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THE ECONOMIC IMPLICATIONS OF PRECISION AGRICULTURE ADOPTION ON FARM PROFITABILITY AND RESOURCE USE EFFICIENCY

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Abstract

The rapid development of precision agriculture (PA) has transformed farming practices by integrating digital technologies such as GPS-guided machinery, variable rate application systems, drones, and sensor-based monitoring

Keywords: Precision agriculture; Farm profitability; Resource-use efficiency; Technology adoption; Variable-rate application; Machine learning in agriculture; Input optimization; Sustainable intensification

INTRODUCTION

Agriculture has experienced radical change since the beginning of the last century, fueled by technological revolution, policy transformations, and shifting consumer tastes. In recent decades, the development of precision agriculture (PA) has been regarded as a fundamental change in agricultural practices, with the potential to boost efficiency, decrease costs, and increase sustainability. Precision agriculture refers to the convergence of technologies like Global Positioning Systems (GPS), Geographic Information Systems (GIS), remote sensing, drones, artificial intelligence (AI), and sensor-based monitoring systems to maximize field-level management of livestock and crops. These technologies allow farmers to apply inputs like water, fertilizers, and pesticides in accurate quantity and place, thus avoiding wastage and improving

tools. This study conducts a systematic review of literature published between 2000 and 2025 to evaluate the economic implications of PA adoption in the United States, with a focus on farm profitability and resource use efficiency. Using the PRISMA framework, 47 relevant studies were identified from peer-reviewed journals, USDA reports, and grey literature. Findings indicate that PA adoption generally improves profitability through cost reductions, yield optimization, and long-term efficiency gains. Profitability increases ranged from 5% to 25%, with large-scale farms realizing the greatest returns due to economies of scale, while smaller farms faced slower returns on investment. Evidence also demonstrates substantial improvements in resource use efficiency, including fertilizer reductions of 10–20%, water savings of 15–30%, and pesticide reductions of up to 15%. However, adoption barriers such as high capital costs, knowledge gaps, and limited access to financing restrict wider implementation, particularly among small and medium-sized farms. The review concludes that while precision agriculture enhances economic and environmental outcomes, targeted policy support is essential to ensure equitable access and maximize national agricultural sustainability goals.

Overall efficiency in resource usage (Gebbers & Adamchuk, 2010).

The U.S. agriculture sector is being increasingly challenged with challenges like increasing input prices, labor scarcity, weather variability, and growing environmental issues (Schimmelpfennig, 2016). Traditional agriculture is based on homogenous application of inputs, leading to inefficiency, excessive use of resources, and adverse environmental spillovers like soil erosion, water pollution, and greenhouse gas emissions. Precision agriculture offers the promise of solving this problem by merging farm management decisions with site-specific requirements, thus enabling farmers to maximize yield potential and reduce input costs and environmental effects Although promising, the economic effects of precision agriculture applications are controversial. On the other hand, advocates are claiming that adoption of precision technology can result in increased profitability in terms of increased yields, decreased input prices, and long-run efficiency returns (Robertson et al., 2012). Critics, on the other hand, refer to a few major impediments in the guise of large initial capital outlays, learning curves with technology, and small compared to large farm range of adoption (Daberkow & McBride, 2003). These barriers also bring into question whether or not the economic benefit is distributed evenly among U.S. farms of varying size and location.

Furthermore, the uptake of precision agriculture intersects with wider policy and sustainability objectives. Government schemes and incentives, as the case of the conservation programs in the U.S. Farm Bill, have increasingly promoted sustainable agriculture that reconciles farm profitability and sound environmental control (USDA, 2021). It is hence imperative to understand how precision agriculture responds to

profitability as well as to resource efficiency in a bid to inform policy institutions, investment choices, and extension services aimed at U.S. farmers.
This research attempts to analyze the economic impact of the implementation of precision agriculture in the US, and most importantly, its influence on farm profitability and resource-use efficiency. Using the available farm-level data and adoption behavior, the research attempts to find out if precision agriculture has quantifiable financial gains, improved input-use efficiency, and environmentally friendly agriculture production. In doing so, the study will advance the current debate about the future of US agriculture and what role digital technologies are going to have in determining it, and illuminate challenges and opportunities for additional use.

Research Objectives

- To assess the effect of embracing precision agriculture on farm profitability as gauged by changes in crop output, production costs, and net returns.
- To determine the extent to which precision agriculture technology increases the efficiency in resource use, especially in the use of inputs like water, fertilizers, and pesticides.
- To contrast the economic performance of farms employing precision agriculture with those employing conventional farming.
- To measure the impact of farm size, capital investment, and technology type on the economic efficiency of precision agriculture adoption.
- To determine the enablers and disablers on the adoption decisions of precision agriculture technology by farmers, with economic factors.
- To synthesize evidence from existing literature and case studies to offer policy and managerial guidelines towards making precision agriculture viable and sustainable. Review of related literature

Economic Implications of Precision Agriculture

The economic implication of precision agriculture (PA) has been sufficiently documented. Griffin et al. (2018) indicated that profitability returns due to PA technologies are extremely diverse and contingent upon size of farm, level of technology, and management intensity. Long-term empirical analyses by Yost et al. (2019) revealed that PA systems continued to remain profitable in the majority of sectors, thus implying that adoption can generate steady financial returns when combined with conservation practices. Pedersen (2023) also noted that adopters of sophisticated PA technology packages possess higher technical efficiency than non-adopters, signifying the importance of integrated approaches to economic benefits.

Resource-Use Efficiency and Environmental Sustainability

A body of literatures have documented the sustainability impacts of PA. Onyango et al. (2021) have undertaken a systematic review and established that plant and soil sensors, GIS, and simulation models significantly enhanced nutrient and water management in smallholder systems. Liakos et al. (2018) have also established that sensor-based irrigation is able to save up to 25% of water without affecting yield performance. Later, Popović et al. (2024) established that PA practice adoption saves about 15% in fertilizer and 20% in crop protection, demonstrating environmental as well as economic savings.

Barriers to Adoption

Adoption continues to be hindered by various barriers despite this. Mitchell et al. (2021) found technology cost and absence of demonstrated value to be major disincentives to adoption in Canadian agriculture production systems. Hundal et al. (2023) built upon these results through a questionnaire of Internet of Things (IoT) enabled PA practice and sketching issues with power demands, wireless communication, and scalability. These outcomes indicate that technical as well as financial factors influence the adoption path of PA for regions and manufacturing systems.

In spite of evidence verifying that PA adoption promotes profitability and resource use efficiency, evidence is patchy by farm size, technology, and geography. Multi-season long-term studies with comparison of packages of technologies are few. This limitation underscores the importance of systematic synthesis to improve understanding of economic and environmental consequences of PA adoption in mixed farming systems.

Farm Profit and Resource Use Efficiency

Precision and digital agriculture have been examined for their ability to transform farm profitability as well as the manner in which inputs (water, crop protection, fertilizer) are managed. Conceptual and initial empirical research laid the groundwork by demonstrating how site-specific management and data-driven decision-making can enhance resource targeting and guide farm management decisions (Bongiovanni & Lowenberg-DeBoer, 2004). That study highlighted that accuracy approaches can balance production objectives and low-input waste, but cautioned against economic and institutional limitations that influence adoption.

Wider vision of PA in food systems placed PA in the context of global world food security and the environment and reasoned that spatially-explicit monitoring and management can enable more sustainable intensification if supplemented by proper decision support and institutional arrangements (Gebbers & Adamchuk, 2010). This research stream highlighted technology potential with emphasis on aligning with agronomic, economic, and social systems.

Empirical tests of profitability have yielded mixed but useful findings

Some farm-level and whole-farm studies indicate positive net returns to adoption of technologies such as variable-rate application (VRA), auto-steer, and yield monitoring where management capacity and scale permit; however, other strong ex-post studies find that aggregate whole-farm profit increases are small and setting-dependent, implying that operating efficiency is not always associated with higher net farm receipts under all circumstances (Schimmelpfennig, 2016; Dhoubhadel, 2021). Collectively, these studies suggest that there is variation by crop, region, and farm size, and that sampled

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profitability is extremely sensitive to horizon, cost allocation, and whether or not learning-curve effects are included.

From the point of view of resource-use efficiency, a number of syntheses and empirical studies report decreases in fertilizer, water, and pesticide use where precision technology is applied effectively.

Machine-assisted sensing and data analysis reviews summarize that sensor-based nutrient management and precision irrigation can save nutrient and water inputs by a significant percentage without incurring yield losses, enhancing economic input efficiency and environmental performance (Liakos et al., 2018; recent precision irrigation reviews). Evidence is shown across various crop systems and climates but the magnitude of savings differs with technology maturity and site conditions. Adoption hurdles are persistently underscored in the literature as driving whom stands to gain economically and environmentally from PA.

High initial capital expenses, indefinite investment return, restricted financial access, information management and interoperability, technical assistance and training inadequacies are termed significant hindrances particularly for small and medium farms by research. Research on IoT and connectivity drivers identifies infrastructure constraints (broadband in rural areas, electricity) and data handling requirements as near-term constraints to optimal economic value of digital technology in agriculture.

Policy and institutional action is therefore widely advocated to increase pervasive, equitable uptake (Hundal et al., 2023; Mitchell et al., 2021). ScienceDirect +1 Lastly, more recent life-cycle and integrated analysis add nuance in thought by considering environmental trade-offs and overall system expense. These analyses demonstrate that, with efficient application and upkeep, PA can decrease input-based emissions and resource bases at the expense of none or even more yield; but they also raise issues about embedded costs (hardware, data subscription, maintenance) and the necessity for longer-term, multi-seasonal analyses in order to catch dynamic effects and depreciation in benefit flows.

This has given rise to demands for increased longitudinal and comparative research that thoroughly examines bundled technologies and heterogeneity across farm sizes and agroecological contexts.

Machine learning in Agriculture

Machine Learning in Agriculture Machine learning (ML) classic supervised and unsupervised, and deep learning (DL) techniques have emerged as an essential tool over the last few years to glean useful information from diverse agri-data (satellite and UAV imagery, proximal sensors, IoT streams, and past yield histories). Early and systematic reviews have established that ML facilitates having applications in crop, soil, water and animal management through improved accuracy of predictions and facilitating automation of previously human observation-dependent tasks. Early syntheses indicate that ML converts multi-source information into decision support in yield forecasting, disease and pest detection, weed mapping, phenotyping, and irrigation scheduling. Deep learning techniques (convolutional and recurrent neural networks) have most notably been impactful on image-based applications like disease diagnosis, fruit identification, and land cover and crop classification from remote sensing. The Kamilaris & Prenafeta-Boldú survey highlights that CNNs and similar architectures always perform better than classical approaches in imagery-based tasks, and noting training data restrictions in terms of requirements, environmental generalization, and requiring annotated datasets. The review advocates for transfer learning and data augmentation as suitable solutions for mitigating the problem of scarcity in the data for most agricultural issues. The most investigated ML application is crop yield prediction. Systematic reviews of yield prediction indicate that ensemble methods, random forests, gradient boosting, and neural networks (including CNNs and LSTM models) tend to be generally better than linear models when used in conjunction with remote sensing variables, weather time-series, and soil information. These reviews do mention the chronic issues of feature engineering, transferability across domains, and high out-of-sample validation — all of which impact the validity of operational yield forecasts. A couple of reviews provide an overview of ML across the entire range of agricultural activities and observe a definite shift away from traditional ML (SVM, RF, k-NN) to deep learning for unstructured data. Liakos et al.'s general overview illustrates how extensively ML techniques have been used to address cover crop management (yield, disease, weed detection), animal tracking (behaviour and welfare), water management, and soil analysis; their contribution shows the importance of integrating knowledge of the domain with the selection of the ML model and proper validation in order to get useful, farm-scale applicability. In addition to algorithmic ability, reviews later on address socio-technical and deployment issues. Benos et al. (2021) report recent synthesis of ML adoption processes, citing data availability, sensor networks (satellite, UAV, in-field), and institutional environments of scalability for ML solutions. Reproducibility, data format interoperability, and economics of data services (subscription schemes, cloud computing charges) are reported to be drivers of whether ML models scale up from research prototypes to farmer-faced tools. Reviews mentioning explicit agronomic challenges (e.g., yield prediction and nitrogen status estimation of yield) emphasize the sensor fusion blending remote sensing, proximal sensors and weather data — to improve estimation accuracy. Chlingaryan, Suk.karieh, & Whelan (2018) reviewed yield and estimation of nitrogen status and noted that the ML methods of multi-sensor fusion provide better estimates than single-source models but need to be adopted in terms of simplifying decision interfaces as well as in economic validation by farmers. Methodological reviews also highlight assessment standards: numerous authors emphasize stronger cross-validation, multi-season validation, and uncertainty metric reporting (RMSE, MAE, R^2) to enable equitable comparison among algorithms and express decision-maker risks. van Klompenburg et al.'s systematic review of crop-yield ML literature implies methodological improvement has been accompanied by inconsistent reporting and minimal multi-region testing that persist as impediments to increased adoption. Lastly, a number of the meta-reviews propose ethical, equity, and infrastructural issues. "Big data" and smart farming reviews pose rural connectivity deficits, data governance, and the concern that ML-based benefits will disproportionately accrue to more extensive and better-off farms unless policy and cooperative schemes make collective access to data and analytics more possible. These socio-technical criticisms contend that unlocking agriculture's ML potential will entail collective investment in data infrastructure, model evaluation standards, and business models that distribute the benefits more widely

Precision Agriculture

Precision agriculture is a spatially and temporally variant data-driven farm management system with spatial and temporal variability in fields included to maximize input allocation in order to maximize economic return and minimize environmental effects (Zhang et al., 2002).

Farm Profitability

Farm profitability is the net monetary surplus that is left after deducting all the costs of production, including capital and labor. It is a crucial measure of farm sustainability and capacity to invest in the long term (Ellis, 1993).

Resource Use Efficiency

Resource use efficiency refers to the degree to which farms can achieve maximum output from a given set of inputs or achieve minimum input utilization for a given level of output compared with a production frontier (Farrell, 1957).

Technology Adoption

Technology adoption refers to the multi-step process through which individuals or organizations move from knowledge of innovation to its adoption and use, motivated by perceived benefits and compatibility among other variables (Rogers, 2003).

Variable-Rate Technology (VRT)

Variable-rate technology is one of the primary precision agriculture tools used for site-specific delivery of inputs like fertilizers, seed, and pesticides to maximize efficiency through consideration of within-field heterogeneity (Pierce & Nowak, 1999).

Sustainable Intensification

Sustainable intensification refers to the process of increasing productivity on existing land cultivated while maintaining ecosystem services and natural capital in favor of longer-term sustainability (Pretty, 2018).

Methodology

This article utilizes a systematic literature review (SLR) in establishing the economic effect of adopting precision agriculture (PA) on farm profitability as well as the efficiency of resource use in the United States. Systematic review approach was utilized to promote transparency, replicability, and complete coverage of evidence. The process followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

Applicable literature was obtained through Web of Science, Scopus, EconLit, ScienceDirect, and USDA Economic Research Service databases from 2000 to 2025. The search strategy was performed on the basis of keywords like "precision agriculture," "digital farming," "farm profitability," "economic impact," "use of resources efficiency," and "United States." Grey literature such as reports by USDA and working papers were also included to minimize publication bias. Studies were considered if they (i) provided economic impact of PA adoption (profit, cost savings, or return on investment), (ii) measured use efficiency of resources (maximization of fertilizer, water, or pesticide), and (iii) addressed U.S. agriculture. Exclusion criteria removed non-economic studies that were technically or agronomically focused and not in the U.S. setting.

Three-stage screening title/abstract screening, full-text review, and eligibility check resulted in inclusion of 47 studies. Study details (author, year, farm size, type of crop/livestock), technologies assessed, methodology employed, and reported results were extracted. Thematic synthesis was applied to categorize findings into two dimensions: (1) economic implications (cost and profitability) and (2) efficiency in resource utilization (optimization of fertilizer, water, and pesticides). Where quantitative findings were similar, descriptive statistics were presented; otherwise, emergent trends and discrepancies were addressed through a narrative synthesis.

The systematic methodology presents a formal assessment of the literature where conclusions are drawn from adequate and varied sources with limitations recognized in terms of heterogeneity of methods and publication bias.

Result

Database search returned 246 records. Following screening and duplicates removal, 47 studies were found to meet the inclusion criteria. Figure 1 (PRISMA flow diagram) shows identification, screening, and eligibility process.

Characteristics of Included Studies

Table 1 summarizes the study characteristics of the included studies. The majority of studies (68%) were on row crops like corn, soybeans, and wheat. Specialty crop studies accounted for 21% of the studies, and livestock-focused studies accounted for 11%. Most commonly reviewed technologies were GPS-guided equipment, variable rate application (VRA), and yield monitors, with increasing interest in drones and sensor irrigation.

Table 1. Characteristics of included studies by production system

Production System	Percentage of Studies (%)
Row crops (corn, soybean, wheat)	**68**
Specialty crops (fruits, vegetables)	**21**
Livestock	**11**

Economic Implications

Literature results provide evidence that PA adoption tends to increase farm profitability, and this varies depending on farm size and technology type. In Table 2, large-scale farms made between 5% and 25% gains in profitability from VRA technologies and auto-steer technology. Medium-scale farms made modest gains (3–10%) from GPS-guided equipment and yield monitors. Small-scale farms made modest (1–5%) gains because of high up-front capital investments and low returns from adoption.

Table 2. Financial effects of embracing precision agriculture by farm size

Farm Size	Profitability Gain (%)	Key Technologies Driving Gains
Large-scale	**5–25**	**VRA, Auto-steer, Yield Monitors**
Medium-scale	**3–10**	**VRA, GPS-guided machinery**
Small-scale	**1–5**	**Low adoption due to high costs**

Resource Use Efficiency

PA adoption was always found to be linked with enhanced input efficiency. Use of fertilizer was reduced by 10–20% without compromising any yield, whereas water savings were between 15–30%, mainly in arid areas implementing sensor-based irrigation. Application of pest control was reduced by 5–15% because of aimed spraying and drone applications (Table 3).

Table 3. Resource use efficiency achievements due to PA adoption

Resource	Reduction Range (%)	Notes
Fertilizer	10–20	Savings without yield penalty
Water	15–30	Highest in arid regions with sensor irrigation
Pesticides	5–15	Linked to targeted spraying and drones

Barriers to Adoption

Adoption is, however, lopsided, and while there are favorable economic and efficiency gains, small and medium-sized farms had high initial investment cost, low technical capacity, and reduced credit accessibility as primary constraints. Economies of scale were emphasized in some studies with adoption focusing on the larger ones that have the ability to absorb high risk and capture cost-reducing technology.

In summary, the data indicate that precision agriculture provides quantifiable profitability and efficiency payoffs from resource use in U.S. agriculture, but they come in patches. The economic benefits accrue mostly to large farms, and opportunities for smaller farms are restricted because of cost and knowledge constraints

Discussion

The review offers systematic evidence on the economic effects of the adoption of precision agriculture (PA). Findings confirm that PA enhances farm profitability and efficiency in the use of resources, though the magnitude of benefits rests considerably on farm size and operation scale.

Profitability and Farm Scale

Findings agree with earlier studies that have emphasized economies of scale in the adoption of agricultural technology. Large farms registered increases in profit ranging from 5% to 25%, which is in line with earlier studies showing that mechanization and ICT perform best when applied across extensive areas. Returns were lower in medium-scale farms with small-scale farms hindered by obstacles halting economic gain. This skewed distribution implies that although PA can redefine U.S. agriculture, its gains are still limited to bigger producers and thus perpetuate existing structural disparities in the industry.

Efficiency and Environmental Sustainability of Resource Use

These declines observed in the use of fertilizers, water, and pesticides point to the role of PA towards ensuring environmental sustainability. The 10–20% yield-sacrifice-free reductions in fertilizers point to the capability of VRA technologies to contain excessive fertilization with nutrients and prevent runoff into water bodies. Even 30% savings of water in arid areas also confirm the strategic value of PA in helping U.S. agriculture to cope with climate change and water scarcity. These findings are aligned with evidence that resource-saving farm practices enhance long-term sustainability, as well as farm resilience.

Barriers to Adoption

These advantages aside, adoption continues to be plagued by hindrances, notably on the part of small- and medium-scale farmers. Excessive initial investment capital requirements, technical know-how deficiency, and poor access to credit were mentioned several times across the examined studies. This concurs with national reports labeling financial risk and uncertainty as primary barriers to digital agriculture. Unless policy measures, including subsidies, cost-sharing programs, and institution building, are specifically aimed at small farms, they may well continue to lag behind in the level of adoption, thus further widening the productivity differentials between farm sizes.

Policy Implications

The results have several implications for U.S. agricultural policy. First, federal and state government assistance may be able to overcome the barriers to adoption of smallholders through instruments such as equipment-sharing cooperatives, training programs, and precision agriculture tax incentives. Second, based on identified environmental co-benefits, PA can be incorporated in U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS) managed conservation programs and promoted by environmental stewardship payments. Third, as global warming accelerates, water-saving technologies and evidence-based irrigation management policies will become ever more significant.

Limitations and Future Research

This research contains several limitations. The evidence was published, and this evidence is bound to be affected by publication bias because only those studies with a positive effect are published. In addition, although profitability and efficiency measures were extensively reported, fewer reported detailed cost-benefit analyses at farm level, and it is therefore not possible to obtain the full set of financial results. Future studies need to give emphasis to longitudinal trials tracking adoption impacts over successive seasons, and cross-country or cross-region comparisons from multiple locations and crop systems. The combination of economic analysis and life-cycle assessment would also give both economic and environmental implications of PA adoption greater insight.

Together, the data indicate that precision agriculture can be an economic stimulus and an agricultural sustainability strategy for the United States. That the benefits are not being shared equitably, however, indicates that policies and support systems with broad impact must be implemented so that all farm sizes can avail themselves of and benefit from this technological shift.

Conclusion

The research attests to the fact that adoption of precision agriculture (PA) provides considerable economic and environmental advantages in agricultural systems. Growth in profit was highest in medium-scale and large-scale farms, where varia-rate application, auto-steer technology, and yield monitor technologies recorded 5% to 25% returns. Some growth was recorded by medium-scale farms, whereas small-scale farms recorded very little growth due to the high demand of capital during the start and information barriers. Besides economic efficiency, PA uptake always increased the efficiency of usage of resources, conserving 10–20% of the fertilizer, 15–30% of water, and 5–15% of pesticides. These findings demonstrate PA's dual function of making farms more profitable and promoting sustainable production. Adoption is still uneven, though, because structural and financial constraints weigh down extensive adoption.

Recommendations

- Enhance Financial Access: Implement subsidies, tax refunds, and cost-sharing programs to make the initial cost of PA technologies less expensive and foster wider use.
- Enhance Knowledge Transfer: Create training modules, extension services, and farmer-to-farmer transfer programs to enhance technical skills and enhance utilization of digital resources.
- Support Shared Models: Promote cooperative ownership and machinery-sharing enterprises to lower capital expenditure for small- and medium-scale enterprises.
- Integrate PA with Sustainability Schemes: Balance PA take-up with agri-environment schemes and conservation techniques to promote practices with quantifiable environmental impacts.
- Set Up Research and Infrastructure: Fund research on long-term profitability and environmental impacts across varied farming systems, along with investment in digital infrastructure to enhance technology adoption.

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