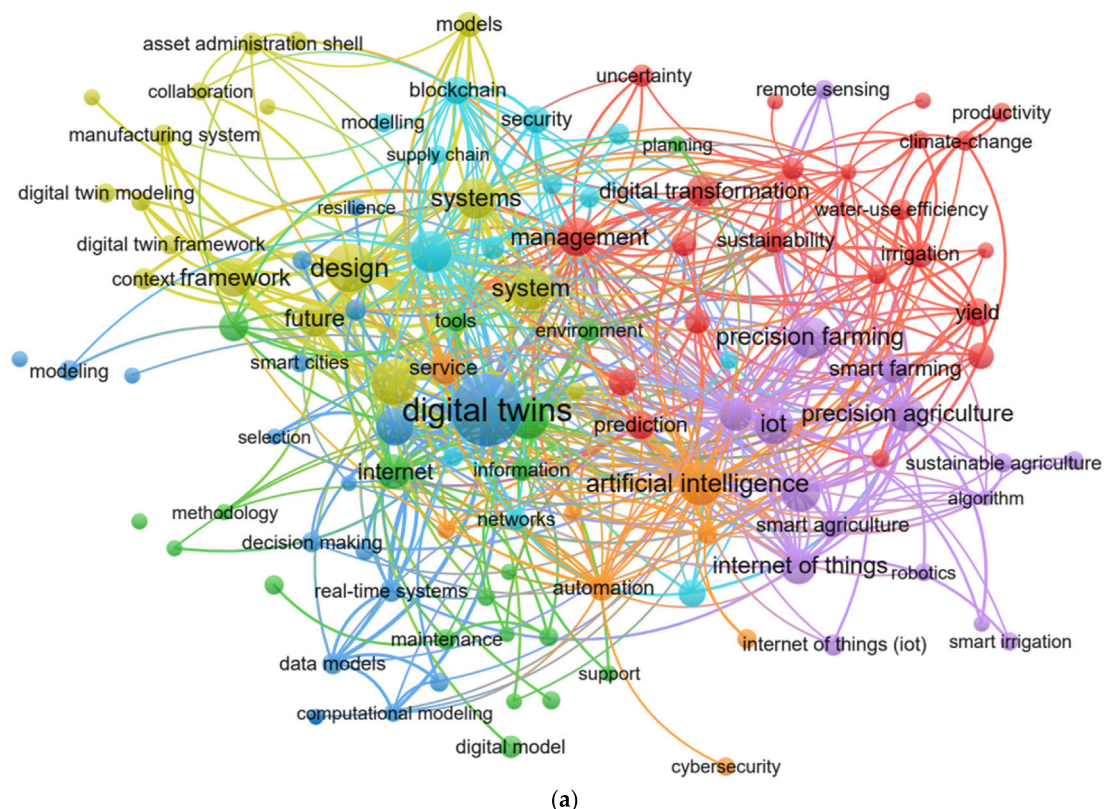


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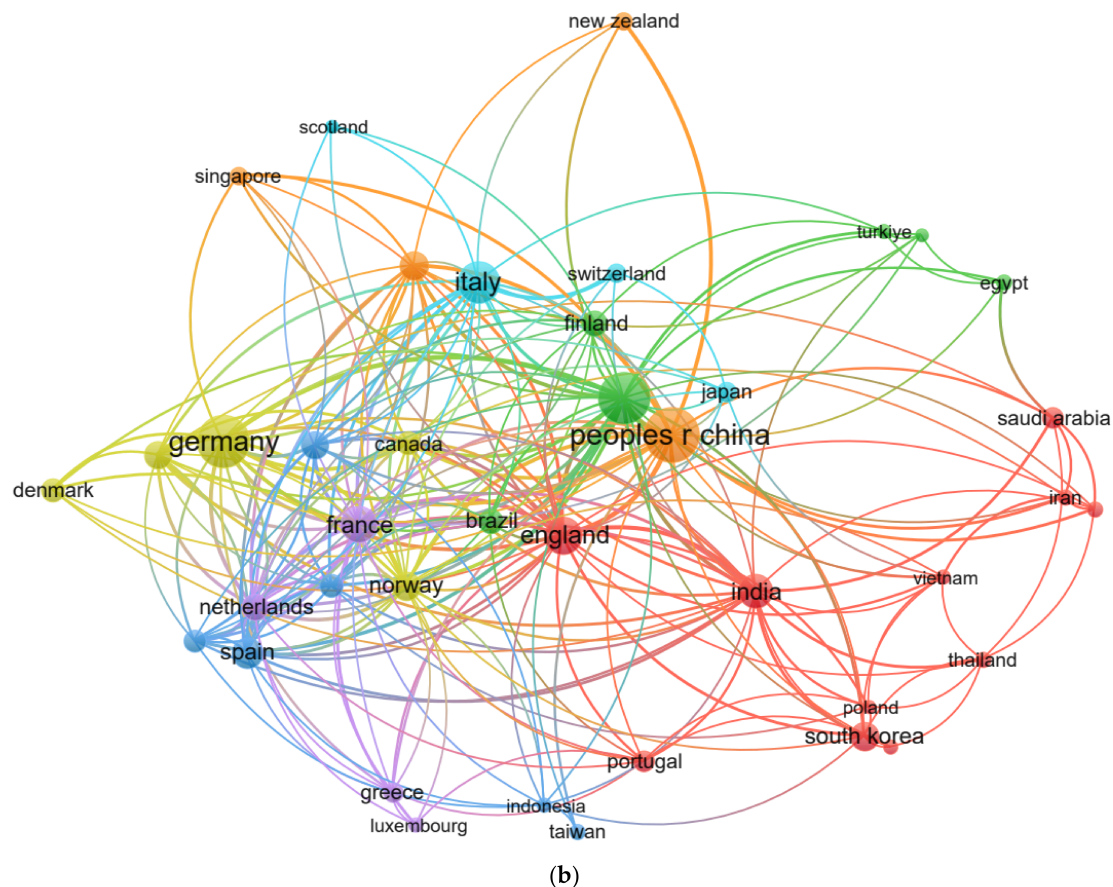


Figure 1. (a): Keyword co-occurrence network map of PA research. This VOSviewer map illustrates thematic clusters in the economics of PA, with node sizes reflecting keyword frequency and connecting lines showcasing co-occurrence. Distinct clusters include technology adoption and economics, resource-use efficiency and sustainability, digital technologies and data management, and environmental impacts. (b): VOSviewer network map illustrating co-authorship and institutional collaboration in PA economics research. Nodes represent authors and institutions, with their size corresponding to publication volume. Lines between nodes indicate co-authorships, while colors differentiate research groups or collaboration periods. The map reveals a concentration of research activity in North America, Europe, and Australia, highlighting a geographic research concentration.

Additional relevant studies were identified through backward and forward citation tracking of highly cited review articles and seminal publications, including Wolfert et al. [8], Finger et al. [13], Lowenberg-DeBoer and Erickson [20], and Balafoutis et al. [4]. To supplement the peer-reviewed literature, selected reports from governmental agencies, international organizations, and industry sources such as the USDA Economic Research Service, World Bank, McKinsey & Company, and Accenture were consulted when peer-reviewed economic evidence was limited or unavailable. These sources primarily provided market projections, industry trends, and emerging innovation perspectives and are explicitly identified throughout the review to distinguish them from peer-reviewed evidence.

2.3. Eligibility Criteria

To ensure the relevance and quality of selected studies, specific inclusion and exclusion criteria were established. Studies were included if they were published in peer-reviewed venues, focused on PA or related fields, reported on economic or resource outcomes, provided evidence on various performance metrics, and were published in English between 2004 and 2026. Conversely, studies were excluded if they primarily addressed engineering design without economic discussion, contained duplicated content, or lacked method-

ological rigor. The screening and selection process followed the PRISMA ScR guidelines, comprising stages of identification, screening, eligibility assessment, and final inclusion (see Figure 2).

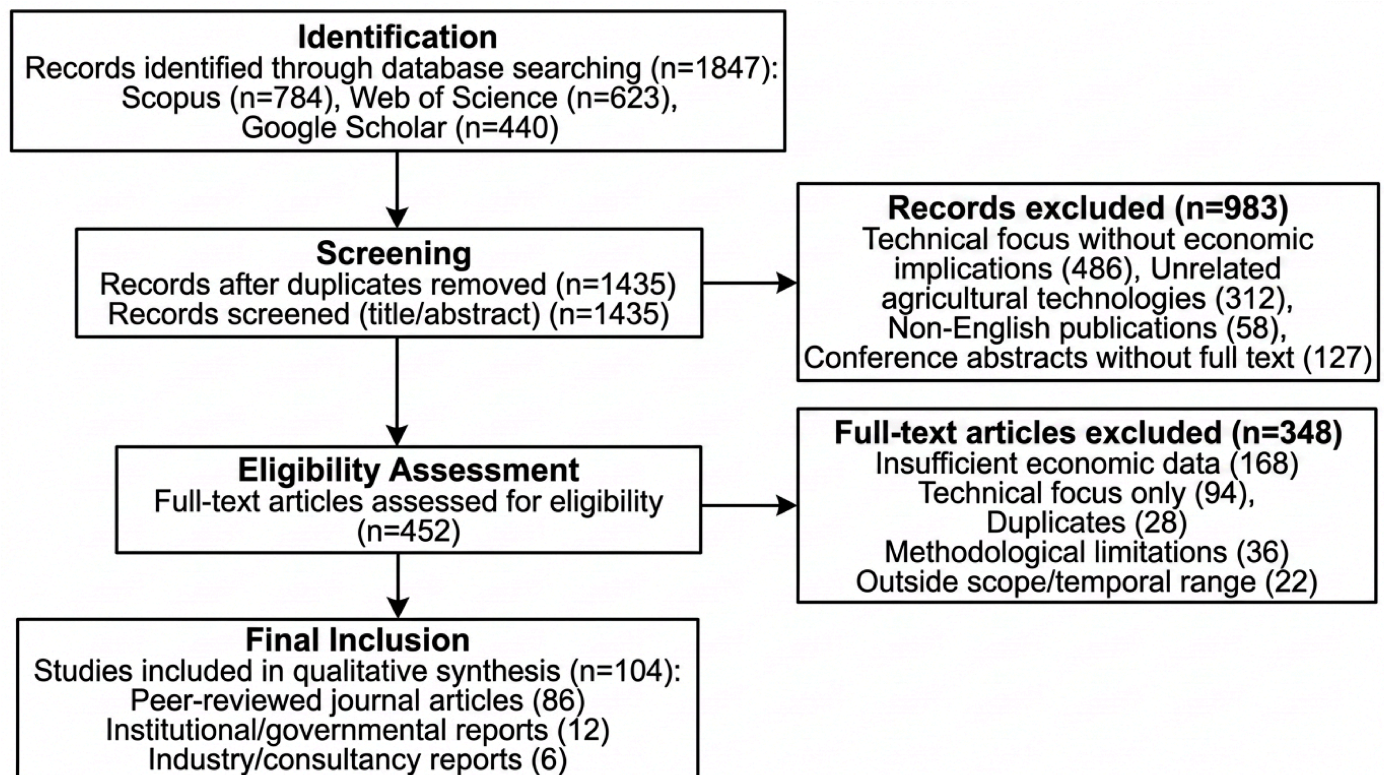


Figure 2. PRISMA flow diagram of literature identification, screening, eligibility assessment, and inclusion process records identified through database searching.

3. Theoretical Foundations

3.1. Technology Adoption Theory

Explanations for the adoption of PA primarily draw from three theoretical frameworks: Diffusion of Innovations Theory, the Technology Acceptance Model, and the Unified Theory of Acceptance and Use of Technology (UTAUT) [25–29]. In agricultural settings, Rogers’ diffusion framework proposes that adoption is influenced by perceived relative advantage, compatibility with existing farming systems, complexity, trialability, and observability. These characteristics determine whether producers perceive digital technologies as economically beneficial relative to conventional production practices [25–28]. Empirical applications of UTAUT further identify performance expectancy, facilitating conditions, social influence, and behavioral intention as significant predictors of PA adoption among farmers [29].

More recent theoretical developments have extended these frameworks by incorporating farm heterogeneity, behavioral economics, institutional constraints, and risk preferences. Farmers facing uncertain returns, high capital requirements, or limited access to credit often delay investment in precision technologies despite their demonstrated long-term profitability [30]. Likewise, information asymmetries arising from inadequate extension services, poor digital literacy, and limited access to reliable agronomic data continue to impede economically rational adoption decisions. Behavioral economic perspectives further demonstrate that loss aversion, uncertainty regarding investment returns, and status quo bias frequently discourage farmers from adopting innovative technologies even when expected economic gains exceed implementation costs [31].

While these theories successfully explain the determinants of technology adoption, they primarily address the behavioral dimension of farmers' decision-making and provide limited explanation for how technology adoption subsequently generates economic value. Adoption theory therefore constitutes the entry point of the broader economic framework developed in this review, identifying the institutional, behavioral, and socioeconomic conditions under which producers become willing to invest in PA technologies (see Figure 3). However, understanding whether adoption translates into improved economic performance requires complementary theoretical perspectives that explain resource allocation and productivity improvements following adoption.

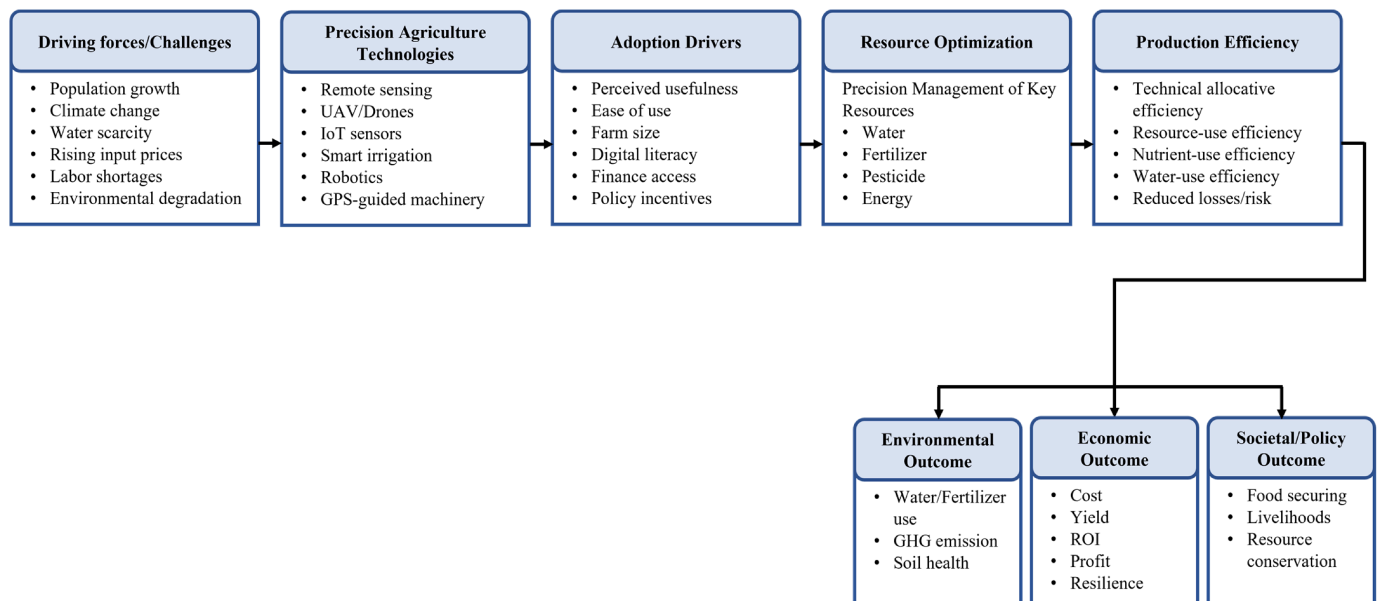


Figure 3. Logical framework of PA and resource efficiency.

3.2. Resource Economics

Resource economics provides the theoretical foundation for understanding why PA generates economic value once adoption occurs. From the perspective of the theory of the firm, producers maximize profits by substituting relatively expensive and scarce production inputs with information, knowledge, and capital whenever the marginal cost of substitution is lower than the marginal value of resource savings [32]. PA operationalizes this principle by replacing uniform input application with spatially differentiated management strategies that optimize the allocation of water, fertilizers, pesticides, energy, and labor according to site-specific production conditions (see Figure 4). Consequently, economic benefits increase as resource scarcity, spatial variability, and input prices rise [33–36].

The growing scarcity of freshwater, escalating fertilizer prices, increasing labor shortages, and tightening environmental regulations have substantially strengthened the economic rationale for PA adoption. Environmental economics further extends conventional resource-allocation theory by incorporating externalities associated with excessive input use, including groundwater depletion, nutrient leaching, greenhouse gas emissions, and biodiversity degradation. Shadow pricing, avoided-cost approaches, and ecosystem-service valuation demonstrate that the societal benefits of PA frequently exceed private financial returns because improved resource-use efficiency reduces environmental damage while enhancing long-term agricultural sustainability [21,22,37].

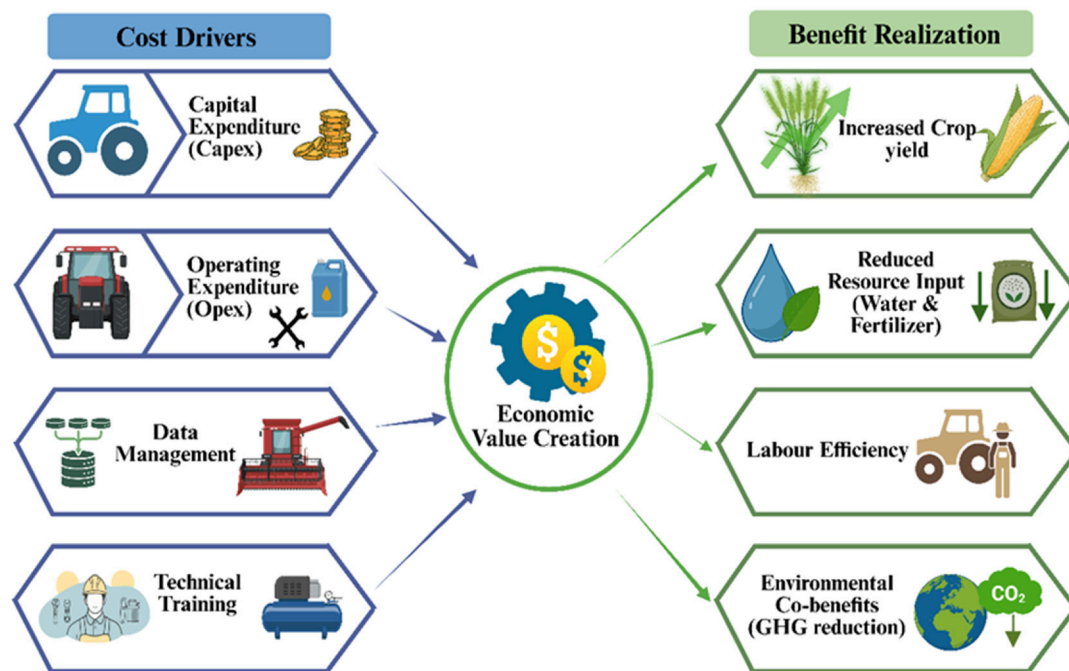


Figure 4. Conceptual framework of PA economics. The framework illustrates the interactions among technology adoption theory, resource economics, and production-efficiency models. PA technologies influence input optimization, resource-use efficiency, productivity, risk management, and environmental sustainability, ultimately affecting farm profitability, economic resilience, and social welfare outcomes.

Resource economics therefore explains the economic mechanisms through which adopted technologies improve allocative efficiency by optimizing the marginal productivity of scarce production factors. Whereas technology adoption theory addresses farmers' investment decisions, resource economics explains why those investments become increasingly profitable under conditions of resource scarcity, environmental regulation, and market volatility. This perspective extends the analysis beyond private profitability by incorporating broader social welfare gains associated with improved environmental performance.

3.3. Production Efficiency Models

Production-efficiency theory explains how improvements in resource allocation are ultimately translated into measurable economic performance. Analytical approaches including stochastic frontier analysis (SFA), data envelopment analysis, and Malmquist productivity indices have been widely employed to quantify changes in technical efficiency, allocative efficiency, and total factor productivity following PA adoption [13]. Empirical evidence consistently demonstrates that adopters of GPS guidance, variable-rate application (VRA), AI-supported decision systems, and precision irrigation achieve higher technical efficiency than comparable non-adopters after accounting for differences in farm size, crop type, and management intensity [4,13].

Efficiency gains, however, are not uniform across production systems. Their magnitude depends on the initial efficiency level of the farm, spatial variability within production fields, technological maturity, management capacity, and data quality. Farms operating substantially below the production frontier generally realize greater marginal improvements because PA enables correction of existing management inefficiencies. Conversely, farms already operating near optimal efficiency often experience smaller incremental gains despite substantial technological investment. These heterogeneous responses high-

light the importance of contextual factors when evaluating the economic performance of PA technologies.

Production-efficiency models therefore provide the analytical mechanism linking optimized resource allocation to observable economic outcomes, including higher productivity, lower production costs, improved profitability, enhanced resilience, and increased competitiveness. Unlike technology adoption theory, which explains adoption behavior, or resource economics, which explains efficient allocation of scarce resources, production-efficiency theory quantifies the realized economic outcomes generated by those decisions. Together, these complementary perspectives establish a coherent causal pathway from technology investment to farm-level economic performance.

3.4. Integrated Theoretical Framework for PA Economics

Although technology adoption theory, resource economics, and production-efficiency models have frequently been applied independently within the PA literature, relatively few studies explicitly integrate these perspectives into a unified economic framework for explaining how PA creates economic value across multiple scales [4,8,13,20]. This review argues that these theories are complementary rather than competing perspectives, each addressing a distinct stage of the economic transformation initiated by digital agriculture. Technology adoption theory explains whether farmers decide to invest in PA by considering behavioral, institutional, and socioeconomic determinants, including perceived usefulness, investment risk, compatibility, digital literacy, and facilitating conditions [25–31]. Resource economics subsequently explains why these technologies create economic value by improving the allocation of increasingly scarce production factors, including land, water, fertilizer, energy, labor, and information, while simultaneously reducing environmental externalities associated with inefficient input use [21,22,32–37]. Production-efficiency theory finally evaluates how these improvements are translated into measurable economic outcomes through increases in technical efficiency, allocative efficiency, total factor productivity, profitability, and long-term economic resilience [4,13,20].

This integrated perspective establishes a sequential economic pathway in which adoption decisions initiate changes in resource allocation that subsequently improve production efficiency and ultimately generate broader economic, environmental, and social outcomes [8,13,20]. At the farm level, these interactions improve profitability, reduce production costs, strengthen resilience to climatic and market uncertainty, and increase the return on digital investments. At the regional and national levels, the cumulative effects contribute to improved resource conservation, enhanced food security, environmental sustainability, and more efficient allocation of public investment in agricultural innovation [2,4,21]. Consequently, the three theoretical perspectives should not be interpreted as isolated analytical approaches but rather as mutually reinforcing components of a comprehensive economic framework that links farmer behaviour, resource optimization, production performance, and policy outcomes.

4. PA Technologies

4.1. Remote Sensing and UAVs

Remote sensing technologies, including satellite platforms, airborne sensors, and UAVs, are now fundamental to PA. They enable continuous monitoring of crop performance, soil conditions, and environmental variability. The economic value of these technologies stems primarily from improving management decisions that enhance resource-use efficiency, reduce production risks, and facilitate earlier interventions, rather than from data generation itself [3,38].

The increasing availability of free satellite imagery, particularly from programs like Sentinel-2, has significantly lowered information acquisition costs and expanded agricultural monitoring opportunities across diverse farming systems. However, converting this data into economic gains heavily relies on farmers' technical capacity, digital literacy, and access to advisory services. These factors remain substantial limitations in many developing regions [39].

Evidence suggests that UAVs can boost farm profitability through more efficient crop scouting, improved detection of biotic and abiotic stresses, and more precise input applications. These applications reduce unnecessary expenditures while minimizing yield losses [40]. Nevertheless, economic outcomes vary considerably across production systems. Large commercial farms often benefit significantly, as labor savings and operational efficiencies can offset capital investments. In contrast, smallholder systems frequently struggle to achieve similar returns due to high fixed costs spread over limited production areas [4,41]. These findings highlight that economies of scale are a major determinant of profitability, indicating that technological effectiveness does not automatically translate into economic viability.

Policy and regulatory environments further influence adoption and financial performance. Restrictive regulations governing UAV operations can increase costs and limit scalability, whereas enabling regulatory frameworks facilitate broader deployment and improve commercial feasibility [40,42]. Consequently, differences in national regulatory systems significantly contribute to regional disparities in technology adoption and economic returns.

Despite promising results, the evidence base is constrained by several methodological limitations. Most economic evaluations are short-term and fail to adequately account for long-term factors such as learning effects, equipment depreciation, software upgrades, maintenance requirements, and data-processing costs [13]. Furthermore, the literature is heavily concentrated in North America, Europe, and Australia, limiting its applicability to developing regions with different farm structures, labor markets, and institutional conditions [20]. As a result, reported ROI estimates may overstate actual benefits, especially where hidden operational costs and implementation barriers are not fully incorporated. Future research should prioritize long-term, regionally diverse evaluations that integrate technical performance with socioeconomic and institutional realities, thereby providing a more robust understanding of the conditions under which remote sensing technologies generate sustainable economic value.

4.2. IoT and Smart Irrigation

The IoT has emerged as a critical technology in PA, enabling real-time monitoring and management through interconnected sensors, actuators, and edge-computing devices. By continuously collecting data on soil moisture, weather conditions, crop growth, and environmental parameters, IoT systems facilitate timely, site-specific management decisions. This improves resource-use efficiency and operational responsiveness [9]. Over the past decade, the economic appeal of IoT technologies has significantly increased due to declining hardware costs, especially for soil moisture sensors and wireless communication devices. This has lowered investment barriers and shortened technology payback periods [13,43]. These advancements enhance the potential of IoT systems to boost profitability through better irrigation management, reduced input waste, and more efficient allocation of labor and resources (see Figure 5).

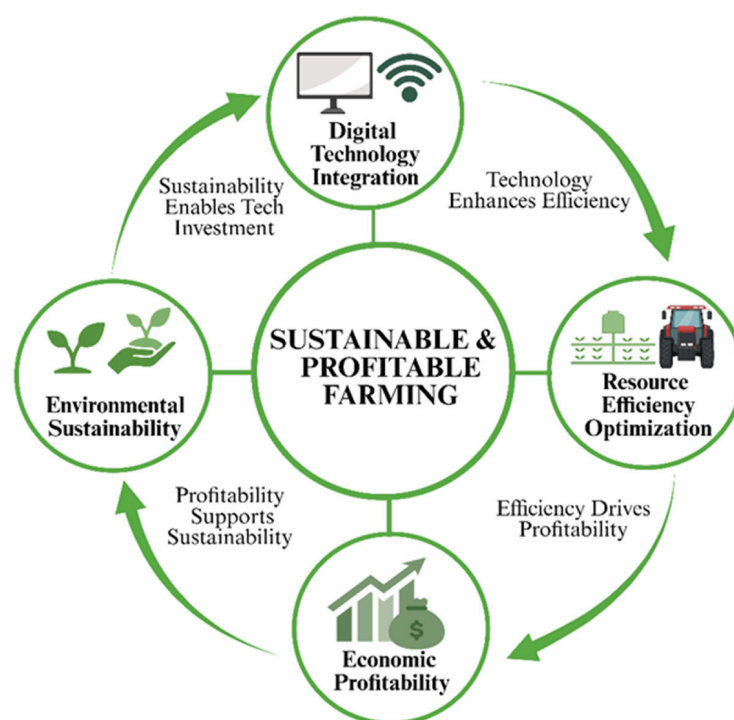


Figure 5. Integrated digital architecture of IoT-enabled smart irrigation systems in PA. The figure illustrates data acquisition through soil moisture sensors, weather stations, crop-monitoring devices, and remote sensing platforms. Information is transmitted through IoT networks to cloud-based analytics and decision-support systems that optimize irrigation scheduling, reduce water consumption, improve WUE, and enhance economic returns.

However, the economic performance of IoT technologies heavily relies on local production conditions, infrastructure availability, and policy environments. Evidence consistently shows that the greatest benefits occur in water-scarce regions, where efficient irrigation management leads to substantial cost savings and improved water productivity [43,44]. In these areas, IoT-enabled irrigation scheduling can reduce water consumption without compromising yields, generating positive long-term economic returns. Conversely, in regions with heavily subsidized irrigation water and energy, private financial incentives for adopting water-saving technologies are often diminished, despite significant environmental benefits. This discrepancy between economic signals and resource scarcity demonstrates that technology adoption is influenced not only by technical performance but also by institutional and policy frameworks governing water pricing, energy subsidies, and resource management [45,46].

Despite growing evidence of positive outcomes, the current economic literature on IoT adoption has significant methodological weaknesses. Many studies emphasize resource savings but fail to comprehensively account for installation expenses, connectivity charges, maintenance requirements, sensor calibration, software subscriptions, and labor costs associated with system management [9]. Such omissions can lead to a systematic overestimation of economic returns, particularly for small-scale farms where fixed costs represent a larger proportion of total expenditures [43]. Furthermore, most evaluations are conducted under controlled experimental conditions or within relatively advanced agricultural systems, which limits the transferability of findings to developing regions characterized by weaker infrastructure and limited technical capacity.

4.3. AI- and -ML-Driven Decision Support Systems (ML-DSSs)

AI and ML-DSSs are increasingly recognized as transformative in PA. These systems convert large, diverse datasets into actionable management insights by integrating infor-

mation from remote sensing, weather forecasts, soil sensors, historical yield records, and market databases. This capability improves the timeliness and precision of agronomic decisions, leading to more efficient crop monitoring, disease detection, yield prediction, irrigation management, and input optimization [39,47,48].

The primary economic benefit of AI is not just reduced operational costs but also enhanced decision quality under uncertainty. This leads to improved resource allocation, reduced production risks, and more strategic farm management. For instance, accurate yield forecasts can enhance marketing strategies, inventory planning, and risk mitigation. Similarly, ML-DSSs can optimize planting schedules, fertilizer applications, and irrigation practices, thereby boosting profitability and resource-use efficiency [10,49].

However, the economic performance of AI technologies varies significantly and cannot be generalized across farming systems. Benefits depend heavily on data quality, local calibration, infrastructure availability, market access, and farmers' ability to implement recommendations effectively [10,47]. Consequently, technologies that deliver substantial gains in large-scale commercial operations may offer limited benefits in resource-constrained environments lacking adequate storage facilities, extension services, and digital infrastructure (see Table 1). This variability highlights a fundamental limitation in current research, which is dominated by short-term studies. These studies often fail to capture long-term learning effects, model refinement, recurring operational costs, and evolving management practices [39]. Furthermore, inconsistent accounting for software costs, data acquisition expenses, labor requirements, and baseline assumptions complicates cross-study comparisons and reduces confidence in reported ROI estimates.

Beyond economic uncertainties, governance and equity concerns are increasingly shaping the future of AI adoption. Issues such as data ownership, privacy, algorithm transparency, and liability can erode farmer trust and slow technology uptake, especially among risk-averse producers and smallholders [50]. Moreover, ML models are developed using datasets from large commercial farms in developed economies, raising concerns about their transferability to diverse agroecological and socioeconomic contexts. Without local adaptation, AI systems might generate suboptimal recommendations that disproportionately disadvantage smallholder farmers, potentially widening existing technological and economic inequalities [39,47].

Therefore, the long-term success of AI-driven agriculture hinges not only on advances in predictive accuracy but also on establishing transparent governance frameworks, rigorous economic evaluation methods, and inclusive innovation strategies. These efforts are crucial to ensure that the benefits of digital agriculture are equitably distributed across regions and farming systems.

Table 1. Major PA technologies, functions, economic benefits, and limitations.

Technology	Primary Function	Key Resource Optimized	Economic Benefits	Major Constraints	References
AI	Yield prediction, disease diagnosis, weather forecasting, farm management optimization	Labor, management decisions, production risk	Improved decision-making; yield enhancement; revenue increase of 5–20%; estimated economic gains of USD 20–60 ha ^{−1}	Data quality dependence, algorithm transparency, high computational requirements, limited interpretability	[10,39,47,49]
IoT Sensors	Real-time monitoring of soil moisture, nutrients, microclimate, and crop status	Water, labor, fertilizer	Water savings of 20–30%; labor reduction; annual returns of USD 150–400 ha ^{−1} ; improved resource-use efficiency	Connectivity limitations, sensor maintenance, high installation costs, cybersecurity concerns	[8,9,43]

Table 1. Cont.

Technology	Primary Function	Key Resource Optimized	Economic Benefits	Major Constraints	References
Remote sensing technologies	Crop health assessment, nutrient monitoring, stress detection, yield estimation	Labor, fertilizer, pesticides	Reduced field scouting costs by 30–50%; improved spatial management; enhanced yield prediction accuracy	Image processing complexity, weather dependency, specialized expertise requirements	[3,38]
UAVs/Drones	High-resolution crop imaging, precision spraying, field surveillance	Pesticides, labor, water	Chemical use reduction of 20–40%; lower labor requirements; rapid field assessment; improved pest and disease detection	Regulatory restrictions, limited flight duration, equipment costs, operator training requirements	[40,41,51]
ML-DSS	Predictive analytics, prescription mapping, risk assessment, management recommendations	Multiple agricultural inputs	Revenue increases of 5–15%; improved resource allocation; reduced management uncertainty	Data ownership concerns, model validation requirements, farmer trust and adoption barriers	[10,47,52]
GPS-Guided Machinery and Auto-Steering Systems	Precision navigation, machinery guidance, controlled traffic farming	Fuel, labor, machinery efficiency	Fuel savings of 5–15%; overlap reduction of 10–20%; improved field operation efficiency; ROI commonly achieved within 3–7 years	High equipment costs, compatibility issues with older machinery, maintenance requirements	[20,35,53]
VRA Systems	Site-specific application of fertilizers, pesticides, seeds, and irrigation water	Fertilizer, pesticides, seed, water	Input savings of 15–25%; improved nutrient-use efficiency; enhanced profitability and environmental performance	Requires high-quality spatial data, calibration complexity, initial investment costs	[13,54,55]
Optical Crop Sensors	Real-time crop nutrient status assessment and variable-rate nutrient recommendations	Nitrogen fertilizer	Nitrogen-use reduction of 10–25%; increased nutrient-use efficiency; lower fertilizer expenditure	Sensor calibration sensitivity, environmental interference, operational complexity	[3,55,56]
Precision Irrigation Systems	Automated irrigation scheduling and water delivery optimization	Water, energy	Water-use reduction of 20–50%; increased WUE; reduced pumping costs; improved yield stability	Infrastructure requirements, high capital investment, technical management skills	[43,57–59]
Big Data Analytics Platforms	Integration and analysis of large agricultural datasets for decision-making	Multiple resources	Improved operational efficiency; enhanced forecasting capability; strategic planning benefits	Data interoperability issues, privacy concerns, large data storage requirements	[8,50]
Digital Twin Systems	Virtual simulation of farm operations and predictive scenario analysis	Water, nutrients, labor, capital	Reduced experimentation costs; optimized management decisions; improved long-term planning accuracy	High computational demand, extensive data requirements, limited commercial maturity	[60]
Autonomous Farming Systems and Robotics	Autonomous planting, spraying, harvesting, and field operations	Labor, fuel, machinery utilization	Labor savings of 30–50%; increased operational efficiency; reduced dependence on seasonal labor; long-term profitability gains	Very high capital costs, regulatory uncertainty, technological complexity	[61–63]
AI-Driven Farm Management Platforms	Integrated autonomous decision-making across production systems	Water, fertilizer, labor, capital	Net revenue improvements of 10–25%; optimized whole-farm management; improved risk mitigation	Data integration challenges, farmer acceptance, algorithm reliability concerns	[10,64]
Smart Irrigation with Dynamic Prediction Models	Predictive irrigation scheduling using AI and spatiotemporal modeling	Water, energy	Water savings of 25–50%; increased WUE; enhanced climate resilience	Model complexity, sensor dependence, computational requirements	[14,65]

4.4. Critical Assessment of PA Economic Evidence

The growing body of research demonstrates broad agreement that PA improves resource-use efficiency, reduces production costs, enhances productivity, and contributes to environmental sustainability through more precise management of agricultural inputs [4,8,13,20]. Technologies such as GPS-guided machinery, remote sensing, IoT-enabled monitoring, VRA, AI thereby increasing production efficiency and supporting farm profitability under appropriate production conditions [3,4,13,35]. Collectively, these findings establish a strong empirical consensus that PA represents a viable strategy for simultaneously improving economic and environmental performance.

Despite this consensus, the magnitude and persistence of economic benefits remain highly context-dependent. Profitability varies considerably according to crop type, farm size, spatial variability, climatic conditions, input prices, labor availability, institutional support, and farmers' managerial capacity [13,20,49]. Large commercial farms generally obtain higher financial returns because capital investments are distributed over larger operational areas and supported by better digital infrastructure, extension services, and access to finance. Conversely, smallholder farms frequently experience lower returns because high initial investment costs, fragmented landholdings, limited technical expertise, and restricted access to credit constrain the realization of economies of scale [20,39,45]. Consequently, technology adoption should not be interpreted as a guarantee of improved profitability but rather as an investment whose economic performance depends on local production and institutional conditions.

A major limitation of the current evidence concerns the methodological diversity used to evaluate economic performance. Existing studies employ a wide range of analytical approaches, including partial budgeting, ROI, NPV, IRR, SEA, CBA, ecosystem-service valuation, shadow pricing, and avoided-cost methods [21,22,35,53,66]. While each approach provides valuable insights into specific dimensions of economic performance, differences in discount rates, planning horizons, treatment of uncertainty, valuation of environmental externalities, and accounting assumptions substantially reduce comparability across studies. Consequently, reported estimates of profitability often reflect methodological choices as much as actual technological performance, limiting the synthesis of evidence and the translation of research findings into practical investment guidelines and public policy.

Another important methodological weakness is the predominance of short-term experimental evaluations. Most studies quantify immediate changes in input use, crop yield, or gross margins but seldom consider the complete economic lifecycle of PA technologies. Costs associated with equipment depreciation, software licensing, sensor replacement, data storage, system maintenance, cybersecurity, technological obsolescence, and farmer learning are frequently omitted from economic assessments [13,20,53]. Likewise, relatively few investigations evaluate how fluctuations in commodity prices, fertilizer costs, water availability, inflation, or climate variability influence long-term investment performance. These omissions may result in systematic overestimation of economic returns, particularly when technologies are evaluated under controlled experimental conditions rather than commercial farming environments.

The current literature also exhibits evidence of publication bias. Studies reporting significant improvements in profitability, productivity, or resource-use efficiency are more likely to appear in peer-reviewed journals than studies documenting neutral or negative outcomes [4,47]. Consequently, unsuccessful technology adoption, implementation failures, discontinuation of digital platforms, and situations where investment costs exceed economic returns remain substantially underrepresented. Greater publication of long-term monitoring studies, comparative evaluations, and negative case analyses would improve the robustness of economic evidence while reducing optimism bias in future syntheses.

An equally important challenge concerns the limited integration of emerging economic issues into existing analytical frameworks. Although AI, digital twins, autonomous machinery, robotics, cloud computing, and integrated digital platforms are increasingly promoted as the next generation of PA technologies, empirical evidence regarding their long-term economic performance remains relatively limited [8,50,60–63]. Similarly, interactions between PA, agricultural insurance, climate-risk management, carbon markets, ecosystem-service payments, and sustainable finance remain insufficiently examined despite their growing importance for investment decisions and policy formulation. Future economic assessments should therefore move beyond traditional profitability indicators by incorporating resilience, risk reduction, environmental externalities, and digital governance into comprehensive evaluation frameworks.

Overall, the available evidence establishes strong consensus regarding the capacity of PA to improve production efficiency and resource allocation while simultaneously revealing considerable uncertainty regarding the magnitude, distribution, and persistence of economic benefits under diverse production systems. Future research should prioritize standardized valuation methodologies, long-term economic monitoring, lifecycle cost assessment, and integrated analytical frameworks capable of simultaneously evaluating private profitability, environmental sustainability, and broader social welfare outcomes. Such advances will substantially strengthen the scientific basis of PA economics while improving the relevance of research for producers, investors, and policymakers.

4.5. Geographic Bias and the Evolution of PA Economics

Although PA has become a global research priority, the economic literature remains geographically concentrated within North America, Europe, and Australia [13,20]. These regions account for the majority of empirical studies evaluating farm profitability, investment performance, resource-use efficiency, and environmental outcomes because they possess highly mechanized agricultural sectors, extensive digital infrastructure, well-established extension systems, and sustained public investment in agricultural innovation [4,8]. Government agencies such as the United States Department of Agriculture (USDA), the European Union through Horizon Europe and the Common Agricultural Policy (CAP), and Australian Rural Research and Development Corporations have collectively supported decades of research into digital agriculture, thereby generating large datasets that underpin much of the existing economic evidence.

Beyond research funding, structural characteristics of agricultural production have strongly influenced the evolution of PA economics. Large commercial farms dominate agricultural landscapes in many developed economies, allowing fixed investment costs associated with GPS guidance, remote sensing, autonomous machinery, and AI platforms to be distributed across extensive production areas [20]. High levels of mechanization, reliable broadband connectivity, advanced machinery markets, and strong private-sector participation further facilitate technology adoption and commercial evaluation (see Figure 6). Consequently, many existing economic models implicitly assume production conditions that are characteristic of capital-intensive commercial agriculture but are less representative of smallholder farming systems that dominate many developing countries.

China represents one of the most significant emerging contributors to PA research. Rapid expansion of digital agriculture has been supported through national initiatives including the Digital Village Strategy, Smart Agriculture Development Plans, BeiDou satellite navigation, AI-enabled decision-support systems, and extensive investment in agricultural modernization. These policies have accelerated adoption of precision irrigation, intelligent machinery, UAV-based crop monitoring, and digital advisory services across diverse production systems. Nevertheless, economic research from China increasingly

emphasizes institutional coordination, government support, digital infrastructure, and service-oriented business models rather than purely technological innovation, reflecting the country's heterogeneous farm structures and ongoing agricultural transformation [67–69].

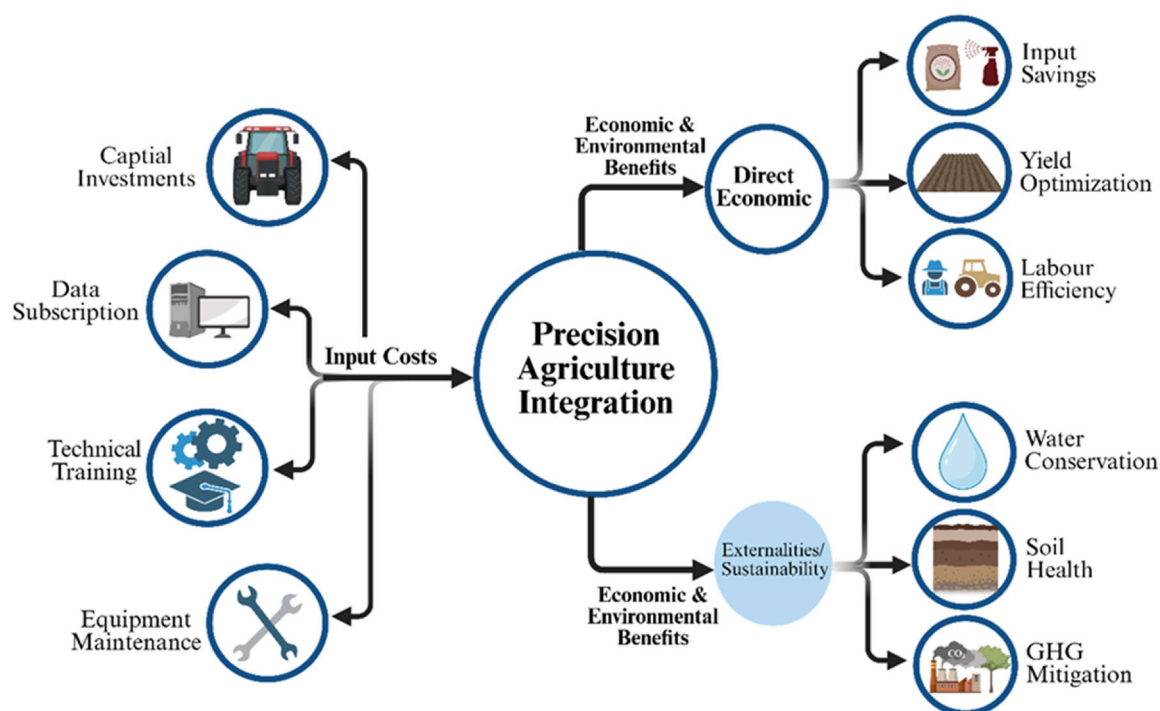


Figure 6. Economic pathways linking PA technologies with resource efficiency and farm profitability. The figure illustrates how remote sensing, IoT systems, AI-driven decision support, GPS guidance, and variable-rate technologies improve resource allocation, reduce input costs, enhance productivity, mitigate production risks, and generate environmental benefits that contribute to sustainable economic performance.

India presents a substantially different development pathway. Agriculture remains dominated by smallholder producers operating under fragmented landholdings, variable climatic conditions, and constrained access to capital. Consequently, the economic feasibility of individual ownership of sophisticated PA technologies is frequently limited. Recent government initiatives, including the Digital Agriculture Mission, expansion of mobile-based advisory platforms, and promotion of precision irrigation under national water management programs, increasingly emphasize low-cost digital solutions and shared service models. Research from India therefore highlights affordability, digital inclusion, co-operative ownership, and service-based delivery as fundamental determinants of successful technology adoption rather than technological capability alone [70–72].

Brazil has similarly emerged as an important contributor to the economics of PA, particularly in soybean, maize, sugarcane, coffee, and integrated crop–livestock production systems. Recent English-language studies demonstrate that the adoption of site-specific nutrient management, variable-rate fertilization (VRF), remote sensing, UAV-based monitoring, precision irrigation, and digital decision-support systems has improved input-use efficiency, reduced production costs, and enhanced profitability under Brazil's diverse tropical production environments [73–76]. Unlike the predominantly temperate production systems represented in North American and European research, Brazilian studies emphasize the economic implications of tropical climate variability, highly heterogeneous soils, large-scale mechanized farming, and integrated crop–livestock systems, providing important evidence for extending PA economic theory beyond temperate agricultural

regions [73,74,76]. These studies demonstrate that the economic performance of PA technologies is strongly influenced by spatial variability, management intensity, and regional production characteristics, reinforcing the need for geographically diverse evidence when developing globally applicable economic frameworks.

In contrast, empirical evidence from Sub-Saharan Africa, Southeast Asia, and many low-income agricultural economies remains comparatively limited despite these regions containing a substantial proportion of the global farming population [39,45]. Persistent barriers including inadequate digital infrastructure, unreliable electricity, weak extension systems, limited financial services, fragmented land tenure, and low digital literacy constrain both technology adoption and empirical research. As a consequence, economic theories developed largely from commercial farming systems may inadequately explain technology adoption under resource-constrained institutional environments where cooperative ownership, contractor services, mobile advisory platforms, and PA as a Service (PAaaS) models often represent more realistic pathways for technological diffusion.

The geographical concentration of empirical evidence has therefore shaped the development of PA economics by emphasizing capital-intensive investment models while underrepresenting institutional innovation, digital service delivery, and inclusive business models designed for smallholder agriculture. Future research should prioritize comparative multi-country studies that evaluate how differences in agricultural structure, public policy, digital infrastructure, financial systems, and institutional capacity influence technology adoption and economic performance. Expanding high-quality empirical evidence from emerging agricultural economies will improve the external validity of PA economic theory while supporting the development of policies that are more responsive to diverse farming systems and regional development priorities.

5. Precision Water Management

5.1. Smart Irrigation Systems

Smart irrigation systems integrate soil moisture sensors, weather data, crop evapotranspiration models, and automated controls to precisely match water delivery with crop demand. These technologies span from basic soil-moisture-based controllers to advanced AI-driven management platforms. For instance, systems utilizing the FAO-56 Penman-Monteith evapotranspiration model, adjusted with real-time sensor data, have demonstrated 20–35% water savings in commercial vegetable production compared to traditional calendar-based scheduling [43]. Further advancements, incorporating crop growth models and seasonal forecasts, optimize irrigation throughout the entire growing season. By aligning applications with predicted phenological water demand curves, these systems achieve an additional 10–15% efficiency gain over simpler sensor-based methods [55,65].

5.2. Water Use Efficiency (WUE)

WUE the ratio of crop production per unit of water consumed is the key metric for evaluating smart irrigation systems. Precision irrigation technologies consistently enhance WUE across various crops and climates (see Table 2). For instance, in Mediterranean tomato production, drip irrigation integrated with soil sensor feedback boosted WUE compared to traditional furrow irrigation [14,58]. Similarly, under semi-arid conditions, deficit irrigation, managed through continuous soil moisture monitoring, achieved comparable wheat yields with 25–30% less water [57,59,77].

Table 2. Economic performance and resource-efficiency outcomes of precision water management technologies.

Technology	System	Primary Function	Water Savings (%)	WUE Improvement (%)	Yield Response (%)	Economic Benefit	Environmental Benefit	Major Constraints	References
Conventional Surface Irrigation	Field crops	Uniform water application	Baseline	Baseline	Baseline	Low WUE and higher operational costs	Greater water losses through runoff and evaporation	Water wastage, low efficiency, limited adaptability	[57,78]
Smart Irrigation Systems	Vegetables and high-value crops	Automated irrigation scheduling using sensors and controllers	20–35	20–40	5–15	Reduced pumping costs, lower water expenditure, improved profitability	Reduced groundwater extraction and energy consumption	Infrastructure investment and technical expertise requirements	[14,43]
AI-Assisted Irrigation Management	Mixed cropping systems	Predictive irrigation optimization using AI algorithms	30–50	30–60	50–20	Improved ROI under water scarcity conditions; reduced operational costs	Enhanced climate adaptation and reduced water withdrawals	High computational requirements and data dependency	[10,65]
IoT-Based Precision Irrigation	Cereals, vegetables, orchards	Real-time monitoring of soil moisture and crop water demand	20–40	25–50	5–15	Reduced labor and irrigation costs; improved resource allocation	Lower water abstraction and improved sustainability	Connectivity limitations and sensor maintenance	[9,43]
Sensor-Based Deficit Irrigation	Wheat	Controlled reduction of irrigation while maintaining productivity	25–30	25–50	0–10	Maintained yields with reduced water inputs and lower production costs	Improved water conservation under scarcity conditions	Risk of yield penalties under severe drought	[59,77]
Precision Drip Irrigation with Sensors	Tomato and horticultural crops	Targeted water delivery based on crop demand	30–50	40–60	10–25	Higher profitability through water savings and yield enhancement	Reduced nutrient leaching and improved soil moisture management	Initial capital investment and maintenance costs	[14,58]
VRI	Large-scale grain production	Spatially differentiated irrigation according to field variability	15–35	15–40	3–12	Improved economic returns through optimized water allocation	Reduced over-irrigation and energy use	Requires detailed spatial data and specialized equipment	[13,55]

Table 2. Cont.

Technology	System	Primary Function	Water Savings (%)	WUE Improvement (%)	Yield Response (%)	Economic Benefit	Environmental Benefit	Major Constraints	References
Remote Sensing-Assisted Irrigation	Field crops and orchards	Irrigation scheduling using satellite and aerial imagery	15–30	15–35	3–10	Reduced field monitoring costs and improved irrigation decisions	Enhanced watershed-scale water conservation	Data processing complexity and image availability	[3,38]
UAV-Assisted Water Stress Monitoring	High-value crops and orchards	Detection of crop water stress through aerial imaging	10–25	10–30	2–10	Reduced scouting costs and improved irrigation targeting	Early stress detection minimizes water losses	Regulatory restrictions and operational costs	[41,51]
Dynamic Spatiotemporal Irrigation Models	Wheat and mixed cropping systems	Predictive irrigation scheduling using ML and climate data	30–50	35–65	5–20	Improved long-term profitability and water allocation efficiency	Strengthened resilience to climate variability and drought	High data and computational requirements	[65]
Integrated Precision Irrigation Platforms	Multi-crop farming systems	Combination of IoT, AI, sensors, and remote sensing	25–50	30–60	5–20	Comprehensive reduction in water, labor, and energy costs; enhanced ROI	Improved sustainability and reduced environmental footprint	High implementation costs and digital infrastructure requirements	[8,9,14]

The economic benefits of these efficiency improvements are directly tied to water supply costs. In regions where water is priced at its full opportunity cost or is subject to regulatory limits, efficiency gains translate into direct financial returns. However, where water is subsidized or not metered, economic incentives for adopting these technologies remain weak, often necessitating regulatory reform to encourage adoption [78].

5.3. Economic Benefits Under Water Scarcity

The economic value of precise water management increases disproportionately with water scarcity. In areas with ample water, the primary justifications for smart irrigation are energy savings from reduced pumping and avoiding penalties due to waterlogging. However, in water-scarce regions where water rights are traded, groundwater depletion leads to regulatory limits, or drought risk is high, the benefits grow to include scarcity rents, greater resilience to drought, and compliance with environmental flow regulations. Scheierling et al. [44] calculated that in arid systems of the western US, smart irrigation technologies yielded NPV of USD 800–2500 per hectare over 15 years when water prices exceeded USD 0.10/m³. As water pricing reforms advance and climate change intensifies the frequency of droughts, the economic returns for precise water management are rising sharply, making these technologies among the most economically sound investments in PA.

6. Economics of VRF

6.1. Economic Rationale and Input Optimization

VRF represents one of the most widely adopted PA technologies because fertilizer expenditures constitute a substantial proportion of total production costs in many cropping systems. By adjusting fertilizer application rates according to spatial variability in soil fertility, crop nutrient requirements, and expected yield responses, VRF seeks to improve nutrient-use efficiency while reducing unnecessary input use [33,35,54].

The economic rationale for VRF is grounded in the principle of marginal optimization, whereby fertilizer is allocated to locations where the marginal value of yield gains exceeds the marginal cost of nutrient application. Unlike uniform-rate fertilization, which assumes there are homogeneous field conditions, VRF recognizes substantial within-field variability in soil characteristics, nutrient availability, and crop response functions. Consequently, VRF can improve allocative efficiency by matching nutrient supply with site-specific crop demand.

However, the profitability of VRF is highly context-dependent and should not be interpreted as universally positive. Economic outcomes vary according to crop type, fertilizer prices, field heterogeneity, farm size, equipment ownership, and management capacity. Fields exhibiting limited spatial variability may generate insufficient economic benefits to justify investment in VRF technologies, whereas highly heterogeneous production environments often provide substantially greater returns. Furthermore, technology acquisition costs, software subscriptions, data-processing requirements, and operator training expenses are frequently excluded from farm-level profitability calculations, potentially leading to overly optimistic assessments of economic performance [20,79].

The existing literature also exhibits considerable methodological variation in the estimation of return ROI, NPV, and payback periods. Many studies evaluate economic outcomes over short time horizons and may not adequately account for equipment depreciation, maintenance costs, inflation, or fluctuations in fertilizer prices. As a result, reported economic returns should be interpreted cautiously, particularly when extrapolated across regions, production systems, or time periods.

6.2. Fertilizer Cost Reduction and Economic Performance

The economic value of VRF is amplified during periods of fertilizer price volatility. During the 2021–2022 global nitrogen fertilizer crisis, fertilizer prices increased dramatically due to disruptions in energy markets, supply-chain constraints, and geopolitical instability. Under these conditions, reductions in fertilizer consumption generated substantially larger economic benefits than during periods of stable input prices [80].

Studies commonly report fertilizer-use reductions ranging from 10–30%, depending on crop type, field variability, and management strategy [53,81]. In many grain-production systems, annual net economic returns from VRF range between USD 20 and 80 ha^{−1}, while higher-value vegetable, orchard, and specialty crop systems often achieve greater economic gains because of their intensive nutrient requirements.

Nevertheless, these average values conceal substantial variability among production environments. Meta-analytical evidence indicates that economic returns from precision nutrient management are influenced by climatic conditions, nutrient response elasticity, farm scale, labor costs, and local fertilizer markets [82]. Consequently, fertilizer savings do not always translate directly into higher profitability. In some cases, lower fertilizer application rates may reduce yield potential if nutrient recommendations are poorly calibrated or if extreme weather events alter crop nutrient demand.

The economics of VRF may also differ significantly between developed and developing regions. In large-scale commercial farming systems, economies of scale often facilitate rapid recovery of technology investments. Conversely, smallholder farmers in sub-Saharan Africa and South Asia frequently face financial constraints, limited access to digital infrastructure, and inadequate technical support, reducing the economic feasibility of individual ownership models. Alternative approaches, including cooperative ownership, contractor-based service provision, and PA-as-a-Service (PAaaS) models, may therefore play a critical role in improving accessibility and affordability among resource-constrained producers [20,26].

6.3. Environmental Benefits and Sustainability Valuation

Precision nutrient management generates economic benefits beyond direct fertilizer savings by reducing environmental externalities associated with nutrient overapplication. Excessive fertilizer use contributes to nitrate leaching, eutrophication, groundwater contamination, and nitrous oxide (N₂O) emissions, which impose significant environmental and societal costs [21].

Precision application strategies reduce nutrient surpluses and can therefore contribute to lower greenhouse-gas emissions and improved water quality. In some jurisdictions, these environmental improvements may generate additional economic value through carbon-credit markets, nutrient-trading programs, or regulatory compliance mechanisms.

However, the economic valuation of these environmental benefits remains one of the least standardized aspects of PA research. Existing studies employ diverse valuation methodologies, including shadow pricing, avoided-cost approaches, ecosystem-service valuation frameworks, carbon-market pricing, and willingness-to-pay methods [21,22,66]. Because these approaches rely on different assumptions regarding environmental damage costs, carbon prices, discount rates, and ecosystem-service value, resulting estimates often vary substantially across studies.

For example, carbon-credit values may fluctuate significantly depending on the selected market, regulatory framework, and reporting methodology. Similarly, avoided-cost estimates for groundwater contamination or eutrophication depend heavily on local environmental conditions and water-treatment expenses. Consequently, environmental economic benefits reported in the literature should be interpreted as indicative rather than definitive estimates.

Another important limitation concerns potential rebound effects. Efficiency improvements achieved through VRF may encourage expansion of cultivated areas or intensification of production, partially offsetting environmental gains. Moreover, the environmental foot-

print associated with the manufacture, operation, and disposal of PA equipment is rarely incorporated into economic assessments. Life-cycle analyses suggest that embedded energy consumption and technology-related emissions should be considered when evaluating the overall sustainability of precision nutrient management systems [83].

Future research should prioritize the development of standardized environmental valuation frameworks that integrate carbon pricing, ecosystem-service assessment, avoided environmental costs, and life-cycle sustainability metrics. Such frameworks would improve comparability among studies, reduce uncertainty in sustainability assessments, and provide more robust evidence for policy design and investment decision-making.

7. Economics of Precision Irrigation and Water Management

7.1. Water Scarcity as an Economic Driver of Precision Irrigation Adoption

Water scarcity is a major challenge for global agricultural production. Agriculture consumes about 70% of the world's freshwater, and this resource is becoming increasingly strained due to competition from industrial and domestic users [2]. Climate change, population growth, groundwater depletion, and more frequent droughts worsen water insecurity, posing significant economic risks for farmers. To address this, precision irrigation technologies have been developed to improve efficiency by precisely matching water application to crop needs. These technologies include soil moisture sensors, weather monitoring systems, remote sensing platforms, automated irrigation controllers, IoT-enabled networks, and AI-driven decision-support systems [47].

From an economic standpoint, water scarcity fundamentally increases the marginal value of irrigation water, thereby strengthening the case for investing in precision irrigation. As water becomes scarcer, the opportunity cost of inefficient water use rises, making technologies that optimize irrigation scheduling and reduce waste more profitable. Resource economics theory indicates that the value of efficiency-enhancing technologies grows with the scarcity and economic value of the managed resource. This makes water-limited regions particularly conducive to precision irrigation adoption [20].

However, the economic appeal of precision irrigation is not universal. Economic outcomes are highly dependent on local hydrological conditions, water pricing, regulatory frameworks, energy costs, crop value, and farm management capabilities. For instance, regions with volumetric water pricing or groundwater extraction restrictions often have stronger economic incentives for adoption than areas where water is inexpensive or heavily subsidized. Therefore, economic evaluations must consider these institutional and environmental differences rather than assuming uniform benefits across all production systems [13,67]. Unlike many PA technologies that primarily reduce input costs, precision irrigation can simultaneously impact water expenditures, energy consumption, nutrient-use efficiency, crop productivity, yield stability, and climate resilience. Consequently, assessments that focus solely on direct water savings may underestimate the broader economic value derived from risk reduction, improved crop quality, and enhanced resilience to climatic variability [47].

7.2. Economic Performance and Resource-Use Efficiency

Numerous studies report that precision irrigation technologies can substantially improve WUE, reduce energy consumption, and enhance crop productivity [47,80]. Water savings typically range from 10–40%, depending on crop type, irrigation system design, climatic conditions, and management practices. Economic benefits stem from reduced water purchases, lower pumping costs, improved nutrient retention, decreased labor requirements, and enhanced yield performance. For high-value crops like fruits, vegetables, vineyards, and horticultural systems, precision irrigation often yields favorable economic returns because water stress directly impacts crop quality and market value.

Despite these reported benefits, economic performance varies widely across production systems. Published ROI estimates differ considerably due to varying assumptions regarding water prices, energy costs, technology depreciation, maintenance expenditures, discount rates, and expected yield responses. Therefore, average profitability estimates in the literature should be interpreted cautiously and not generalized across regions without considering local economic and environmental conditions [13,20].

Moreover, many economic analyses focus on short-term gains, overlooking recurring costs such as software subscriptions, sensor calibration, communication infrastructure, equipment maintenance, and eventual technology replacement. Such omissions can overestimate net economic benefits and contribute to publication bias toward positive economic outcomes. The prevalence of short-duration field trials also limits understanding of long-term profitability under fluctuating climatic, technological, and market conditions [68–70,80].

Climate variability introduces further uncertainty. Irrigation requirements can vary substantially year-to-year due to differences in rainfall, evapotranspiration rates, and temperature extremes. Consequently, economic returns observed during favorable climatic conditions may not persist under prolonged droughts, extreme weather events, or changing water-allocation policies. Future research should prioritize long-term and multi-regional evaluations to improve the reliability of economic performance assessments.

7.3. Smallholder Adoption and Developing-Country Perspectives

Precision irrigation could significantly advance agricultural development in water-stressed regions of Africa, South Asia, and Southeast Asia. These areas frequently suffer from chronic water shortages, inefficient irrigation, and growing climate vulnerability, making effective water management crucial for food security and rural livelihoods. Beyond just increasing productivity, precision irrigation offers improved climate resilience, greater water security, and reduced production risks. However, several factors limit its adoption among smallholder farmers, including high upfront costs, a lack of technical expertise, insufficient digital infrastructure, weak extension services, and limited access to financing [20,68–72]. Many precision irrigation systems, originally designed for large commercial farms, are often not economically viable for individual smallholders.

Consequently, alternative adoption models are gaining traction. Cooperative ownership, contractor-operated technologies, mobile advisory systems, and PAaaS platforms could lower financial barriers and increase accessibility for resource-constrained farmers. These models enable producers to use advanced technologies without bearing the full ownership costs, making them particularly relevant in developing countries where capital is scarce [26]. Despite increasing interest in digital agriculture, most research on precision irrigation focuses on North America, Europe, and Australia. There is a notable lack of rigorous studies assessing the economic feasibility, scalability, and long-term sustainability of these systems within the specific socioeconomic, institutional, and infrastructural contexts of sub-Saharan Africa, South Asia, and Southeast Asia. This geographical imbalance limits the applicability of current economic findings and points to a critical research gap that needs more empirical investigation [13].

7.4. Environmental Benefits and Economic Valuation Challenges

Beyond direct farm-level profitability, precision irrigation enhances environmental sustainability by reducing water withdrawals, groundwater depletion, nutrient leaching, and energy consumption. These outcomes yield broader societal benefits that extend beyond individual farms. Despite frequently being cited as major advantages of precision irrigation, the economic valuation of these environmental benefits remains methodologically challenging (see Table 3). Existing studies utilize diverse approaches, including shadow pricing,

avoided-cost methods, ecosystem-service valuation, contingent valuation, and willingness-to-pay frameworks. Each of these relies on different assumptions regarding environmental damage, water scarcity values, discount rates, and societal preferences [21,22], leading to substantial variation in economic estimates of sustainability benefits across studies.

Table 3. Economic and environmental outcomes of precision nutrient management.

Indicator	Conventional Fertilization	Precision/VRF	Improvement (%) / Economic Value	Economic and Environmental Significance	References
Total fertilizer use	Uniform application across fields	Site-specific application based on crop demand	15–25% reduction	Lower input costs and reduced nutrient wastage	[54,55]
Nitrogen application rate	Fixed application rates	Spatially optimized rates	18–22% reduction	Improved nutrient allocation and cost savings	[56,81]
Phosphorus application	Uniform application	VRA according to soil fertility	10–20% reduction	Reduced risk of nutrient accumulation and runoff	[13,55]
Fertilizer expenditure	High and often inefficient	Optimized fertilizer investment	USD 30–60 ha ^{−1} savings	Direct increase in farm profitability	[35,53]
Nutrient-use efficiency (NUE)	Baseline	Enhanced nutrient uptake efficiency	10–35% increase	Greater yield per unit nutrient applied	[13,55]
Crop yield response	Variable; often limited by over/under-fertilization	More uniform nutrient availability	3–15% increase	Increased productivity and revenue generation	[36,54]
Yield stability	Greater spatial variability	Improved within-field consistency	5–20% improvement	Reduced production risk and income variability	[35,36]
Nitrogen surplus	High nutrient excess in some field zones	Reduced excess nutrient accumulation	25–40% reduction	Lower nutrient losses and improved efficiency	[21,55]
Nitrate leaching	Elevated under excessive fertilizer use	Reduced through targeted nutrient application	15–35% reduction	Improved groundwater protection	[13,55]
Phosphorus runoff	Greater nutrient transport to water bodies	Reduced nutrient export	10–30% reduction	Lower eutrophication risk	[13,54]
N ₂ O emissions	Higher due to over-application of N fertilizers	Lower due to optimized nutrient management	15–30% reduction	Reduced greenhouse gas emissions	[4,21]
Carbon footprint of fertilization	High due to fertilizer manufacture and losses	Reduced fertilizer demand and emissions	10–25% reduction	Supports climate-smart agriculture goals	[4,80]
Energy consumption	Greater fertilizer production and application energy requirements	Reduced fertilizer and machinery use	5–20% reduction	Lower production costs and emissions	[4]
Water quality protection	Limited protection from nutrient contamination	Improved nutrient retention and reduced runoff	Moderate to high improvement	Enhanced ecosystem services and watershed sustainability	[13,22]
Soil fertility management	Often characterized by nutrient imbalances	Balanced nutrient distribution	Improved soil nutrient status	Long-term soil productivity enhancement	[71]
Biodiversity protection	Higher chemical loading affects non-target organisms	Reduced nutrient pollution pressure	Moderate improvement	Supports ecosystem resilience and beneficial organisms	[13,22]
Carbon credit potential	Minimal	Moderate to high	Emerging revenue stream	Additional financial incentives through carbon markets	[21,66]
ROI	Conventional management baseline	Positive returns in most intensive systems	Typically 8–18% ROI	Stronger profitability under high fertilizer prices	[35,53]
Contribution to circular economy	Limited nutrient recycling efficiency	Improved matching of nutrient supply with demand	Moderate to high improvement	Reduced waste and improved resource recovery	[71]

For instance, the monetary value of groundwater conservation is contingent on local aquifer conditions, future water demand projections, extraction costs, and regulatory constraints. Similarly, estimates of avoided nutrient pollution vary based on assumptions about ecosystem restoration expenditures, water-treatment costs, and environmental thresholds. These methodological differences complicate cross-study comparisons and introduce uncertainty into assessments of the true economic value of environmental sustainability outcomes.

Another significant limitation is that many environmental benefits are external to private farm-level decision-making. Unless farmers receive direct compensation through mechanisms such as water markets, ecosystem-service payments, conservation incentives, nutrient-trading programs, or carbon-credit mechanisms, the societal value generated by reduced water use and environmental protection may not be fully reflected in farm profitability calculations [21]. This divergence between private and social benefits can lead to underinvestment in precision irrigation technologies, despite their broader sustainability advantages.

8. Cost–Benefit Evaluation of PA Investments

8.1. ROI

ROI remains one of the most frequently applied indicators for evaluating the financial performance of PA technologies because it provides a simple and intuitive measure of the relationship between economic benefits and initial capital expenditure [13,35]. Numerous studies report positive ROI for GPS-guided machinery, VRA, remote sensing, AI, IoT systems, and precision irrigation, reflecting improvements in input-use efficiency, labor productivity, operational accuracy, and crop performance [4,20,43]. Reported ROI values generally range between 8% and 35%, with higher returns commonly observed in large commercial farms, high-value horticultural systems, and regions experiencing elevated water or fertilizer prices [13,35,53].

Although ROI provides an accessible measure of financial performance, it should not be interpreted as a universally comparable indicator of investment success because its value is highly sensitive to methodological assumptions and production conditions. Differences in farm size, crop value, climatic variability, spatial heterogeneity, management capacity, technology utilization, and local market conditions frequently produce substantial variation in reported ROI estimates even for identical technologies [20,49]. Consequently, profitability reflects not only technological performance but also the broader economic and institutional environment within which technologies are implemented.

An additional limitation concerns the inconsistency with which investment costs are incorporated into ROI calculations. While some studies evaluate only equipment acquisition costs, others include installation, maintenance, software subscriptions, calibration, technical support, operator training, connectivity charges, and data management expenses [13,53]. These methodological differences substantially influence reported returns and reduce comparability among studies. Furthermore, many investigations estimate ROI over relatively short evaluation periods without accounting for technological depreciation, replacement cycles, inflation, or declining marginal productivity as management practices improve over time. Such omissions may systematically overestimate long-term investment performance.

ROI also provides limited information regarding investment risk and uncertainty. Conventional ROI calculations generally assume stable commodity prices, predictable climatic conditions, and constant input costs despite increasing volatility associated with climate change, fertilizer markets, energy prices, and global supply-chain disruptions [53,80]. Consequently, technologies exhibiting similar average ROI values may differ substantially in their ability to reduce production risk, improve climate resilience, or stabilize farm income during adverse environmental conditions. From an investment perspective, technologies that generate slightly lower average returns but substantially reduce financial uncertainty

may provide greater long-term economic value than technologies with higher but more volatile returns.

Equally important, ROI captures only private financial performance and rarely incorporates broader societal benefits generated through improved environmental management. Reductions in greenhouse gas emissions, groundwater depletion, nutrient losses, biodiversity degradation, and ecosystem damage often remain external to conventional ROI calculations despite representing important economic outcomes from a social welfare perspective [21,22]. Consequently, relying exclusively on ROI may undervalue technologies that produce significant public environmental benefits while simultaneously biasing investment decisions toward technologies with higher short-term private returns. Integrating environmental externalities into economic assessment would therefore provide a more comprehensive evaluation of PA investments and improve their relevance for agricultural policy and sustainable resource management.

Accordingly, ROI should be interpreted as an important but incomplete indicator of economic performance. Its greatest value lies in providing a standardized measure of short- to medium-term financial returns, whereas broader investment decisions require complementary indicators capable of evaluating long-term profitability, uncertainty, environmental externalities, and strategic resilience.

8.2. NPV

NPV provides a more comprehensive assessment of PA investments by incorporating the time value of money and evaluating the cumulative balance between discounted costs and future economic benefits throughout the technology lifecycle [53]. Unlike ROI, which primarily measures proportional financial returns, NPV explicitly recognizes that investment costs and benefits occur over different time horizons and therefore provides a more realistic evaluation of long-term economic performance. Positive NPV values reported for integrated PA systems indicate that investments in digital agriculture can generate sustained economic benefits over extended planning periods, particularly in large-scale grain production, irrigated agriculture, and high-value horticultural systems where efficiency gains accumulate over time [20,53,79].

Despite its theoretical advantages, NPV remains highly dependent on methodological assumptions that differ considerably among studies. Discount rates, planning horizons, maintenance costs, inflation, equipment replacement schedules, commodity prices, and expected productivity improvements all influence estimated NPV values [35,53]. Small changes in these assumptions may substantially alter investment outcomes, particularly for technologies characterized by high initial capital requirements and relatively long payback periods such as precision irrigation infrastructure, autonomous machinery, and integrated digital management platforms. Consequently, NPV estimates reported in different studies should be interpreted cautiously unless calculated using comparable analytical assumptions.

Another important limitation concerns uncertainty associated with future economic conditions. Traditional NPV models frequently assume deterministic cash flows despite increasing uncertainty arising from climate variability, fluctuating input prices, technological innovation, labor shortages, and changing environmental regulations [80]. Because PA technologies often operate within dynamic production environments, static NPV calculations may underestimate both investment risks and the flexibility that digital technologies provide in responding to unexpected market or climatic conditions. Scenario analysis, stochastic simulation, and sensitivity analysis therefore represent important extensions that improve the robustness of long-term investment appraisal.

Sensitivity analyses consistently identify water prices, fertilizer costs, commodity market fluctuations, climatic variability, and discount rates as the principal determinants of NPV performance [43,53,80]. This finding demonstrates that the economic attractiveness of PA depends not only on technological efficiency but also on the broader resource and policy environment within which technologies operate. For example, increasing water scarcity, carbon pricing, or fertilizer price volatility generally improve NPV by increasing the financial value of resource-efficient technologies, whereas extensive input subsidies may reduce long-term investment incentives despite positive environmental outcomes.

From a policy perspective, NPV offers several advantages over conventional profitability indicators because it accommodates long-term planning and facilitates comparison between private and public investment strategies. Governments evaluating subsidy programs, digital infrastructure investments, irrigation modernization, or climate-smart agricultural initiatives require analytical approaches capable of capturing benefits that accumulate over many years and extend beyond individual farm enterprises [21,22]. Incorporating environmental externalities, ecosystem-service value, avoided environmental damages, and climate-resilience benefits into NPV analysis would therefore improve its capacity to evaluate the full economic contribution of PA within sustainable agricultural development.

Nevertheless, NPV should not be regarded as a universally sufficient decision-making criterion. Because long-term projections remain sensitive to assumptions regarding future prices, technological change, environmental regulation, and climate conditions, NPV is most effective when interpreted alongside complementary investment indicators such as ROI, payback period, lifecycle costing, and risk-adjusted financial assessment. Integrating these approaches provides a more comprehensive understanding of economic performance while improving the comparability of investment evaluations across technologies, production systems, and policy environments.

8.3. Payback Period, Investment Risk, and Lifecycle Economic Performance

Payback period remains an important investment indicator because it estimates the time required for cumulative financial benefits to recover the initial cost of adopting PA technologies [20,43]. Farmers frequently use this measure when making investment decisions because it provides an easily understood assessment of liquidity requirements and financial risk. Existing studies indicate considerable variation among technologies, with software-based decision-support systems, remote sensing services, and UAV monitoring generally achieving payback within two to four years, whereas infrastructure-intensive investments such as precision irrigation systems, autonomous machinery, and integrated digital platforms often require four to ten years before capital costs are fully recovered [13,20,53].

Although the payback period is widely applied in farm-level investment analysis, it possesses important limitations that reduce its suitability as a stand-alone indicator of economic performance. Unlike NPV, the payback period ignores the time value of money and excludes all financial benefits generated after the investment has been recovered. Consequently, technologies with relatively long payback periods may ultimately generate substantially greater lifetime economic returns than technologies that recover their initial investment more rapidly [35,53]. This limitation is particularly relevant for PA technologies because many digital systems continue generating productivity gains, resource savings, and environmental benefits over extended operational lifespans.

The economic performance of PA investments should therefore be evaluated across their complete lifecycle rather than solely during the initial recovery period. Long-term ownership involves recurring expenditures including software subscriptions, cloud-computing services, data storage, sensor calibration, equipment maintenance, cybersecurity

protection, replacement of electronic components, operator training, and technological upgrades [8,50]. These ongoing costs are frequently omitted from conventional payback calculations despite substantially influencing long-term profitability. Likewise, technological obsolescence has become an increasingly important consideration because rapid advances in AI, sensing technologies, autonomous machinery, and digital communication systems may shorten the commercial lifespan of existing equipment, thereby altering projected investment performance.

Investment risk has also become increasingly important under conditions of climate change, resource scarcity, and volatile agricultural markets. Climatic variability, fluctuations in commodity prices, fertilizer price shocks, labor shortages, energy costs, and changing environmental regulations introduce considerable uncertainty into future cash flows, making deterministic financial evaluation less reliable [53,80]. Consequently, economic assessments should increasingly incorporate stochastic modelling, sensitivity analysis, Monte Carlo simulation, and scenario-based evaluation to quantify the probability distribution of future investment outcomes rather than relying solely on average financial returns.

An equally important but frequently overlooked benefit of PA concerns its capacity to reduce production risk. Digital monitoring systems, AI-driven decision-support tools, remote sensing, IoT sensor networks, and predictive analytics improve farmers' ability to respond proactively to drought, pest outbreaks, nutrient deficiencies, and extreme weather events [10,47,50]. Although these risk-reduction benefits are often difficult to express through conventional profitability indicators, they enhance farm resilience by reducing yield variability, improving production stability, and lowering financial exposure to environmental uncertainty. Under increasingly variable climatic conditions, these resilience benefits may equal or exceed the direct economic value generated through input savings alone.

Accordingly, investment appraisal should move beyond simple payback analysis toward lifecycle economic evaluation that simultaneously considers long-term profitability, operational costs, technological uncertainty, environmental performance, and climate resilience. Such multidimensional assessment provides a more realistic representation of the economic contribution of PA while improving investment decisions for farmers, financial institutions, and policymakers.

8.4. Comparative Assessment of Economic Valuation Methods and Policy Applicability

The diversity of valuation methods employed within the PA literature represents one of the principal challenges for evidence synthesis and policy translation. Although ROI, NPV, payback period, CBA, IRR, lifecycle costing, ecosystem-service valuation, and environmental economic assessment all seek to evaluate investment performance, each addresses different dimensions of economic value and therefore serves different analytical purposes [21,22,35,53,66]. Consequently, direct comparison among studies is often difficult because reported outcomes depend not only on technological performance but also on the selection of valuation methodology.

ROI remains particularly useful for evaluating short-term financial performance and comparing alternative technologies from the perspective of individual producers because of its simplicity and straightforward interpretation [13,35]. However, ROI provides only limited information regarding long-term investment sustainability, uncertainty, environmental externalities, or strategic adaptation to changing market conditions (see Table 4). NPV addresses several of these limitations by incorporating the time value of money and evaluating cumulative financial performance over extended planning horizons, making it particularly appropriate for long-term infrastructure investments and public-sector project appraisal [53].

Table 4. Comparative characteristics of major economic valuation methods applied in PA.

Valuation Method	Primary Objective	Major Strengths	Key Limitations	Most Appropriate Application	References
ROI	Short-term profitability	Simple, intuitive, easily compared	Ignores time value of money and externalities	Farm investment decisions	[13,35,53]
NPV	Long-term investment performance	Incorporates discounted cash flows	Sensitive to discount rate and assumptions	Infrastructure investment and strategic planning	[35,53]
IRR	Investment efficiency	Facilitates project comparison	Multiple solutions possible for irregular cash flows	Capital budgeting	[53]
Payback Period	Investment recovery	Easy assessment of liquidity risk	Ignores post-payback benefits and discounting	Farmer financing decisions	[20,43]
CBA	Private and social welfare	Includes environmental externalities	Data intensive and assumption dependent	Public policy and subsidy evaluation	[21,22]
Lifecycle Costing	Total ownership costs	Captures complete technology lifecycle	Requires long-term cost information	Digital infrastructure planning	[83]
Ecosystem-Service Valuation	Environmental benefits	Values non-market ecosystem services	High methodological uncertainty	Climate and conservation policy	[21,22,66]
Stochastic/Monte Carlo Analysis	Investment uncertainty	Explicitly incorporates climatic and market risks	Computational complexity	Climate-risk and investment assessment	[53,80]
Real Options Analysis	Managerial flexibility	Evaluates adaptive investment decisions	Limited empirical application in PA	Technology adoption under uncertainty	[53]

CBA extends conventional financial evaluation by incorporating environmental and social externalities that are not reflected in private market transactions. Carbon sequestration, reductions in greenhouse gas emissions, improved groundwater quality, biodiversity conservation, nutrient-loss reduction, and ecosystem-service provision all generate economic value that extends beyond individual farm enterprises [21,22]. Consequently, CBA provides a more appropriate analytical framework for evaluating public investment, environmental policy, conservation incentives, and climate-smart agricultural programs than purely financial indicators based on private profitability.

Emerging analytical approaches further expand the scope of PA economic evaluation. Lifecycle costing incorporates acquisition, operation, maintenance, replacement, and disposal costs throughout the complete lifespan of digital technologies, thereby improving long-term investment planning [83]. Real-options analysis recognizes that producers may delay, expand, or modify technology adoption in response to evolving market conditions, thereby capturing managerial flexibility that conventional investment models frequently overlook. Similarly, stochastic simulation and Monte Carlo analysis explicitly incorporate climatic variability, market volatility, and production uncertainty into financial evaluation, generating probability distributions of investment outcomes rather than single deterministic estimates.

The selection of valuation methodology should therefore reflect the specific decision-making context. Farm managers primarily require indicators capable of evaluating operational profitability and investment feasibility, whereas governments require analytical approaches that additionally quantify environmental externalities, public welfare, food security, climate resilience, and rural development [21,22,66]. Financial institutions may

prioritize risk-adjusted cash flow analysis, insurance providers emphasize uncertainty and loss probability, while environmental agencies focus on ecosystem-service valuation and avoided environmental costs. No single valuation method is therefore sufficient to capture the multidimensional economic contribution of PA across all decision contexts.

Future research should prioritize methodological harmonization through the development of integrated evaluation frameworks capable of simultaneously assessing financial profitability, lifecycle costs, investment risk, environmental externalities, climate resilience, and broader social welfare outcomes. Such standardized approaches would substantially improve comparability among studies while strengthening the scientific basis for evidence-based policy formulation, investment planning, and sustainable agricultural development.

9. Economic Constraints, Adoption Barriers, and Uncertainty in PA

9.1. Capital Requirements and Technology Accessibility

Despite the documented economic benefits of PA, its adoption is hindered by significant financial barriers. Initial investments in sensors, GPS equipment, autonomous machinery, data-management platforms, and communication infrastructure are often prohibitively expensive, especially for smallholder farmers and producers in low-margin agricultural systems [20,45]. This uneven distribution of capital creates substantial disparities in technology adoption between large commercial farms and resource-constrained producers.

To mitigate these entry costs and broaden access, alternative delivery models have emerged, including cooperative ownership, contractor services, and PAaaS. However, the long-term financial sustainability and scalability of these models require further empirical evaluation, particularly in developing countries with limited institutional support [26].

9.2. Data Governance, Digital Infrastructure, and Interoperability

The economic performance of PA increasingly depends on the effective management of digital resources. However, concerns regarding data ownership, privacy, cybersecurity, and interoperability continue to impede adoption. Farmers frequently express uncertainty about who controls farm-generated data and how technology providers might commercially utilize it [8,50].

In addition, limited broadband connectivity, inadequate digital infrastructure, and incompatibility among hardware and software platforms increase operational costs and reduce system efficiency. These barriers are particularly pronounced in developing regions, where technological infrastructure often lags behind the requirements of advanced digital agriculture systems. Consequently, technological innovation alone is unlikely to ensure widespread adoption without parallel investments in digital infrastructure and governance frameworks.

9.3. Uncertainty in Economic Evaluation

A significant challenge stems from the inherent uncertainty in measuring economic performance (see Table 5). Current research utilizes a wide array of methodologies, assumptions, discount rates, and valuation frameworks, which hinders direct comparisons [13]. Additionally, publication bias may skew results by overrepresenting successful case studies and underreporting less favorable outcomes. Valuing environmental benefits further compounds this uncertainty. While carbon sequestration, ecosystem services, biodiversity protection, and avoided environmental damage are commonly cited advantages of PA, their economic estimates fluctuate considerably based on the valuation methodology, market conditions, and regulatory environment [21,22,66]. Therefore, future research should prioritize the development of standardized economic assessment frameworks that incorporate private profitability, environmental externalities, and long-term sustainability outcomes.

Table 5. Cost-benefit indicators and investment performance of PA technologies.

Technology	Initial Investment Cost (USD)	Annual Operational Savings (USD ha ^{−1})	ROI (%)	NPV	Payback Period (Years)	Profitability Category	Suitable Farm Type	Major Economic Benefits	Key Adoption Constraints	References
GPS-guided machinery and auto-steering systems	5000–30,000	10–40	10–25	Positive	3–7	Moderate	Medium- to large-scale grain farms	Reduced fuel consumption, lower machinery overlap, improved field efficiency	High capital investment for smallholders	[20,35,53]
VRF	10,000–50,000	30–60	8–18	Positive	3–6	Moderate–High	Grain, cereal, and intensive crop systems	Reduced fertilizer expenditure, improved nutrient-use efficiency	Spatial data requirements and calibration complexity	[53–55]
VRI	15,000–75,000	50–150	10–25	Positive	4–7	Moderate–High	Irrigated grain and row crops	Water savings and improved irrigation efficiency	High installation costs and technical requirements	[13,14]
Remote sensing systems	2000–20,000	20–80	15–35	Positive	2–5	High	Grain, horticultural, and mixed farms	Reduced scouting costs and improved management decisions	Data processing expertise required	[3,4,38]
UAV-based monitoring systems	5000–50,000	30–100	15–30	Positive	2–5	High	High-value horticulture and specialty crops	Rapid field assessment and targeted interventions	Regulatory restrictions and training requirements	[40,41]
IoT-based irrigation Systems	15,000–40,000	100–400	20–40	Positive	3–5	High	Irrigated vegetables, orchards, and greenhouse systems	Water savings, reduced labor costs, improved yield stability	Connectivity and infrastructure limitations	[9,43]
Sensor-based deficit irrigation systems	10,000–35,000	50–200	15–35	Positive	2–5	High	Water-scarce regions and cereal production	Reduced irrigation costs while maintaining yields	Yield risks under severe drought conditions	[59,77]
ML-DSS	2000–25,000	20–100	15–35	Positive	2–4	High	Commercial farms and agribusiness operations	Improved resource allocation and reduced management uncertainty	Data ownership and model validation concerns	[10,52]
AI Farm Management Platforms	5000–50,000	50–250	15–40	Positive	2–4	High	Large-scale commercial farms	Whole-farm optimization and risk management	High-quality data requirements	[10,39,64]
Big data analytics platforms	10,000–60,000	30–150	10–30	Positive	3–6	Moderate–High	Medium- and large-scale enterprises	Improved forecasting and strategic planning	Data interoperability and privacy concerns	[8,50]
Digital twin systems	20,000–100,000	50–300	Emerging	Potentially Positive	4–8	Emerging	Advanced commercial farms	Reduced experimentation costs and enhanced decision-making	High computational and data requirements	[60]
Autonomous farming systems and robotics	50,000–500,000+	100–600	20–50	Positive (long term)	5–10	High (long-term)	Large-scale mechanized farms	Labor substitution, operational efficiency, increased productivity	Very high capital costs and regulatory uncertainty	[61–63]
Integrated PA platforms (AI + IoT + Sensors + remote sensing)	25,000–150,000	150–800	20–45	Strongly Positive	2–5	Very High	Large commercial and high-value crop systems	Simultaneous optimization of water, fertilizer, labor, and energy use	Significant capital and technical capacity requirements	[8,13,81]

9.4. Translating Economic Evidence into Agricultural Policy

The growing evidence demonstrating the economic benefits of PA has important implications for agricultural policy; however, translating research findings into practical policy interventions remains challenging because reported economic outcomes are highly sensitive to methodological assumptions, production systems, institutional environments, and regional socioeconomic conditions [13,20,21]. While indicators such as ROI, NPV, IRR, and CBA provide valuable measures of private financial performance, they frequently exclude broader environmental externalities, public goods, and long-term resilience benefits that are central to sustainable agricultural development [21,22,53]. Consequently, policy decisions based solely on farm-level profitability may underestimate the wider societal value generated through improved resource-use efficiency, reduced greenhouse gas emissions, enhanced water conservation, and ecosystem protection.

Methodological differences further complicate policy translation. Studies evaluating identical technologies often employ different discount rates, planning horizons, valuation techniques, and assumptions regarding labor costs, resource prices, technological depreciation, and climate variability, thereby producing substantially different estimates of economic performance [21,35,53,66]. These inconsistencies limit cross-study comparability and reduce the ability of policymakers to identify which technologies provide the greatest economic and environmental returns under specific production conditions. The development of standardized economic evaluation frameworks that integrate private profitability with environmental and social benefits would therefore substantially improve evidence-based agricultural policymaking.

The applicability of PA also varies across different policy environments. In regions where water resources are priced according to scarcity or groundwater abstraction is regulated, precision irrigation technologies generate strong financial incentives because reductions in water consumption translate directly into lower production costs [43,44,57]. Conversely, where irrigation water, electricity, or fertilizer inputs remain heavily subsidized, the private economic incentive for adopting resource-efficient technologies may be considerably weaker despite substantial environmental benefits [45,78]. These contrasting policy environments demonstrate that economic performance is influenced not only by technological capability but also by institutional incentives, regulatory frameworks, and market structures.

Public investment therefore plays a critical role in accelerating technology adoption where positive social returns exceed private financial incentives. Investment support mechanisms, including capital subsidies, concessional credit, tax incentives, digital infrastructure development, farmer training, extension services, and research funding, can reduce financial barriers while improving technology accessibility among smallholder producers and resource-constrained farming systems [20,39,45]. Likewise, ecosystem-service payments, carbon-credit mechanisms, nutrient-trading schemes, and climate-smart agricultural incentives provide opportunities to internalize environmental externalities that are rarely captured through conventional farm-level economic analyses [21,22,66].

Future agricultural policy should increasingly adopt integrated evaluation frameworks capable of simultaneously assessing economic efficiency, environmental sustainability, climate resilience, and social equity. Such multidimensional approaches would improve the consistency of investment decisions while ensuring that PA contributes not only to higher farm profitability but also to broader objectives relating to food security, natural resource conservation, rural development, and sustainable economic growth. Accordingly, future research should prioritize harmonized economic valuation methodologies that facilitate comparison across technologies, production systems, and policy contexts while strengthening the scientific basis for evidence-based decision-making.

10. Sustainability Outcomes

10.1. Water Scarcity Economics

Water scarcity is evolving from an environmental issue into a key economic factor driving the adoption of PA in irrigated regions globally. As water becomes scarcer and more expensive due to market pricing, regulatory limits, or aquifer depletion, the economic benefits of efficient water use increase proportionally. For example, in the Colorado River Basin, where water rights trade for USD 200–800 per acre-foot, smart irrigation technologies that reduce water use by 25% on a 100-hectare farm can save USD 15,000–60,000 annually in water costs or conserved water rights [44]. This significant saving provides a strong incentive for investment. A similar pattern is observed in other major irrigated regions facing groundwater depletion, such as the Mekong Delta, Murray-Darling Basin, and Indo-Gangetic Plain. This widespread trend supports the idea that water scarcity is the most significant economic force behind the global adoption of precision irrigation.

However, the economic response to water scarcity is not uniform across regions. In the Indo-Gangetic Plain, where groundwater pumping costs are subsidized and electricity for irrigation is provided at below-market rates, the economic incentive for precision irrigation adoption is substantially weaker, with farmers exhibiting lower willingness to pay for water-saving technologies despite significant aquifer depletion [45,46,72]. This highlights that water pricing and subsidy regimes critically mediate the relationship between physical water scarcity and economic adoption incentives, often decoupling market signals from hydrological realities.

10.2. Fertilizer Price Volatility

Fertilizer price volatility, stemming from natural gas fluctuations, geopolitical supply disruptions, and trade policy, creates an economic climate where precision nutrient management becomes an attractive risk mitigation strategy. The 2021–2022 nitrogen price spike, which saw urea prices increase by 180% within 12 months, highlighted the significant financial vulnerability of high-input agricultural systems to fertilizer market shocks. Precision technologies can reduce total fertilizer application, thereby offering a natural hedge against price volatility by decreasing the volume purchased at any price point [84]. This risk management value, separate from and in addition to direct cost savings, should be included in investment appraisals, especially for farms with high nitrogen intensity and limited capacity to pass increased costs on to buyers.

The value of this hedge depends on the elasticity of substitution between fertilizer and precision management. Under high price volatility, the option value of PA the ability to rapidly adjust fertilizer application rates in response to price signals increases significantly. Real-options models indicate this flexibility can account for 15–30% of the total economic benefit of VRF adoption during periods of price instability [53]. This suggests that traditional ROI estimates, which assume stable input prices, systematically understate the risk-reduction benefits of precision nutrient management.

10.3. Labor Shortages

Agricultural labor shortages are intensifying in both developed and developing economies, creating strong incentives to adopt PA automation and remote monitoring. In the US, the Farm Bureau estimates an annual shortage of over 500,000 seasonal agricultural workers. This scarcity has driven wages up by 20–40% in labor-intensive sectors including fruit, vegetable, and nut production [85,86]. Autonomous PA technologies, such as precision seeding, robot weeding, and UAV-based scouting, directly replace this scarce labor, offering economic returns that can be assessed against the shadow wage in tight labor markets. Similarly, in Japan, demographic aging has reduced the agricultural labor pool by

40% since 2000. Government-supported PA programs there have led to the rapid adoption of autonomous transplanting, harvesting, and spray systems. Farm surveys indicate labor savings of 30–50% and net benefits that help maintain farm viability despite severe labor constraints [61,63,87].

The labor substitution economics of PA are more complex than simple wage-cost comparisons suggest. While automation reduces demand for manual labor, it simultaneously creates demand for skilled labor to operate and maintain precision equipment. In the U.S., agricultural equipment dealers report that the shortage of trained technicians for GPS and sensor systems is a binding constraint on PA adoption, with repair service wait times exceeding two weeks in some regions [86]. This skill gap represents an implicit cost of labor substitution rarely included in economic assessments, yet it materially affects the effective ROI of PA technologies. Furthermore, the distributional impacts of labor substitution are uneven: seasonal workers with limited digital skills bear the brunt of displacement, while those with technical training capture wage premiums, potentially exacerbating rural income inequality.

10.4. Climate Change Adaptation

Climate change is fundamentally reshaping the economic landscape of PA by altering agronomic risks and the marginal productivity of precision management in increasingly variable conditions. Greater temperature variance, shifting precipitation patterns, and more frequent extreme weather events such as droughts, floods, and late frosts enhance the economic value of PA technologies. These technologies enable rapid, data-driven responses to in-season stress.

Adaptation-focused PA applications, including stress-responsive irrigation scheduling, dynamic nitrogen management for variable growing season lengths, and predictive disease management under altered pathogen-climate dynamics, primarily generate economic value through risk reduction and increased resilience, rather than solely through efficiency improvements [88]. The economic value of climate adaptation through PA is inherently difficult to quantify because it depends on the probability distribution of future climate states, which is subject to substantial model uncertainty. However, contingent valuation studies with farmers in drought-prone regions of Australia indicate that willingness to pay for PA technologies that provide early warning of heat stress and water deficit exceeds the expected savings from average-year efficiency gains by a factor of 2–3, reflecting significant risk aversion and the non-linear nature of climate-related yield losses [79].

Furthermore, carbon markets and climate insurance products are creating additional economic incentives for PA adoption. By rewarding documented precision management, these mechanisms embed PA within the broader economy of climate-smart agriculture as a key adaptation strategy. The emergence of index-based insurance products which use satellite-derived vegetation indices to trigger payouts creates a complementary incentive structure: farmers who adopt precision monitoring technologies can access better insurance terms because their documented management practices reduce information asymmetry with insurers [70]. This improved access to insurance amplifies the economic case for PA beyond its direct effects on yield and input costs, especially in regions with high climate risk and underdeveloped formal insurance markets.

10.5. Critical Assessment: The Scarcity–Adoption Nexus

While the preceding sections establish a strong conceptual link between resource scarcity and the adoption of PA, several critical caveats warrant explicit acknowledgment. First, the relationship between scarcity and adoption is not automatic or linear; it is mediated by institutional factors such as water pricing regimes, fertilizer subsidy policies,

and labor market regulations. These factors can either amplify or attenuate market signals [78]. For instance, in contexts where water is heavily subsidized, even acute physical scarcity may fail to generate sufficient price signals to incentivize precision irrigation adoption, explaining the persistent adoption gaps documented in parts of South Asia and North Africa.

Second, the scarcity–adoption relationship is asymmetrical: farmers may respond more strongly to increases in scarcity than to decreases, reflecting loss aversion and the psychological weighting of potential losses versus gains [31]. During the 2021–2022 fertilizer price spike, adoption rates for VRF in the U.S. Corn Belt increased by an estimated 18% among farmers who had previously considered but not adopted the technology. However, subsequent price declines of 40% in 2023 led to only a 5% reduction in adoption rates [84]. This asymmetry suggests that scarcity shocks can catalyze durable adoption behavior, with hysteresis effects that persist beyond the immediate price signal. Third, the economic value of PA under scarcity conditions is subject to diminishing returns. As more farmers adopt precision technologies, the competitive advantage conferred by early adoption diminishes. Consequently, the marginal value of aggregate resource savings may decline as water markets equilibrate or input prices adjust. This suggests that the economic incentives for PA adoption may be strongest during the early stages of resource scarcity, with subsequent adoption driven more by competitive parity than by scarcity-driven efficiency gains. Fourth, the scarcity–adoption framework implicitly assumes that farmers are rational economic actors with full information about technology performance and resource conditions. In practice, information asymmetries, limited digital literacy, and behavioral biases frequently lead to adoption delays that persist despite clear economic signals [28]. This behavioral dimension implies that policy interventions including demonstration farms, peer-to-peer learning networks, and subsidized trials remain essential even when resource scarcity creates strong economic incentives. Farmers may not act on market signals without complementary information and trust-building mechanisms.

These critical considerations do not undermine the fundamental proposition that resource scarcity drives PA adoption, but they do qualify its scope and mechanism. The relationship is conditional on institutional context, asymmetric in response, subject to diminishing returns, and mediated by behavioral factors. Recognizing these complexities is essential for designing effective policies that align economic incentives with adoption outcomes, particularly in regions where scarcity is acute but institutional and behavioral barriers remain binding constraints.

10.6. PA, Agricultural Insurance, and Risk Management

Although existing research has primarily evaluated PA through improvements in productivity and resource-use efficiency, an emerging body of literature recognizes that digital agriculture also creates substantial economic value through enhanced agricultural risk management and insurance innovation [70,86–91]. Climate change, increasing weather variability, market volatility, and production uncertainty have significantly increased financial risks faced by agricultural producers, creating growing demand for technologies capable of improving risk assessment, early warning systems, and adaptive farm management.

Digital technologies including remote sensing, satellite imagery, IoT sensor networks, UAVs, AI, and ML increasingly provide high-resolution information that improves the accuracy of agricultural insurance products by reducing information asymmetry between insurers and producers [8,10,50]. Continuous monitoring of crop growth, soil moisture, vegetation indices, and weather conditions enables insurers to evaluate production risks more accurately while reducing administrative costs associated with field inspections and post-disaster damage assessments. Consequently, digital agriculture strength-

ens actuarial efficiency while improving the transparency and credibility of agricultural insurance systems.

Particular attention has recently focused on weather-index and parametric insurance, where compensation is triggered by objectively measured climatic indicators such as rainfall deficits, temperature extremes, drought indices, or remotely sensed vegetation conditions rather than conventional field-based loss assessments [70,86]. Because these insurance products depend heavily on accurate environmental monitoring, PA technologies substantially improve index calibration, reduce basis risk, and accelerate claims processing. Farmers simultaneously benefit from lower transaction costs, faster compensation following climatic shocks, and improved access to formal financial services.

AI further expands opportunities for agricultural risk management by integrating historical production records, weather forecasts, market information, and remote sensing observations to generate predictive assessments of yield variability, pest outbreaks, disease occurrence, and climate-related production risks [10,47]. These predictive capabilities improve farm-level decision-making while enabling financial institutions to develop more accurate credit-risk assessments and insurance pricing models. As climate uncertainty continues to increase, the integration of AI-based forecasting with insurance products is expected to become an increasingly important component of climate-resilient agricultural systems.

Digital twin technologies represent another emerging innovation with considerable economic potential for agricultural risk management [60–63]. By creating virtual representations of agricultural production systems that continuously assimilate real-time environmental and operational data, digital twins enable producers and insurers to simulate alternative management strategies under different climatic and market scenarios before implementation. These scenario analyses improve investment planning, optimize resource allocation, and support proactive adaptation strategies that reduce financial exposure to production shocks. Although current applications remain largely experimental, digital twins are expected to become increasingly valuable decision-support tools as computational capacity, sensor integration, and cloud-based analytical platforms continue to advance.

Despite these opportunities, important challenges remain. Digital insurance systems require reliable internet connectivity, high-quality environmental data, transparent governance arrangements, cybersecurity protection, and clear regulations concerning ownership and sharing of farm-generated data [8,50]. Furthermore, many developing countries continue to face institutional constraints including limited digital infrastructure, inadequate insurance markets, weak financial institutions, and restricted access to affordable credit, thereby limiting widespread implementation of digitally enabled risk-management systems [39,45]. These barriers highlight that technological innovation alone is insufficient to ensure equitable access to digital insurance services without complementary investments in institutional capacity, regulatory frameworks, and rural digital infrastructure.

Future research should therefore move beyond evaluating PA solely as a productivity-enhancing technology and increasingly investigate its contribution to integrated agricultural risk management, climate adaptation, financial resilience, and sustainable rural development. Standardized methodologies capable of jointly assessing productivity gains, insurance benefits, climate-risk reduction, environmental externalities, and long-term economic resilience will provide a more comprehensive understanding of the full economic value generated by digital agriculture. Such integrated approaches will also strengthen the relevance of PA research for policymakers, insurers, financial institutions, and development agencies seeking to promote climate-smart and economically resilient agricultural systems.

11. Sustainability Outcomes

11.1. Greenhouse Gas Reduction

The potential of PA to mitigate greenhouse gas emissions offers a significant, yet often underestimated, economic co-benefit. Precision nutrient management, by reducing fertilizer application rates, directly decreases N₂O emissions, the primary agricultural contributor to crop system GHG inventories. Meta-analyses show that VRF can reduce field-level N₂O emissions compared to uniform-rate application, thus generating measurable carbon credits under voluntary protocols like the Verified Carbon Standard [21]. Furthermore, precision irrigation indirectly lowers methane emissions by allowing for soil moisture management that prevents anaerobic conditions in paddy and wetland systems. Overall, widespread adoption of PA in global grain production is projected to reduce agricultural greenhouse gas (GHG) emissions compared to conventional methods. This reduction is equivalent to removing 300–450 million tonnes of CO₂-equivalent annually, resulting in an estimated social cost saving of USD 15–45 billion per year at current carbon shadow prices [4,66].

However, these estimates are highly sensitive to the assumed social cost of carbon (SCC), which varies significantly across integrated assessment models. For instance, using a lower discount rate (2.5%) yields social cost estimates approximately three times higher than those derived from the 5% discount rate commonly used in agricultural economics, thus broadening the range of estimated benefits [14]. This methodological sensitivity implies that policy decisions based on lower-bound estimates might lead to underinvestment in PA adoption relative to the social optimum. Conversely, upper-bound estimates risk overstating benefits if actual climate damage proves less severe than modeled.

Furthermore, the GHG reduction potential of PA depends on its adoption being additional to existing practices. If farmers would have reduced fertilizer use due to price signals irrespective of PA adoption [73,75,76,92–94], the emissions reductions directly attributable to PA technology may be considerably smaller than what simple comparisons of average application rates suggest. This requirement for additionality has implications for carbon credit markets: only reductions beyond business-as-usual trajectories qualify for crediting. Consequently, early adopters whose baseline management was already relatively efficient may capture limited carbon revenue [21].

11.2. Resource Conservation

PA conserves resources, offering benefits beyond greenhouse gas mitigation. It also protects biodiversity, preserves soil health, and sustains aquifers, all of which have intrinsic environmental value and long-term economic significance. For instance, by limiting pesticide application to areas with demonstrated pest pressure, targeted spray systems reduce exposure for non-target organisms, including beneficial insects and soil microbiota [95]. This reduced pesticide use provides measurable economic value through enhanced pollination services (globally valued at USD 235–577 billion annually) and improved biological pest control from natural enemy communities [22,73,74,95]. The valuation of pollination services, however, relies on production function analysis that assumes linear relationships between pollinator abundance and crop yields. This assumption may overestimate service value in intensively managed systems where alternative pollination mechanisms or compensatory inputs exist [22]. Moreover, the global aggregate valuation combines highly heterogeneous cropping systems, masking substantial regional variation in pollination dependence. For largely self-pollinating or wind-pollinated crops like wheat, rice, and maize, the pollination service value of reduced pesticide use is negligible, whereas the benefits are substantial for high-value horticultural crops.

Furthermore, precision nutrient management reduces nutrient surpluses, thereby curbing surface water eutrophication and protecting water resources vital for drinking, fisheries, and recreation. Avoided damage cost methods estimate the value of reduced nitrate leaching based on the cost of water treatment, lost recreational opportunities, or ecosystem restoration. Although widely applied, these methods capture only a subset of total welfare effects and vary substantially depending on whether they include use values (e.g., recreation), non-use values (e.g., existence value), or both [96–99]. While these ecosystem service benefits are rarely included in farm-level analyses, they are crucial for a comprehensive social welfare assessment of PA adoption.

11.3. Circular Economy Contributions

PA advances circular economy principles by optimizing input utilization, minimizing waste, and recovering value from agricultural byproducts. For instance, applying organic amendments at variable rates, using the same sensor and mapping technologies as mineral fertilizers, enhances manure utilization efficiency. This method matches application rates to crop uptake capacity, thereby reducing nutrient losses and maximizing the fertilizer's replacement value [71].

Similarly, precision crop residue management, guided by remote sensing and machine vision, optimizes biomass distribution for building soil organic matter, harvesting bioenergy feedstock, and controlling erosion. These practices collectively boost long-term land productivity and lessen reliance on imported mineral inputs. Integrating PA into circular bioeconomy frameworks where nutrient recovery, biomass valorization, and carbon sequestration are economically incentivized is a crucial next step. This integration will extend PA's economic and environmental benefits beyond the farm. However, the circular economy benefits of PA are geographically heterogeneous and depend on the availability of organic amendment sources, the infrastructure for biomass processing, and the regulatory environment for nutrient recycling. In regions where livestock production is concentrated and manure exceeds local crop uptake capacity, precision application may reduce but not eliminate nutrient surpluses, and complementary measures including nutrient trading or manure export remain necessary [71].

11.4. Methodological Considerations in Environmental Valuation

Carbon credit valuation typically employs the SCC, an estimate of the marginal economic damage from each additional tonne of CO₂-equivalent emitted. Current shadow prices applied in PA studies range from USD 50 to 200 per tonne CO₂-e, reflecting substantial uncertainty in damage estimates across various discount rates, climate sensitivity parameters, and regional impact models [14,15]. The IPCC's Sixth Assessment Report (2022) emphasizes that the SCC may vary by a factor of 3–5 depending on the chosen discount rate, with lower discount rates yielding significantly higher valuations. This methodological variability directly translates into the wide range of estimated annual social cost savings [4,66].

Ecosystem service valuation for pollination and biological pest control relies primarily on avoided cost methods and contingent valuation approaches [22]. For instance, the global pollination valuation of USD 235–577 billion annually is based on production function analysis. This analysis assumes there are linear relationships between pollinator populations and crop yields, an assumption that may overestimate service value in intensively managed systems where alternative pollination mechanisms exist. Similarly, willingness-to-pay surveys for water quality protection typically exhibit substantial hypothetical bias, with stated preferences often exceeding revealed preferences by 30–50% [98].

For nutrient-related environmental benefits, avoided damage cost methods estimate the economic value of reduced nitrate leaching and phosphorus runoff. These methods calculate the cost of water treatment, lost recreational opportunities, or ecosystem restoration, approaches that capture only a subset of total welfare effects. The meta-analysis by Brander et al. [99] demonstrated that ecosystem service valuations can vary by more than 100% depending on whether use values (e.g., recreation), non-use values (e.g., existence value), or both are included. This methodological heterogeneity explains why the economic benefits of precision nutrient management are often understated in farm-level studies that ignore off-site environmental benefits while simultaneously being overstated in aggregate welfare assessments that assume perfect substitution between natural and man-made capital.

These methodological limitations shadow price uncertainty, hypothetical bias, incomplete valuation scope, and heterogeneous substitution assumptions represent critical knowledge gaps, as identified in Table 5. Current research lacks standardized protocols for integrating environmental co-benefits into PA investment appraisals. This absence of methodological consensus complicates policy design by making it difficult to compare benefit-cost ratios across studies or to determine optimal subsidy levels for PA adoption. Future research should prioritize (i) sensitivity analyses across alternative valuation methods and discount rate assumptions, (ii) field-based validation of avoided damage estimates, and (iii) development of standardized environmental accounting frameworks for agricultural systems. Until these methodological challenges are addressed, environmental benefit estimates should be interpreted as indicative rather than definitive, and policy decisions should incorporate a range of plausible valuations rather than relying on point estimates.

11.5. Remaining Knowledge Gaps and Future Research Priorities

Despite substantial progress in understanding the economics of PA, important knowledge gaps remain regarding the mechanisms through which digital technologies generate long-term economic, environmental, and social value under diverse agricultural systems [4,13,20]. Existing research has established broad consensus that PA improves resource-use efficiency, productivity, and farm profitability under appropriate production conditions; however, considerably less agreement exists regarding the magnitude, durability, and distribution of these benefits across different farm sizes, institutional environments, and policy settings [13,20,49]. Future research should therefore move beyond demonstrating whether PA is economically beneficial and instead identify the conditions under which different technologies produce the greatest private and societal returns.

One of the most significant research priorities concerns the development of standardized economic evaluation methodologies. Current studies employ heterogeneous approaches including ROI, NPV, IRR, partial budgeting, SEA, ecosystem-service valuation, shadow pricing, and avoided-cost methods, making direct comparison among studies difficult [21,22,35,53,66]. Harmonized analytical frameworks capable of integrating private profitability, environmental externalities, climate resilience, and social welfare would substantially improve evidence synthesis while strengthening the policy relevance of future economic evaluations.

Another major knowledge gap relates to the geographical distribution of existing evidence. Most empirical research continues to originate from North America, Europe, and Australia, where agricultural production is characterized by relatively large commercial farms, advanced mechanization, and extensive institutional support [13,20]. Comparatively little evidence is available from Sub-Saharan Africa, South Asia, Southeast Asia, and many Latin American production systems despite these regions accounting for a substantial proportion of the global agricultural workforce [39,45]. Future comparative studies should therefore examine how differences in farm structure, digital infrastructure, institutional ca-

capacity, financial systems, and public policy influence technology adoption, profitability, and long-term sustainability. Such research will improve the external validity of PA economic theory while supporting more inclusive models of digital agricultural development.

Emerging digital technologies also present important opportunities for future investigation. Although AI, digital twins, robotics, autonomous agricultural machinery, cloud computing, and integrated decision-support systems are increasingly recognized as transformative innovations, rigorous empirical evaluations of their long-term economic performance remain relatively scarce [10,50,60–63]. Existing studies have largely focused on technological capabilities and short-term operational efficiency, whereas considerably less attention has been devoted to lifecycle costs, investment risk, labor-market adjustment, algorithm transparency, cybersecurity, interoperability, and producer acceptance. Future research should therefore adopt interdisciplinary approaches that integrate economics, computer science, engineering, environmental science, and agricultural systems analysis to evaluate the broader socioeconomic implications of digital transformation.

Similarly, important gaps remain in understanding the interaction between PA and agricultural risk management. Digital technologies increasingly support weather-index insurance, climate-risk assessment, carbon accounting, ecosystem-service payments, and sustainable agricultural finance; however, these topics remain fragmented across multiple disciplines and are seldom incorporated into comprehensive economic evaluations [21,22,70,86]. Integrating insurance benefits, climate adaptation, financial resilience, and risk reduction into conventional investment appraisal would provide a more complete assessment of the economic contribution of PA under increasing climatic uncertainty.

The governance of agricultural data represents another emerging research frontier. Questions surrounding data ownership, privacy, interoperability, cybersecurity, algorithm accountability, and equitable access to digital technologies have become increasingly important as agricultural production systems generate larger volumes of real-time information [8,50]. These institutional dimensions influence not only technology adoption but also competition within digital agricultural markets, farmer autonomy, and the distribution of economic benefits among producers, technology providers, financial institutions, and public agencies. Consequently, future economic research should extend beyond production efficiency to examine how digital governance frameworks shape innovation, market structure, and long-term agricultural competitiveness.

Finally, greater emphasis should be placed on systems-level evaluation rather than isolated assessment of individual technologies. Most existing studies evaluate specific innovations independently despite increasing integration among remote sensing, IoT networks, AI, robotics, autonomous machinery, precision irrigation, and digital farm management platforms [8,10]. Future research should develop integrated analytical frameworks capable of simultaneously assessing interactions among technological innovation, resource economics, production efficiency, environmental sustainability, climate resilience, and public policy. Such multidimensional approaches will provide a more realistic understanding of how digital agriculture contributes to sustainable food systems under increasingly complex economic and environmental conditions.

Collectively, these priorities indicate that the future evolution of PA economics depends not only on continued technological innovation but also on methodological harmonization, broader geographical representation, stronger integration of risk management and sustainability valuation, and the development of comprehensive theoretical frameworks capable of linking farmer behavior, resource allocation, productivity, environmental performance, and policy outcomes. Addressing these knowledge gaps will strengthen both

the scientific foundations and the practical relevance of PA economics while supporting evidence-based strategies for sustainable agricultural transformation.

12. Future Innovations

12.1. Autonomous Farming Systems

Autonomous farming systems represent the cutting edge of PA's economic potential. These systems encompass self-driving tractors, robotic platforms for planting and harvesting, autonomous spraying drones, and AI-coordinated machine fleets (see Table 6). Unlike current PA technologies that primarily aid human decision-making, autonomous systems replace human labor with machine intelligence and capabilities throughout the entire production cycle.

McKinsey [44] projected that fully implementing agricultural robotics could generate an annual value of USD 150–200 billion for global agricultural economies. However, this projection requires careful interpretation. It stems from a consultancy model that assumes the following: (i) linear scaling from pilot studies to global adoption, (ii) uniform technology availability across regions, and (iii) constant input prices and policy regimes. The assumptions underlying these grand projections are rarely tested against empirical data. Sensitivity analyses indicate that even modest deviations in adoption rates or technology costs could alter the estimated value by $\pm 40\%$.

Early commercial applications, such as autonomous weeding robots, are already proving economically competitive. These robots offer mechanical or laser-based precision control at 5–10 cents per weed, making them competitive with herbicide-based management in high-value vegetable systems. This suggests a significant disruption to input-intensive conventional farming practices [89].

From a critical economic perspective, autonomous systems introduce novel structural concerns not adequately addressed in existing literature. First, the high capital costs of autonomous machinery, with fully autonomous combine harvesters reaching up to USD 500,000, will likely exacerbate industry concentration [62]. This places these technologies beyond the reach of all but the largest operations, potentially leading to a bifurcated agricultural economy. Large-scale, capital-intensive operations could gain competitive advantages through labor savings and precision management, while small-to-medium farms without access to investment capital face increasing cost pressures. Second, the labor market implications extend beyond simple substitution. While autonomous systems reduce demand for seasonal manual labor, they simultaneously create demand for new, scarce skill sets in rural communities, including data analytics, robotics maintenance, and algorithmic management [63]. This transition from manual to digital labor may therefore cause structural unemployment among workers lacking digital skills, potentially worsening rural-urban migration and social inequality. Third, autonomous systems introduce new operational and regulatory uncertainties. The legal liability framework for autonomous equipment failures, cybersecurity vulnerabilities, and questions of algorithmic accountability remain unresolved in most jurisdictions [61]. These uncertainties increase the effective risk premium on autonomous investments, potentially slowing adoption rates beyond what capital-cost models alone would predict.

Table 6. Future research priorities and knowledge gaps in PA economics.

Research Area	Current State of Knowledge	Major Knowledge Gap	Economic Significance	Methodological Limitation	Future Research Priority	Expected Impact	References
Smallholder adoption of PA	Adoption evidence largely concentrated in developed countries and large-scale farms	Limited understanding of economic viability under resource-constrained conditions	Restricts technology diffusion among smallholders who constitute a large share of global agricultural producers	Short-term studies and insufficient representation of developing regions	Longitudinal studies assessing profitability, affordability, and adoption pathways among smallholders	Improved inclusiveness and equitable technology adoption	[20,26]
AI-based Farm management	AI applications increasingly used for prediction and decision support	Limited long-term validation of economic performance under real farming conditions	Uncertainty regarding long-term ROI and risk reduction benefits	Predominance of experimental and pilot-scale studies	Multi-year field evaluations linking AI recommendations to profitability outcomes	More reliable investment decisions and improved farm profitability	[10,39,64]
ML-DSS	Increasing use in crop management and yield forecasting	Lack of comparative evaluations across production systems and agroecological zones	Economic performance remains difficult to generalize across regions	Limited external validation and transferability	Cross-regional economic assessments and benchmarking studies	Enhanced scalability and decision-making efficiency	[10,47]
Digital twin technologies	Emerging concept with growing interest in agriculture	Economic valuation and commercial feasibility remain poorly understood	Adoption hindered by uncertain cost-benefit relationships	Limited real-world implementation studies	Comprehensive cost-benefit and life-cycle economic assessments	Improved investment confidence and technology uptake	[60]
Precision irrigation economics	Evidence demonstrates substantial water savings and efficiency gains	Limited knowledge of long-term profitability under climate variability	Water scarcity increasingly affects agricultural profitability	Most studies evaluate short-term performance only	Multi-season assessments incorporating drought risk and climate uncertainty	Improved resilience and water resource management	[43,65]
Variable-rate nutrient management	Demonstrated reductions in fertilizer use and environmental impacts	Limited integration of economic and environmental valuation frameworks	Underestimation of ecosystem service benefits	Few studies incorporate external environmental costs and benefits	Development of integrated techno-economic-environmental assessment models	Better valuation of sustainability benefits	[13,54]
Big data analytics in agriculture	Large volumes of farm data increasingly available	Economic value creation from agricultural data remains poorly quantified	Data monetization opportunities remain unclear	Lack of standardized valuation approaches	Development of farm-data valuation and business models	Creation of new revenue streams and digital markets	[8,50]
Agricultural Data governance and ownership	Growing concern regarding data privacy and sharing	Limited economic analysis of data ownership structures	Data-sharing barriers may slow innovation adoption	Insufficient legal-economic research	Evaluation of alternative governance and compensation frameworks	Improved trust and digital ecosystem development	[50]

Table 6. Cont.

Research Area	Current State of Knowledge	Major Knowledge Gap	Economic Significance	Methodological Limitation	Future Research Priority	Expected Impact	References
Carbon markets and ecosystem Service payments	Increasing interest in climate-smart agriculture and carbon credits	Limited farm-level evidence regarding profitability and participation barriers	Potential new revenue source for producers	Carbon accounting methods remain inconsistent	Integration of carbon markets into PA economic models	Diversified farm income and climate mitigation benefits	[21,66,80]
Autonomous agriculture and robotics	Early commercialization occurring in several agricultural sectors	Scalability, labor impacts, and long-term profitability remain uncertain	Potentially transformative effects on labor productivity	Few large-scale commercial evaluations	Comprehensive economic assessments of autonomous farming systems	Increased operational efficiency and labor substitution	[61–63]
Climate change adaptation through PA	Precision technologies increasingly promoted as adaptation tools	Limited quantification of adaptation value under extreme climatic conditions	Climate-related risks increasingly influence farm profitability	Insufficient integration of climate scenarios into economic analyses	Dynamic economic modeling under future climate scenarios	Improved adaptation planning and resilience	[77,88]
Resource scarcity and economic resilience	Resource constraints recognized as drivers of technology adoption	Limited understanding of threshold conditions triggering adoption	Resource scarcity influences investment behavior and profitability	Existing studies often examine single-resource constraints	Multi-resource economic resilience frameworks	Improved strategic planning and investment decisions	[35,44,85,91]
PA in developing economies	Research dominated by North American and European case studies	Significant knowledge gaps regarding institutional and economic barriers in low-income regions	Limits global applicability of findings	Geographic bias in available evidence	Comparative international studies and region-specific economic assessments	Greater global relevance and adoption potential	[20,26,29]
Integrated PA Platforms	Emerging convergence of AI, IoT, remote sensing, robotics, and analytics	Lack of whole-farm economic evaluation frameworks	Potential synergies remain poorly quantified	Technologies often studied independently	Systems-level economic assessment of integrated digital farming ecosystems	Optimization of resource use and profitability	[8,9,64]
Sustainability valuation and circular economy integration	Environmental benefits increasingly documented	Economic valuation of ecosystem services remains incomplete	Sustainability benefits often excluded from profitability assessments	Lack of standardized valuation methodologies	Integration of ecosystem service valuation into farm-level economic models	Improved sustainability accounting and policy support	[21,22,71]

12.2. AI-Driven Farm Management

The next generation of AI-driven farm management platforms will move beyond current decision support systems, which require human interpretation and action. These new platforms will become autonomous, closed-loop systems that can sense, analyze, decide, and act without human involvement in the management process (see Table 6). By adapting foundation model architectures for agricultural data and integrating various inputs such as satellite imagery, sensor data, weather forecasts, market signals, and agronomic knowledge these systems are beginning to achieve agronomist-level performance in complex crop management tasks [64]. The economic advantage of AI farm management isn't just about optimizing individual decisions; it's about coordinating decisions consistently throughout the entire growing season. This avoids the suboptimal, sequential decision-making often seen in human management when cognitive load is high. Early commercial applications in precision viticulture and controlled environment agriculture show increased net revenue compared to skilled human management, mainly due to more consistent quality and efficient resource use.

However, the shift to AI-driven management brings up important questions about decision authority and accountability. When algorithmic recommendations conflict with a farmer's intuition, whose judgment should take precedence? Research on human-AI interaction in agriculture suggests that over-reliance on algorithms can diminish a farmer's decision-making skills and situational awareness [47,48]. Conversely, under-reliance, where farmers disregard valid algorithmic recommendations, negates potential economic benefits. This human-AI coordination challenge is an often-overlooked economic friction that impacts actual ROI.

Furthermore, the data requirements for robust AI farm management are significant and frequently underestimated. Training effective crop management models demands thousands of field-season observations covering diverse weather conditions, soil types, and management practices. The scarcity of such high-quality training data in most production systems limits model generalizability and creates a "cold start" problem for farms adopting AI platforms. This means initial recommendations may be unreliable until sufficient local data accumulate over several seasons [10]. This delay in model performance reduces the NPV of AI investments, especially for early adopters who incur data generation costs without immediately realizing full benefits.

12.3. Digital Twins, Predictive Analytics, and Intelligent Risk Management

Digital twin technology represents one of the most significant recent advances in PA, extending conventional digital decision-support systems toward continuously updated virtual representations of agricultural production systems. Digital twins integrate real-time information from IoT sensors, remote sensing, UAVs, weather stations, farm machinery, and historical production records to create dynamic simulation models capable of representing crop growth, soil processes, irrigation scheduling, nutrient dynamics, pest development, machinery operation, and whole-farm management under changing environmental conditions [92,93]. Unlike conventional decision-support systems that primarily provide descriptive or reactive recommendations, digital twins enable predictive, scenario-based decision-making by continuously assimilating real-time data and simulating alternative management strategies before field implementation. This capability allows producers to evaluate the economic consequences of multiple production scenarios while simultaneously optimizing productivity, resource-use efficiency, environmental performance, and financial risk under uncertain climatic and market conditions [93,94].

The economic value of digital twins arises from reducing trial-and-error experimentation, improving operational planning, optimizing resource allocation, and supporting

strategic investment decisions. Recent studies demonstrate that integrating digital twins with AI-driven predictive analytics substantially improves irrigation scheduling, fertilizer optimization, machinery utilization, and yield forecasting while reducing unnecessary operational expenditures and management uncertainty [92,93]. These benefits become increasingly important under conditions of climate variability, volatile input markets, and tightening environmental regulations, where accurate prediction of production outcomes directly influences farm profitability and long-term resilience.

An emerging area of research links digital twins with agricultural insurance and climate-risk management. Rather than functioning solely as production management tools, digital twins increasingly support weather-index insurance, parametric insurance products, and climate-risk assessment by generating continuously updated estimates of crop growth, expected yields, soil moisture, drought stress, flood exposure, and production losses [96,97]. The integration of satellite observations, IoT sensor networks, and predictive crop models reduces information asymmetry between farmers and insurers, improves actuarial accuracy, facilitates rapid damage assessment, and lowers transaction costs associated with traditional field inspections. Consequently, digital twins provide a common analytical platform through which producers, insurers, financial institutions, and policymakers can evaluate production risks and develop more effective climate adaptation strategies.

Digital twins also complement autonomous agricultural systems by providing the predictive intelligence required for real-time operational optimization. Autonomous tractors, robotic sprayers, UAVs, autonomous harvesters, and AI-enabled machinery increasingly depend upon digital twin environments to simulate field conditions, optimize navigation, schedule operations, and evaluate management alternatives before autonomous implementation [94]. The convergence of digital twins, artificial intelligence, robotics, and cloud computing therefore represents a transition from precision farming toward intelligent autonomous agricultural ecosystems capable of continuously adapting management decisions as environmental conditions change.

Nevertheless, important barriers continue to limit widespread adoption. Data interoperability, model validation, computational complexity, cybersecurity, cloud-computing infrastructure, and the continuous acquisition of high-quality field data remain major technical and economic challenges [92,93]. Furthermore, the economic viability of digital twins differs considerably among production systems. High-value perennial crops, greenhouse horticulture, vineyards, orchards, and intensive livestock enterprises generally obtain the greatest returns because management errors generate substantial financial losses that justify sophisticated predictive systems. Conversely, adoption within low-margin cereal production remains constrained by high development costs, limited digital infrastructure, and uncertain long-term financial returns, particularly among smallholder producers.

12.4. Innovation, Entrepreneurship, and the Human Capital Imperative

Realizing the full economic potential of PA hinges not only on technological advancement but also on developing human capital capable of deploying, managing, and innovating within digital agricultural systems. The knowledge, skills, and entrepreneurial capacities of the next generation of agricultural professionals will fundamentally shape PA adoption rates and the distribution of its economic benefits. Recent evidence from China highlights the importance of practical education in agricultural universities for fostering agricultural entrepreneurship. Hou et al. [90] found that students' participation in rural social practice, volunteer service, entrepreneurship competitions, and agricultural labor education increased their likelihood of pursuing agricultural entrepreneurship by 11.0% per additional type of practical education. Notably, professional value perception mediated 16.1% of this effect, the strongest pathway examined suggesting that experiential

learning shapes not only skills but also professional identity and career commitment to agriculture. Furthermore, entrepreneurship support policies moderated the relationship between perceived economic benefits and social status perceptions on entrepreneurial intentions, underscoring how institutional support complements educational outcomes in driving entrepreneurial action.

These findings have direct implications for PA innovation systems. They suggest that investments in digital infrastructure and technology R&D must be paired with investments in agricultural education that prioritizes experiential learning, entrepreneurial skill development, and positive professional identity formation [100]. Without such human capital development, even the most sophisticated PA technologies may remain underutilized, especially in developing economies where the agricultural workforce faces an aging demographic and digital literacy gaps.

Moreover, the entrepreneurial dimension of PA innovation extends beyond on-farm adoption to encompass the broader innovation ecosystem, including agtech startups, service providers, and digital platform developers. The human capital requirements of this ecosystem spanning data science, software engineering, robotics, and agronomy exceed the capacities of most current agricultural education systems. Bridging this skill gap will necessitate interdisciplinary training programs that integrate agricultural sciences with computer science, engineering, and business management, a transformation requiring strategic investment and policy coordination.

13. Conclusions

PA has evolved from a collection of site-specific management technologies into a comprehensive digital agricultural paradigm capable of improving productivity, resource-use efficiency, environmental sustainability, and farm profitability. The evidence synthesized in this review demonstrates that technologies including GPS, GISs, remote sensing, variable-rate technologies, AI, IoT sensor networks, and smart irrigation systems consistently improve the allocation of water, fertilizers, pesticides, energy, and labor while enhancing production efficiency under appropriate agronomic and institutional conditions. Collectively, these findings establish strong scientific consensus that PA represents an economically viable pathway for promoting sustainable agricultural intensification and improving the resilience of modern farming systems.

Unlike previous reviews that primarily emphasize technological development or adoption trends, this review advances the economics of precision agriculture by integrating technology adoption theory, resource economics, and production-efficiency models within a unified analytical framework that explains how digital technologies generate economic value across farm, regional, and policy scales. The review further provides a systematic comparison of major economic valuation approaches, including ROI, NPV, lifecycle costing, cost-benefit analysis, and ecosystem-service valuation, thereby highlighting the methodological challenges that currently limit comparability among economic studies and constrain evidence-based policy formulation.

The synthesis also reveals that important knowledge gaps remain despite the rapid expansion of the literature. Most empirical evidence continues to originate from North America, Europe, and Australia, where large commercial farming systems, advanced mechanization, and substantial public investment have shaped both technology adoption and economic evaluation. Consequently, the applicability of existing economic models to emerging agricultural economies, including China, India, Brazil, Sub-Saharan Africa, and Southeast Asia, remains insufficiently understood. Expanding rigorous empirical research across diverse agroecological, institutional, and socioeconomic contexts is therefore essential for improving the global relevance and external validity of PA economic theory.

Another important finding is that future economic evaluation should extend beyond conventional profitability indicators to incorporate environmental externalities, climate resilience, agricultural insurance, digital finance, ecosystem-service valuation, and long-term investment risk. Emerging technologies, including digital twins, autonomous agricultural systems, robotics, and AI-enabled predictive analytics, offer considerable opportunities to strengthen decision-making, optimize resource allocation, improve climate adaptation, and support intelligent risk management. However, robust long-term empirical evidence evaluating their economic performance under commercial farming conditions remains limited.

From a policy perspective, maximizing the benefits of PA requires more than technological innovation alone. Effective implementation depends on supportive institutional frameworks, investment in digital infrastructure, access to affordable financing, farmer training, extension services, interoperable data systems, and policies that recognize both private financial returns and broader societal benefits derived from improved environmental stewardship and resource conservation. Integrating agricultural insurance, climate adaptation strategies, and ecosystem-service incentives into digital agriculture policies will further enhance the resilience and sustainability of agricultural production systems.

Future advances in PA economics will depend on methodological harmonization, broader geographical representation, interdisciplinary collaboration, and stronger integration of engineering, agricultural economics, environmental science, data science, and public policy. Standardized economic evaluation frameworks capable of simultaneously assessing profitability, lifecycle costs, environmental externalities, climate resilience, and social welfare will substantially improve the comparability of future research and strengthen evidence-based decision-making. By providing an integrated conceptual framework, identifying methodological and geographical limitations, and outlining a comprehensive future research agenda, this review contributes to the development of a more robust and policy-relevant economic foundation for the sustainable digital transformation of global agriculture.

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References

1. WWAP (UNESCO World Water Assessment Programme). The United Nations World Water Development Report 2019: Leaving No One Behind. UNESCO. 2019. Available online: <https://unesdoc.unesco.org/ark:/48223/pf0000367306> (accessed on 3 May 2026).
2. World Bank. Fertilizers and Food Security. World Bank Commodities Price Forecast. 2022. Available online: <https://www.worldbank.org/en/research/commodity-markets> (accessed on 3 May 2026).
3. Mulla, D.J. Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosyst. Eng.* **2013**, *114*, 358–371. [CrossRef]
4. Balafoutis, A.; Beck, B.; Fountas, S.; Vangeyte, J.; Van der Wal, T.; Soto, I.; Gómez-Barbero, M.; Barnes, A.; Eory, V. Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. *Sustainability* **2017**, *9*, 1339. [CrossRef]

5. Mansoor, S.; Iqbal, S.; Popescu, S.M.; Kim, S.L.; Chung, Y.S.; Baek, J.-H. Integration of smart sensors and IOT in precision agriculture: Trends, challenges and future perspectives. *Front. Plant Sci.* **2025**, *16*, 1587869. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Raj, M.; Prahadeeswaran, M. Revolutionizing agriculture: A review of smart farming technologies for a sustainable future. *Discov. Appl. Sci.* **2025**, *7*, 937. [\[CrossRef\]](#)
7. Ruder, S.L.; Faxon, H.O.; Orzel, E.C.; Devkota, R.; Bronson, K. Reviewing the evidence on precision agriculture and environmental sustainability. *npj Sustain. Agric.* **2026**, *4*, 9. [\[CrossRef\]](#)
8. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.J. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [\[CrossRef\]](#)
9. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [\[CrossRef\]](#)
10. Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artif. Intell. Agric.* **2020**, *4*, 58–73. [\[CrossRef\]](#)
11. Miller, T.; Mikiciuk, G.; Durlik, I.; Mikiciuk, M.; Łobodzińska, A.; Śnieg, M. The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. *Sensors* **2025**, *25*, 3583. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Tilman, D.; Balzer, C.; Hill, J.; Befort, B.L. Global food demand and the sustainable intensification of agriculture. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 20260–20264. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Finger, R.; Swinton, S.M.; El Benni, N.; Walter, A. Precision farming at the nexus of agricultural production and the environment. *Annu. Rev. Resour. Econ.* **2019**, *11*, 313–335. [\[CrossRef\]](#)
14. Lakhiar, I.A.; Yan, H.; Zhang, C.; Wang, G.; He, B.; Hao, B.; Han, Y.; Wang, B.; Bao, R.; Syed, T.N.; et al. A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints. *Agriculture* **2024**, *14*, 1141. [\[CrossRef\]](#)
15. Smith, P.; Martino, D.; Cai, Z.; Gwary, D.; Janzen, H.; Kumar, P.; McCarl, B.; Ogle, S.; O'Mara, F.; Rice, C.; et al. Agriculture. In *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A., Eds.; Cambridge University Press: Cambridge, UK, 2007. Available online: <https://www.ipcc.ch/site/assets/uploads/2018/02/ar4-wg3-chapter8-1.pdf> (accessed on 4 May 2026).
16. Ritchie, H.; Rosado, P.; Roser, M. “Environmental Impacts of Food Production”. OurWorldinData.org. 2022. Available online: <https://ourworldindata.org/environmental-impacts-of-food> (accessed on 4 May 2026).
17. Mgendi, G. Unlocking the potential of precision agriculture for sustainable farming. *Discov. Agric.* **2024**, *2*, 87. [\[CrossRef\]](#)
18. Jwaideh, M.A.A.; Dalin, C. The multi-dimensional environmental impact of global crop commodities. *Nat. Sustain.* **2025**, *8*, 396–410. [\[CrossRef\]](#)
19. Padhiary, M.; Kumar, A.; Sethi, L.N. Emerging technologies for smart and sustainable precision agriculture. *Discov. Robot.* **2025**, *1*, 6. [\[CrossRef\]](#)
20. Lowenberg-DeBoer, J.; Erickson, B. Setting the record straight on precision agriculture adoption. *Agron. J.* **2019**, *111*, 1552–1569. [\[CrossRef\]](#)
21. Snyder, C.S.; Davidson, E.A.; Smith, P.; Venterea, R.T. Agriculture: Sustainable crop and animal production to meet human needs and eliminate hunger. In *Geotherapy: Innovative Methods of Soil Fertility Restoration, Carbon Sequestration, and Reversing CO₂ Increase*; Goreau, T.J., Larson, R.W., Campe, J., Eds.; CRC Press: Boca Raton, FL, USA, 2014; pp. 55–96. [\[CrossRef\]](#)
22. Gallai, N.; Salles, J.M.; Settele, J.; Vaissière, B.E. Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. *Ecol. Econ.* **2009**, *68*, 810–821. [\[CrossRef\]](#)
23. Snyder, H. Literature review as a research methodology: An overview and guidelines. *J. Bus. Res.* **2019**, *104*, 333–339. [\[CrossRef\]](#)
24. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *PLoS Med.* **2021**, *18*, e1003583. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Rogers, E.M.; Singhal, A.; Quinlan, M.M. Diffusion of innovations. In *An Integrated Approach to Communication Theory and Research*; Routledge: London, UK, 2014; pp. 432–448.
26. Ramadan, E.; Abdalla, S.; Al Ahbabi, A.; Gibreel, T.; Al Hosani, N. Towards sustainable urban agriculture in the arid GCC states: Drivers of technology adoption among small-scale farmers. *City Environ. Interact.* **2025**, *28*, 100222. [\[CrossRef\]](#)
27. Larvoe, N.; Che Mustapa, M.A.; de Herralde, F.; Kallas, Z. Predicting EU orchard farmers’ adoption intentions for pesticide-reducing innovations using an extended theory of planned behavior. *Crop Prot.* **2026**, *200*, 107460. [\[CrossRef\]](#)
28. Michels, M.; Bonke, V.; Musshoff, O. Understanding potato farmers’ precision irrigation technology adoption: Do economic, social, and personal factors matter? *Agric. Water Manag.* **2020**, *229*, 105954. [\[CrossRef\]](#)
29. Tey, Y.S.; Brindal, M. Factors influencing the adoption of precision agricultural technologies: A review for policy implications. *Precis. Agric.* **2012**, *13*, 713–730. [\[CrossRef\]](#)
30. Genius, M.; Koundouri, P.; Nauges, C.; Tzouvelekas, V. Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *Am. J. Agric. Econ.* **2014**, *96*, 328–344. [\[CrossRef\]](#)

31. Dessart, F.J.; Barreiro-Hurlé, J.; van Bavel, R. Behavioural factors affecting the adoption of sustainable farming practices: A policy-oriented review. *Eur. Rev. Agric. Econ.* **2019**, *46*, 417–471. [\[CrossRef\]](#)
32. Teece, D.J. A capability theory of the firm: An economics and (Strategic) management perspective. *N. Z. Econ. Pap.* **2019**, *53*, 1–43. [\[CrossRef\]](#)
33. Anselin, L.; Bongiovanni, R.; Lowenberg-DeBoer, J. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. *Am. J. Agric. Econ.* **2004**, *86*, 675–687. [\[CrossRef\]](#)
34. Moon, W.; Chang, J.B.; Asirvatham, J. Identifying Factors Driving US Citizens' Preferences about Multifunctional Agriculture. In Proceedings of the Southern Agricultural Economics Association's 2016 Annual Meeting, San Antonio, TX, USA, 6–9 February 2016. [\[CrossRef\]](#)
35. Schimmelpfennig, D. Farm Profits and Adoption of Precision Agriculture. Economic Research Report, USDA Economic Research Service, No. 217. 2016. Available online: <https://www.ers.usda.gov/media/8791/err-217.pdf?v=90122> (accessed on 4 May 2026).
36. Trevisan, R.G.; Bullock, D.S.; Martin, N.F. Spatial variability of crop responses to agronomic inputs in on-farm precision experimentation. *Precis. Agric.* **2021**, *22*, 342–363. [\[CrossRef\]](#)
37. Woodward, R.T. Double-dipping in environmental markets. *J. Environ. Econ. Manag.* **2011**, *61*, 153–169. [\[CrossRef\]](#)
38. Hunt, E.R.; Daughtry, C.S.T. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *Int. J. Remote Sens.* **2018**, *39*, 5345–5376. [\[CrossRef\]](#)
39. Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. *Comput. Electron. Agric.* **2018**, *147*, 70–90. [\[CrossRef\]](#)
40. Radoglou-Grammatikis, P.; Sarigiannidis, P.; Lagkas, T.; Moscholios, I. A compilation of UAV applications for precision agriculture. *Comput. Netw.* **2020**, *172*, 107148. [\[CrossRef\]](#)
41. Mogili, U.R.; Deepak, B.B.V.L. Review on application of drone systems in precision agriculture. *Procedia Comput. Sci.* **2018**, *133*, 502–509. [\[CrossRef\]](#)
42. Pena, J.M.; Torres-Sánchez, J.; de Castro, A.I.; Kelly, M.; López-Granados, F. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle images. *PLoS ONE* **2013**, *10*, e77151.
43. Pardossi, A.; Incrocci, L. Traditional and new approaches to irrigation scheduling in vegetable crops. *HortTechnology* **2011**, *21*, 309–313. [\[CrossRef\]](#)
44. Scheierling, S.M.; Young, R.A.; Cardon, G.E. *Water Conservation in Irrigated Agriculture: Trends and Challenges in the Face of Emerging Demands*; The World Bank Policy Research Working Paper; The World Bank: Washington, DC, USA, 2018; p. 7064. [\[CrossRef\]](#)
45. Bajaj, A.; Singh, S.P.; Nayak, D. Are farmers willing to pay for groundwater irrigation? Insights from informal groundwater markets in Western Uttar Pradesh, India. *Agric. Water Manag.* **2023**, *288*, 108458. [\[CrossRef\]](#)
46. Mitra, A.; Balasubramanya, S.; Brouwer, R. Can Cash Incentives Modify Groundwater Pumping Behaviors? Evidence from an Experiment in Punjab. *Am. J. Agric. Econ.* **2023**, *105*, 861–887. [\[CrossRef\]](#)
47. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Cravero, A.; Sepúlveda, S.; Gutiérrez, F.; Muñoz, L. From precision agriculture to intelligent agricultural ecosystems: A systematic review of machine learning and big data applications. *Agronomy* **2026**, *16*, 516. [\[CrossRef\]](#)
49. Crane-Droesch, A. Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. *Environ. Res. Lett.* **2018**, *13*, 114003. [\[CrossRef\]](#)
50. Wiseman, L.; Sanderson, J.; Zhang, A.; Jakku, E. Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. *NJAS-Wageningen. J. Life Sci.* **2022**, *90–91*, 100301. [\[CrossRef\]](#)
51. Gongal, A.; Amatya, S.; Karkee, M.; Zhang, Q.; Lewis, K. Sensors and systems for fruit detection and localization: A review. *Comput. Electron. Agric.* **2015**, *116*, 8–19. [\[CrossRef\]](#)
52. Elavarasan, D.; Vincent, P.M.D.R.; Srinivasan, K.; Chang, C.Y. Forecasting yield by integrating agrarian factors and machine learning models: A survey. *Comput. Electron. Agric.* **2018**, *155*, 257–282. [\[CrossRef\]](#)
53. Griffin, T.W.; Lambert, D.M.; Lowenberg-DeBoer, J. Economics of lightbar and autosteer adoption by corn-belt maize producers. *Precis. Agric.* **2018**, *19*, 653–679.
54. Bongiovanni, R.; Lowenberg-DeBoer, J. Precision agriculture and sustainability. *Precis. Agric.* **2004**, *5*, 359–387. [\[CrossRef\]](#)
55. Hedley, C. The role of precision agriculture for improved nutrient management on farms. *J. Sci. Food Agric.* **2015**, *95*, 12–19. [\[CrossRef\]](#) [\[PubMed\]](#)
56. Corti, M.; Gallina, P.M.; Cavalli, D.; Cabassi, G. Hyperspectral imaging of spinach canopy under combined water and nitrogen stress to estimate biomass, water, and nitrogen content. *Biosyst. Eng.* **2017**, *158*, 38–50. [\[CrossRef\]](#)
57. Fereres, E.; Soriano, M.A. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* **2007**, *58*, 147–159. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Carrijo, D.R.; Lundy, M.E.; Linquist, B.A. Rice yields and water use under alternate wetting and drying irrigation: A meta-analysis. *Field Crops Res.* **2017**, *203*, 173–180. [\[CrossRef\]](#)

59. Belkher, S.; Latrech, B.; Bekri, W.; Markwordt, F.; Rahim, M.A.; Dupont, C.; Ben Abdallah, M.A.; Daghari, H.; Rezig, M. Deficit Irrigation and an IoT-Based System for Improving Yield and Water Use Efficiency of Winter Wheat Grown Under Semi-Arid Conditions. *Agronomy* **2025**, *15*, 157. [\[CrossRef\]](#)
60. Jones, J.W.; Antle, J.M.; Basso, B.; Boote, K.J.; Conant, R.T.; Foster, I.; Godfray, H.C.J.; Herrero, M.; Howitt, R.E.; Janssen, S.; et al. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agric. Syst.* **2017**, *155*, 269–288. [\[CrossRef\]](#) [\[PubMed\]](#)
61. Becker, M.; Angulo, C. The evolution of lowland rice-based production systems in Asia: Historic trends, determinants of change, future perspective. In *Advances in Agronomy*; Academic Press: Cambridge, MA, USA, 2019; Volume 157, pp. 293–327. [\[CrossRef\]](#)
62. Rotz, S.; Gravelly, E.; Mosby, I.; Duncan, E.; Finnis, E.; Horgan, M.; Lewis, J.; Martin, R.; Neufeld, H.T.; Nixon, A.; et al. Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *J. Rural Stud.* **2019**, *68*, 112–122. [\[CrossRef\]](#)
63. Cuaton, G.P.; Delina, L.L. Two decades of rice research in Indonesia and the Philippines: A systematic review and research agenda for the social sciences. *Humanit. Soc. Sci. Commun.* **2022**, *9*, 372. [\[CrossRef\]](#) [\[PubMed\]](#)
64. Xu, L.; Yu, A.; Li, X.; He, M. Agricultural knowledge graph construction and application: A systematic review. *Comput. Electron. Agric.* **2021**, *184*, 106099. [\[CrossRef\]](#)
65. Fang, Y.; Zheng, J.; Shen, X.; Zhang, C.; Siddique, K.H.M. Optimization of watersaving irrigation decision using dynamic spatiotemporal graph neural networks. *Sci. Rep.* **2026**. [\[CrossRef\]](#) [\[PubMed\]](#)
66. Temasek. The Business Case for Carbon Pricing [Discussion Paper]. Ecosperity. 2019. Available online: https://www.ecosperity.sg/content/dam/ecosperity-aem/en/reports/Business-Case-for-Carbon-Pricing_May2019.pdf.coredownload.pdf (accessed on 3 May 2026).
67. Rossi, V.; Caffi, T.; Salinari, F. Helping farmers face the increasing complexity of decision-making for crop protection. *Phytopathol. Mediterr.* **2012**, *51*, 457–479.
68. Savary, S.; Willocquet, L.; Pethybridge, S.J.; Esker, P.; McRoberts, N.; Nelson, A. The global burden of pathogens and pests on major food crops. *Nat. Ecol. Evol.* **2019**, *3*, 430–439. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Kondo, E.; Asem, F.E.; Osei-Asare, Y.; Mensah-Bonsu, A.; Onumah, E.E.; Ofori, S.; Osae, M. Economic and behavioural effects of farmers' adoption of integrated pest management practices in low- and middle-income countries: A systematic review and meta-analysis. *NJAS Impact Agric. Life Sci.* **2025**, *97*, 2534478. [\[CrossRef\]](#)
70. Lysholm, S.; Chatters, G.L.; Di Bari, C.; Hughes, E.C.; Huntington, B.; Rushton, J.; Thomas, L. A framework for quantifying the multisectoral burden of animal disease to support decision making. *Front. Vet. Sci.* **2025**, *12*, 1476505. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Arangurí, M.; Mera, H.; Noblecilla, W.; Lucini, C. Digital Literacy and Technology Adoption in Agriculture: A Systematic Review of Factors and Strategies. *AgriEngineering* **2025**, *7*, 296. [\[CrossRef\]](#)
72. Adams, A.; Jumpah, E.T. Agricultural technologies adoption and smallholder farmers' welfare: Evidence from Northern Ghana. *Cogent Econ. Financ.* **2021**, *9*. [\[CrossRef\]](#)
73. Cherubin, M.R.; Damian, J.M.; Tavares, T.R.; Trevisan, R.G.; Colaço, A.F.; Eitelwein, M.T.; Martello, M.; Inamasu, R.Y.; Pias, O.H.D.C.; Molin, J.P. Precision Agriculture in Brazil: The Trajectory of 25 Years of Scientific Research. *Agriculture* **2022**, *12*, 1882. [\[CrossRef\]](#)
74. Laurenti, N.; Pezzopane, J.R.M.; Guimarães, E.d.S.; Bernardi, A.C.d.C.; Rodrigues, J. Spatial variability of soil and vegetation properties in integrated production systems. *Rev. Bras. Eng. Agríc. Ambient.* **2024**, *28*, e280481. [\[CrossRef\]](#)
75. Bolfe, É.L.; Jorge, L.A.D.C.; Sanches, I.D.; Luchiari Júnior, A.; da Costa, C.C.; Victoria, D.D.C.; Inamasu, R.Y.; Grego, C.R.; Ferreira, V.R.; Ramirez, A.R. Precision and digital agriculture: Adoption of technologies and perception of Brazilian farmers. *Agriculture* **2020**, *10*, 653. [\[CrossRef\]](#)
76. Lopes, M.A.; Martha, G.B., Jr. Pathways to sustainability in Brazilian agriculture: Technological drivers, governance, and policy linkages. *Curr. Opin. Environ. Sustain.* **2025**, *77*, 101583. [\[CrossRef\]](#)
77. Solgi, S.; Ahmadi, S.H.; Sepaskhah, A.R.; Edalat, M. Wheat yield modeling under water-saving irrigation and climatic scenarios in transition from surface to sprinkler irrigation systems. *J. Hydrol.* **2022**, *612*, 128053. [\[CrossRef\]](#)
78. Ward, F.A.; Pulido-Velázquez, M. Water conservation in irrigation can increase water use. *Proc. Natl. Acad. Sci. USA* **2008**, *105*, 18215–18220. [\[CrossRef\]](#) [\[PubMed\]](#)
79. Tozer, P. Uncertainty and investment in precision agriculture—Is it worth the money? *Agric. Syst.* **2009**, *100*, 80–87. [\[CrossRef\]](#)
80. Wang, H.; Bai, Q.; Ma, L.; Wan, Y.; Dang, X.; Li, J.; Wang, R.; Wang, T. Optimizing drip irrigation and nitrogen fertilization to increase net ecosystem carbon budget and economic benefits with reduced carbon footprint in maize agroecosystems. *Soil Tillage Res.* **2026**, *259*, 107040. [\[CrossRef\]](#)
81. Kovács, E.; Szöllösi, L. Economic Aspects of Precision Crop Production: A Systematic Literature Review. *Agriculture* **2026**, *16*, 820. [\[CrossRef\]](#)
82. Lan, J.; Ban, Q. The farm-level economic and environmental benefits of precision agriculture technology adoption: A meta-analysis of global evidence. *Sustainability* **2025**, *17*, 11223. [\[CrossRef\]](#)

83. Bahmutsky, S.; Grassauer, F.; Arulnathan, V.; Pelletier, N. A review of life cycle impacts and costs of precision agriculture for cultivation of field crops. *Sustain. Prod. Consum.* **2024**, *52*, 347–362. [\[CrossRef\]](#)
84. USDA Economic Research Service. Adoption of Genetically Engineered Crops in the United States [Data Product]. 2025. Available online: <https://www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-united-states> (accessed on 3 May 2026).
85. Rutledge, Z. Farm Labor Shortages, Their Implications, and Policy Options to Help Promote the Domestic Fresh Produce Industry. International Fresh Produce Association. 2024. Available online: <https://www.freshproduce.com/siteassets/files/advocacy/farm-labor-shortages.pdf> (accessed on 6 May 2026).
86. USDA Economic Research Service. Farm Labor. 2025. Available online: <https://www.ers.usda.gov/topics/farm-economy/farm-labor> (accessed on 3 May 2026).
87. Mohanty, S.; Bhandari, H.; Mohapatra, B.K.; Baruah, S. The ongoing transformation of rice farming in Asia. *Rice Today* **2015**, *14*. Available online: <https://ricetoday.irri.org/the-ongoing-transformation-of-rice-farming-in-asia/> (accessed on 4 May 2026).
88. Rötter, R.P.; Appiah, M.; Fichtler, E.; Kersebaum, K.C.; Trnka, M.; Hoffmann, M.P. Linking modelling and experimentation to better capture crop impacts of agroclimatic extremes—A review. *Field Crops Res.* **2018**, *221*, 142–156. [\[CrossRef\]](#)
89. Garnett, T.; Appleby, M.C.; Balmford, A.; Bateman, I.J.; Benton, T.G.; Bloomer, P.; Burlingame, B.; Dawkins, M.; Dolan, L.; Fraser, D.; et al. Sustainable intensification in agriculture: Premises and policies. *Science* **2013**, *341*, 33–34. [\[CrossRef\]](#) [\[PubMed\]](#)
90. Hou, W.; Song, H.; Yang, Q.; Luo, L.; Ding, J.; Cao, Y.; Hu, R.; Li, G.; Ma, H. Promoting agricultural entrepreneurship through practical education in Chinese universities. *PLoS ONE* **2026**, *21*, e0340670. [\[CrossRef\]](#) [\[PubMed\]](#)
91. Pierpaoli, E.; Carli, G.; Pignone, E.; Rinaldi, M. Drivers of precision agriculture technologies adoption: A literature review. *Procedia Technol.* **2013**, *8*, 61–69. [\[CrossRef\]](#)
92. Verdouw, C.; Tekinerdogan, B.; Beulens, A.; Wolfert, S. Digital twins in smart farming. *Agric. Syst.* **2021**, *189*, 103046. [\[CrossRef\]](#)
93. Srivastav, A.K.; Das, P. Digital Twins in Agriculture. In *Biotechnology and IoT in Agriculture and Food Production*; Apress: Berkeley, CA, USA, 2025. [\[CrossRef\]](#)
94. Awais, M.; Wang, X.; Hussain, S.; Aziz, F.; Mahmood, M.Q. Advancing Precision Agriculture Through Digital Twins and Smart Farming Technologies: A Review. *AgriEngineering* **2025**, *7*, 137. [\[CrossRef\]](#)
95. Zhang, J.; Huang, Y.; Pu, R.; Gonzalez-Moreno, P.; Yuan, L.; Wu, K.; Huang, W. Monitoring plant diseases and pests through remote sensing technology: A review. *Comput. Electron. Agric.* **2019**, *165*, 104943. [\[CrossRef\]](#)
96. Carter, M.; de Janvry, A.; Sadoulet, E.; Sarris, A. Index insurance for developing country agriculture: A reassessment. *Annu. Rev. Resour. Econ.* **2017**, *9*, 421–438. [\[CrossRef\]](#)
97. OECD. Future-Proofing Real Estate Investment: Place-Based Risks. In *OECD Urban Studies*; OECD Publishing: Paris, France, 2025. [\[CrossRef\]](#)
98. Yin, M.; Reja, V.K.; Wei, R.; Brilakis, I.; Sheil, B.; Perrotta, F.; Marie D’Avigneau, A.; Lu, L. Exploring the value of digital twins for information management in highway asset maintenance. *Dev. Built Environ.* **2025**, *21*, 100614. [\[CrossRef\]](#)
99. Brander, L.M.; de Groot, R.; Schägner, J.P.; Guisado-Goñi, V.; van ’t Hoff, V.; Solomonides, S.; McVittie, A.; Eppink, F.; Sposato, M.; Do, L.; et al. Economic values for ecosystem services: A global synthesis and way forward. *Ecosyst. Serv.* **2024**, *66*, 101606. [\[CrossRef\]](#)
100. Wu, R.; Feng, D.; Zhao, J.; Cui, X. Resource endowments and entrepreneurial environment matter: How digital infrastructure shapes agricultural technology innovation in China. *Front. Sustain. Food Syst.* **2026**, *10*, 1762008. [\[CrossRef\]](#)

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