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From Efficiency to Sustainability Governance: A Bibliometric and Critical Review of Precision Agriculture's Economic and Policy Impacts

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Abstract

Precision agriculture (PA) is increasingly promoted as a "more-with-less" pathway that can raise farm efficiency while supporting sustainability goals. This paper provides a bibliometric and critical review of PA's economic and policy impacts, with emphasis on diffusion patterns, evidence quality, and the data foundations needed for sustainability governance. Using approximately 3,600 Web of Science records—about 2,000 in general PA research and 1,600 in PA-and-economics—this study maps keyword co-occurrence networks in VOSviewer and compares how themes emerge across the two literatures. Three dominant clusters structure the PA-and-economics field: input optimization, information/externalities, and predictive analytics. Across clusters, economic evaluation consistently lags technological and agronomic innovation by roughly 2.25 years, creating an "economic verification gap" in which adoption and policy interest can advance before credible estimates of profitability, risk, and public environmental benefits are available. Evidence synthesis further indicates that PA returns are heterogeneous and often modest on average, shaped by fixed costs, managerial capacity, complementarities, and infrastructure (e.g., connectivity and data systems). Closing the verification gap will require improved measurement and government documentation capacity, data standards, and adaptive incentives that target binding constraints while supporting equitable diffusion.

Keywords: Precision agriculture; Sustainability policy; Technology adoption; Farm profitability; Monitoring, reporting and verification (MRV)

JEL Classification:
Q16 (R&D; Agricultural Technology; Agricultural Extension Services)
Q18 (Agricultural Policy; Food Policy)
Q52 (Pollution Control Adoption Costs; Environmental Policy; Firm/Industry Studies)
O33 (Technological Change: Choices and Consequences; Diffusion Processes)

1. Introduction

Precision agriculture (PA) refers to a broad set of digital and data-enabled practices that use sensing, mapping, automation, and analytics to manage spatial and temporal variability in agricultural production (Misara et al., 2022). In practice, PA enables producers to apply seed, fertilizer, pesticides, water, labor, and machinery time more precisely, while also generating records that can support management and documentation (Schimmelpfennig, 2016). Core applications include GPS/GNSS guidance and auto-steer, yield monitoring and mapping, variable-rate technology (VRT), remote and proximal sensing, and integrated decision-support platforms that combine multiple data streams (Lowenberg-DeBoer & Erickson, 2019; McFadden et al., 2023). These technologies are widely promoted as delivering "more with less" by maintaining or improving yields while reducing waste and limiting environmental harm (Khanna, 2021; Nowak, 2021).

PA's policy salience has strengthened as agriculture faces intersecting sustainability pressures, including volatile input markets, intensified water scarcity and heat stress in many regions, and rising regulatory and market expectations around nutrient runoff, pesticide risk, greenhouse gas emissions, traceability, and "climate-smart" production (Lan & Ban, 2025; U.S. Government Accountability Office [GAO], 2024). In principle, PA can help align private profitability with public environmental objectives by improving input-use efficiency and reducing negative externalities such as nutrient losses, chemical drift, and groundwater depletion (Bahmutsky et al., 2024; Schimmelpfennig, 2018). From a sustainability governance perspective, the value proposition therefore extends beyond private productivity gains to include socially valuable outcomes—cleaner water, lower emissions, and improved resilience—enabled by better measurement and more targeted management (Bahmutsky et al., 2024).

However, PA's economic and sustainability impacts are not automatic. Adoption typically involves substantial fixed costs—equipment, software, connectivity, training, and data management—and uncertain payoffs that depend on local conditions, managerial capacity, and technology performance (Kroupová et al., 2025). These features create heterogeneous returns and generate economies of scale that can lead to uneven diffusion across farm sizes and production systems (Lowenberg-DeBoer & Erickson, 2019). If PA becomes embedded in compliance systems, sustainability certification, or buyer requirements, unequal access to technology and data infrastructure can translate into unequal market access and long-run competitiveness (Lowenberg-DeBoer & Erickson, 2019).

Despite rapid growth in the broader PA literature, the evidence base most directly relevant for sustainability-oriented policy design remains fragmented. Many studies focus on technical performance and agronomic outcomes, while fewer provide rigorous economic evaluation of net returns, adoption intensity, risk reduction, or the value of environmental benefits (Lan & Ban, 2025; Lowenberg-DeBoer et al., 2021; Medici et al., 2021). Where economic evidence exists, it often indicates operational cost and efficiency gains but modest, context-dependent profitability effects (Dhoubhadel, 2021; Wang et al., 2023). Environmental benefits are likewise difficult to quantify at scale because they depend on implementation quality, technology "stacking", and local biophysical conditions, and because public datasets often lack granular measures of practice intensity and integration. Without clearer synthesis and explicit recognition of these measurement constraints, it is difficult to design cost-effective incentives, target binding constraints, or evaluate whether PA adoption delivers measurable public value.

In this paper, we seek to fill these gaps by providing a critical, policy-relevant review of PA's economic and policy impacts, with emphasis on evidence quality, data foundations, and actionable directions for sustainability policy. We contribute in three ways. First, we develop a conceptual framework that treats PA as both an investment under uncertainty and an information infrastructure that reshapes production decisions, compliance capabilities, and the provision of environmental public goods. Second, we conduct a bibliometric analysis using Web of Science data and VOSviewer to compare how PA-and-economics research has evolved relative to the broader PA research frontier. While recent studies apply bibliometrics to general PA research (Rejeb et al., 2024; Xu et al., 2024), we focus on the intersection between general PA and its economic impacts. Third, we identify an "economic verification gap", whereby emerging PA themes appear in the general literature and only later receive formal economic assessment—an important dynamic for policymakers and funders who often act before definitive estimates of profitability, risk, and public benefits exist.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework linking PA to investment under uncertainty, information as a productive asset, diffusion dynamics, and environmental externalities. Section 3 describes our literature selection approach and bibliometric methodology. Section 4 reports bibliometric results on thematic clustering, temporal trends, and the economic verification gap. Section 5 synthesizes evidence on economic outcomes, adoption patterns, environmental impacts, market structure, and policy initiatives. Section 6 identifies limitations in the current evidence base and highlights priority data and research needs for sustainability-oriented evaluation. Section 7 concludes with policy directions and implications for producers, technology developers, and public agencies.

2. Conceptual Framework: Precision Agriculture, Economic Mechanisms, and Sustainability Policy

Precision agriculture (PA) is a management approach that uses technology and data to improve how farms allocate inputs and make decisions under spatial and temporal variability (Finger, 2023; Khanna et al., 2024; Nowak, 2021). We treat PA as an integrated system spanning guidance and automation, variable-rate technologies (VRT), sensing and mapping, automation and robotics, and data analytics platforms. By aligning management with site-specific conditions, PA aims to increase productivity while improving input-use efficiency (Lan & Ban, 2025). Industry and empirical summaries often report modest yield gains alongside reductions in fertilizer, chemical, fuel, and water use (Association of Equipment Manufacturers [AEM], 2024; Wang et al., 2023), consistent with PA's role in climate-smart and economically sustainable farming (Finger, 2023).

2.1 Studies of Precision Agriculture from an Economic Perspective

Economically, PA shifts management from uniform field treatment to differentiated decisions that respond to spatial heterogeneity in soils and crop performance. The U.S. Government Accountability Office defines PA as technologies that improve resource allocation and operational efficiency through data-driven decision-making (GAO, 2024). This definition reflects the principle of applying "the right input, in the right place, at the right time, and in the right amount" (GAO, 2024). We therefore conceptualize PA as an investment in capital and information infrastructure that can reshape production decisions and input demand.

Three features are central. First, PA involves high fixed and upfront costs (equipment, software, and learning), creating economies of scale that can favor larger operations (GAO, 2024). Second, PA generates information that can accumulate as a productive asset and improve decision quality over time (Wang et al., 2023). Third, PA tools are often complementary, so returns may depend on technology "stacking" rather than isolated adoption (Shang et al., 2021; Wang et al., 2023). This framing helps explain why measured returns are heterogeneous across farms and contexts (Khanna et al., 2024).

2.2 Adoption and Diffusion Theory

Adoption and diffusion theory explains why PA spreads unevenly across farms and regions. Farmers are more likely to adopt when expected benefits exceed perceived risks, or when competitive pressures raise the cost of non-adoption (Di Corato & Zormpas, 2022; Spiegel et al., 2021). In the United States, adoption is concentrated among larger and more capital-intensive farms with stronger managerial capacity and technical readiness (Khanna et al., 2024; GAO, 2024). Slower uptake among smaller farms reflects interacting constraints, including high upfront costs, uncertain returns, limited support services, and inadequate connectivity (Sanders et al., 2022; GAO, 2024). Social learning also matters: peers, trusted advisors, and extension systems shape perceived usefulness and credibility, affecting both adoption timing and implementation quality (McFadden et al., 2023).

2.3 Regulatory and Environmental Compliance

PA intersects with environmental regulation and sustainability policy because it improves both targeting and documentation. By enabling more precise applications and verifiable records, PA can support compliance with water-quality and chemical-use expectations while reducing input costs (GAO, 2024). For example, VRT fertilizer applications can reduce runoff risk and improve resource efficiency, aligning private incentives with public goals (Finger, 2023). Improved targeting may also reduce environmental harms such as groundwater contamination, though outcomes remain context dependent (Getahun et al., 2024). As a result, PA can generate public benefits, but realization at scale depends on implementation quality and credible monitoring, reporting, and verification (MRV).

3. Methods: Literature Selection and Bibliometric Approach

This study combines (i) a structured qualitative synthesis of evidence on precision agriculture (PA) and economic/sustainability impacts with (ii) a bibliometric analysis that maps how economic and policy-oriented PA research has evolved relative to the broader PA literature. The dual approach is intended to provide both an interpretable map of research themes and a focused assessment of what the evidence does—and does not—support for sustainability-oriented decision-making.

3.1 Study Design and Rationale

Bibliometric analysis has been widely applied in recent PA reviews (e.g., Misara et al., 2022; Paudel et al., 2025; Rejeb et al., 2024), but relatively few studies explicitly examine the intersection between PA and its economic impacts. Our methodological premise is that PA's policy relevance depends not only on technical feasibility, but also on whether economic evaluation, adoption evidence, and environmental valuation develop in step with technological innovation. To assess this alignment, we implement a dual-dataset design using the Web of Science (WoS) Core Collection, separating (i) a general PA knowledge base from (ii) a PA-and-economics (PA & Econ) sub-literature. This structure allows direct comparison of thematic emphasis and timing across two related research ecosystems. In parallel, we synthesize recent peer-reviewed studies and key government reports to interpret bibliometric patterns in terms of policy-relevant outcomes (profitability, diffusion constraints, environmental impacts, and the role of public programs and data systems).

3.2 Data Source and Bibliometric Dataset Construction (Web of Science)

Bibliometric records were harvested from the WoS Core Collection. We constructed two datasets. First, the PA & Econ dataset includes approximately 1,600 documents filtered to capture research at the intersection of PA technologies and economic/business/management themes. The intent is to approximate the applied literature most likely to address adoption behavior, profitability, market organization, and policy-related outcomes. Second, the PA General dataset includes the top 2,000 most-cited documents drawn from an initial pool of over 12,000 records, serving as a proxy for the field's core technical and agronomic trajectory.

The WoS search logic, keyword filters, and dataset construction parameters are reported in Appendix Table A1, which serves as the replication anchor for field tags, inclusion rules, and thresholds.

3.3 Bibliometric Mapping and Visualization

We use VOSviewer (version 1.6.20) to generate bibliometric maps and visualize the conceptual structure and evolution of the PA & Econ literature. We apply three elements. First, we construct keyword co-occurrence networks to identify clusters of research themes; clustering is based on association strength. Second, we apply cluster detection using a modularity-based approach to partition the network into thematic clusters, enabling an interpretable separation between traditional farm-level efficiency themes and newer themes related to digital systems, sustainability, and predictive analytics. Third, we produce overlay (temporal) visualizations to track the timing of keyword prominence and identify shifts from earlier emphases (e.g., yield monitoring) toward more recent emphases (e.g., digital integration and sustainability framing). Visualization thresholds and figure settings are reported in Appendix Table A1, consistent with parameter transparency in bibliometric research (Mukherjee et al., 2022).

3.4 Measuring the "Economic Verification Gap" (Time-Lag Procedure)

To quantify whether economic evaluation follows technological innovation, we implement a keyword-based time-lag comparison across the two datasets. For a selected set of high-salience keywords, we compute the average publication year in the PA General dataset and compare it with the average publication year in the PA & Econ dataset. We interpret systematic delays—where the PA & Econ average publication year is later—as an economic verification gap, reflecting the time between emerging technical themes and subsequent economic assessment relevant to profitability, risk, and policy evaluation.

3.5 Qualitative Evidence Synthesis and Policy-Relevant Source Integration

The bibliometric results are complemented by a structured synthesis of recent peer-reviewed studies and government publications on PA's economic and sustainability implications. We emphasize adoption patterns, technology-specific adoption rates, cost and efficiency outcomes, and policy interactions, while using national statistics and typologies from USDA and GAO sources where relevant. To keep the synthesis decision-relevant, evidence is organized around policy-linked outcome domains: (i) private economic outcomes (cost efficiency, net returns, risk management); (ii) adoption and distributional outcomes (constraints for small and mid-sized farms, learning and support systems, connectivity); (iii) environmental and compliance outcomes (input reductions, resource efficiency, documentation for program participation); and (iv) market and institutional context (platformization, service markets, public programs).

3.6 Methodological Limitations

This approach has three limitations that matter for interpretation and research design. First, coverage and classification limits: WoS coverage and keyword-based filtering can omit relevant work outside indexed journals or described using different terminology, and keyword choices affect which documents fall into PA & Econ. Second, inference limits: keyword co-occurrence mapping identifies themes and associations, but it does not establish causal relationships, effect sizes, or welfare implications; we therefore use bibliometrics to map research evolution and gaps rather than to infer impact magnitudes. Third, constraints in the underlying evidence base: many economic and environmental evaluations rely on short horizons and incomplete measurement of implementation intensity and technology "stacking," limiting confidence in long-run sustainability conclusions—an issue we revisit in the gaps section.

4. Bibliometric Results: How PA Economics Has Evolved and Where Policy-Relevant Evidence Lags

In this section, we report results from the Web of Science–based mapping of the PA & Econ literature and interpret them through a sustainability and policy lens. The analysis highlights how the PA-and-economics research space is organized, how its emphasis has shifted over time, and how formal economic evaluation tends to lag emerging PA themes.

4.1 Thematic Structure of the PA & Econ Literature: Three Clusters with Distinct Policy Relevance

The keyword co-occurrence network (Figure 1(a)) identifies three dominant clusters, each reflecting a different pathway through which PA generates value.

Cluster 1, Input Optimization, links agronomic terms (e.g., soil, nitrogen, maize) with management concepts (e.g., spatial variability). This cluster corresponds to the traditional production-economics framing of PA: improving allocative efficiency via more precise input application and operational control, with emphasis on farm-level cost minimization and profitability.

Cluster 2, Information & Externalities, connects digital terms (e.g., IoT, big data, smart farming) with sustainability-oriented concepts (e.g., irrigation, sustainability, food security). This cluster reflects a shift from private cost savings toward governance-relevant questions, including documentation, valuation of externalities, and policy instruments that align private adoption with public outcomes.

Cluster 3, Predictive Analytics, centers on AI-related terms (e.g., deep learning, prediction). This cluster signals growing attention to forecasting and decision-support systems, where economic value is often framed in terms of risk management and resilience, especially under climate variability.

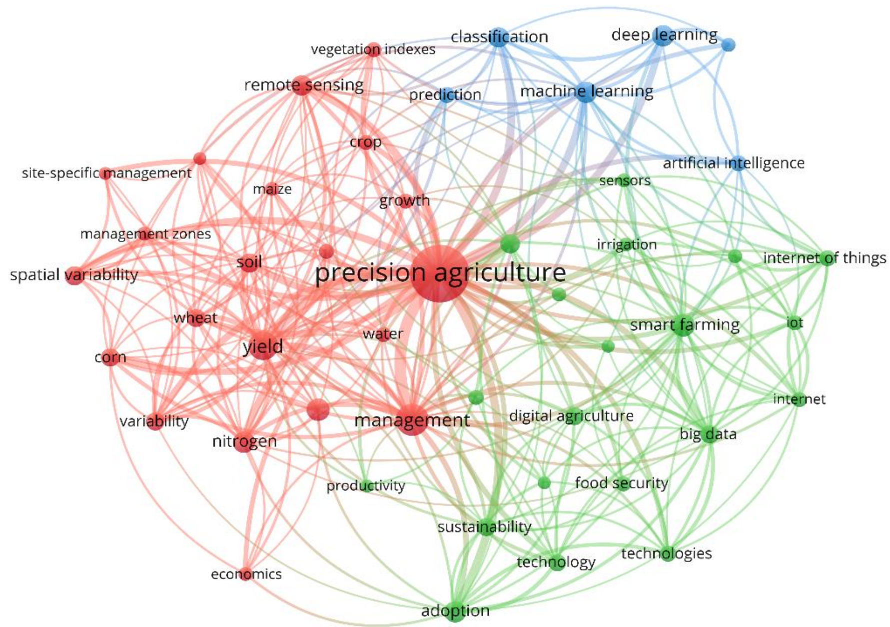

Figure 1(a). Network Visualization of keywords in PA & Econ Literature

Key parameters: see Appendix Table A1.
Only the lines with minimum connection strength of 5 are displayed.

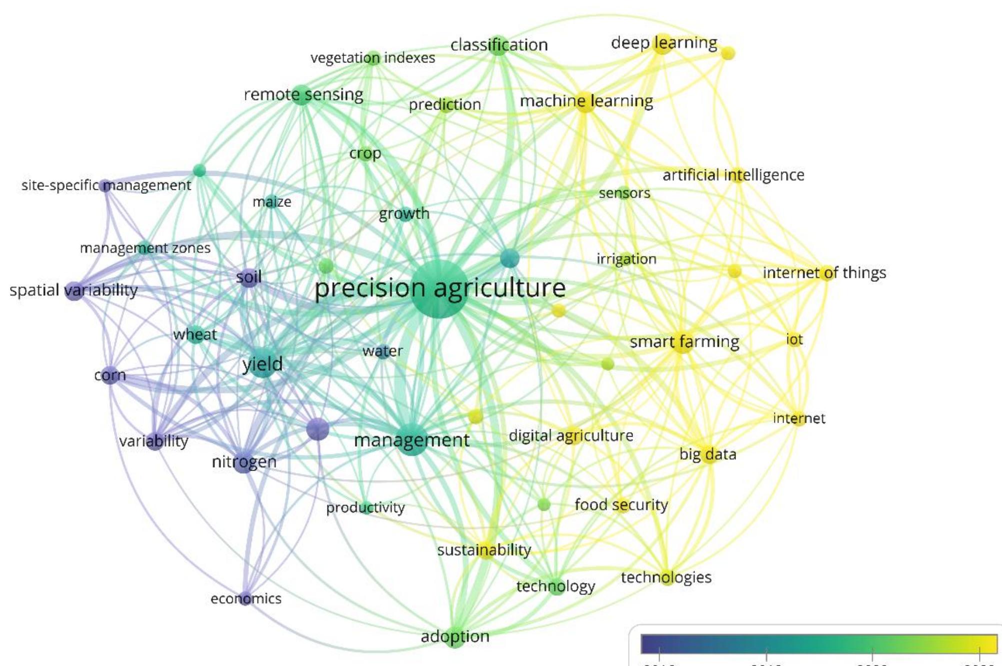

Figure 1(b). Overlay Visualization of keywords in PA & Econ Literature

Key parameters: see Appendix Table A1.
Only the lines with minimum connection strength of 5 are displayed.

4.2 Temporal Evolution: From Field-Level Input Efficiency to Societal Return and Digital Integration

The overlay visualization (Figure 1(b)) indicates a clear temporal shift. Earlier work in PA & Econ is dominated by the Input Optimization cluster, consistent with mature research on site-specific input management and variable-rate applications. More recent work increasingly concentrates in Information & Externalities and Predictive Analytics, suggesting that the frontier is moving toward digital integration, documentation, and broader social-return framing. For policy audiences, this shift matters because it changes the evaluation question: from whether PA reduces input costs to whether PA can be scaled as part of sustainability governance—through improved measurement, lower verification costs, and better targeting of resource use.

4.3 The "Economic Verification Gap": Evidence that Economic Evaluation Systematically Lags Innovation

A central result emerges when we compare keyword timing between the PA General dataset and the PA & Econ dataset. Across selected high-salience topics, the average publication year in PA & Econ occurs later than in PA General, implying that economic and business evaluation tends to follow technological and agronomic innovation rather than lead it. Table 1 summarizes this pattern, with an average gap of about 2.25 years.

We interpret this as an economic verification gap: technologies and themes often become visible in the broader PA literature first, while credible economic assessment of profitability, risk, and potential public benefits arrives only after field implementation generates sufficient data. For sustainability policy, the implication is practical: agencies and funders may need to decide on incentives, broadband, or MRV-linked program rules before mature economic evidence is available. This supports the case for adaptive program designs that embed learning and evaluation.

Table 1. Comparison of Average Publication Years for Select Keywords

Key Word	Avg. pub. Year in "PA & Econ"	Avg. pub. Year in "PA General"	Difference (Years)
deep learning	2023.4	2021.2	2.2
computer vision	2023.4	2019.6	3.8
artificial intelligence	2023.2	2021.2	2.0
smart agriculture	2023.0	2021.2	1.8
machine learning	2023.0	2020.6	2.4
digital agriculture	2022.7	2020.9	1.8
smart farming	2022.6	2020.8	1.8
internet of things (iot)	2022.4	2020.6	1.8
food security	2022.3	2019.8	2.5
sustainability	2022.1	2019.7	2.4
Average			**2.25**

4.4 Bridging the Gap: Emerging Topics with High Sustainability/Policy Salience

Using the verification-gap logic, we identify topics prominent in the PA General literature that appear less developed in the PA & Econ literature (Table 2). These "missing links" suggest near-term research opportunities with direct policy relevance.

First, novel sensing technologies (e.g., hyperspectral imaging, UAV-based sensing) raise a value-of-information question: whether higher-resolution data provide sufficient marginal economic value relative to lower-cost alternatives, especially for monitoring and verification.

Second, irrigation and climate resilience topics highlight a mechanism-design problem: technical solutions are advancing, but economic work on incentives and institutional arrangements that promote adoption for resilience (rather than yield only) remains comparatively limited.

Third, granular object management and robotics point to potential labor–capital substitution and new service models, which may be important for diffusion among farms that cannot finance large up-front investments.

Table 2. Keywords with Emerging Potential for PA & Econ Research

Group	Representative Keywords
1: Novel Sensing Technologies	hyperspectral imaging; unmanned aerial vehicle; remote sensing; semantic segmentation;
2: Macro-Challenges	challenges; irrigation; climate change;
3: Granular Object Management	identification; leaf; classification; crops; object detection

4.5 Implications for Sustainability Policy and Evidence Priorities

Taken together, the bibliometric results suggest that PA economics is increasingly oriented toward sustainability governance and resilience, but that the most policy-relevant evaluations tend to lag technical development. This creates three practical implications for the remainder of the review. First, policy should be designed for heterogeneity and learning. The cluster structure signals that PA impacts span farm-level efficiency, public-good provision, and risk management. Programs that assume uniform ROI or uniform environmental benefits are likely to underperform. Second, evaluation capacity is itself a constraint. The verification gap indicates that robust economic assessment is downstream of data availability and field implementation. For sustainability programs, this underscores the importance of data infrastructure, documentation standards, and embedded evaluation designs. Third, high-value research frontiers are increasingly policy-facing. Emerging topics—sensing for MRV, irrigation and climate resilience, and robotics—are not only technology questions but also governance and equity questions.

5. Evidence Synthesis: Economic, Environmental, and Policy Impacts of Precision Agriculture

Building on Sections 2–4, we synthesize decision-relevant evidence on PA's economic outcomes, diffusion constraints, environmental/resource implications, and the policy environment that shapes adoption and evaluation.

5.1 Farm-Level Profitability and Cost-Benefit Performance

Across economic studies, precision agriculture (PA) most consistently creates value through operational efficiencies and targeted input reductions, while average gains in net profitability are modest and heterogeneous across farms, crops, and management conditions. A multi-scenario assessment finds that six of seven PA applications reduce input costs, with variable-rate technology (VRT) producing the largest savings through improved fertilizer targeting and reduced overlap in field operations (Schimmelpfennig & Ebel, 2016). USDA ERS evidence likewise indicates that near-term payoffs are driven more by cost savings than systematic yield gains: for U.S. corn, auto-steer guidance is associated with roughly $15 per acre in savings (fuel, labor, and machinery wear), and yield mapping/monitoring is linked to further reductions in production costs (McFadden et al., 2023; Schimmelpfennig & Ebel, 2016).

These efficiency gains do not automatically translate into sustained increases in net returns once fixed capital costs, software and data expenses, learning time, and management complexity are included. A difference-in-differences analysis using Kansas Farm Management Association data finds that PA investments often recoup costs through savings but do not yield statistically significant improvements in long-run net farm returns (Dhoubhadel, 2021). Evidence for early adopters in corn similarly points to small positive profit effects, implying that PA can be profitable but is rarely transformative on average; realized benefits depend on implementation quality, scale, and the farm's ability to convert information into better decisions (Schimmelpfennig & Ebel, 2016).

5.2 Adoption and Diffusion Patterns: Who Adopts, Why, and Who Is Left Behind

The adoption literature links PA uptake to farm size, education, wealth, and technological capacity, with non-adopters more likely to face skill, financing, or confidence constraints in managing data-intensive tools. Diffusion also depends on training, trusted advisors, broadband connectivity, and local support ecosystems that reduce uncertainty and improve implementation quality.

Disparities by farm scale are pronounced. ERS-based evidence indicates that over 70% of large U.S. crop farms use GPS-guided auto-steering, compared with fewer than 15% of small farms, consistent with economies of scale and differences in managerial capacity and risk tolerance (McFadden et al., 2023). Smaller farms face interacting barriers, including high upfront costs, uncertain returns, limited technical support, and inadequate connectivity (GAO, 2024). These constraints are policy-relevant because they can limit participation in technology-enabled compliance, sustainability certification, or buyer requirements, thereby widening gaps in market access and competitiveness.

National statistics show rapid diffusion for some tools but persistent limits overall. ERS reporting based on ARMS documents the rise of GPS-guided auto-steer in row crops—for example, from 5.3% of corn acres in 2001 to 58% by 2016 (McFadden et al., 2023). Yet GAO reports that only about 27% of U.S. farms and ranches use any precision technology, with adoption concentrated in major field crops and strongly associated with farm size (GAO, 2024). Taken together, diffusion is substantial where scale and infrastructure support exist, but uneven across farm types and production systems.

5.3 Environmental and Resource-Efficiency Outcomes: From Co-Benefits to Policy Metrics

PA is often justified by its potential to reduce negative externalities through improved input targeting and documentation. Industry summaries report that improved targeting can translate into meaningful input reductions; for example, a 7% reduction in nitrogen fertilizer use at scale could reduce nitrous oxide emissions and nutrient runoff risk, linking PA to climate and water-quality objectives (AEM, 2024). PA can also support compliance and verification by generating more complete records of management actions (GAO, 2024).

Water management is a particularly salient intersection of sustainability and economics. Sensor-informed scheduling and AI-enabled controllers are commonly discussed as ways to improve water productivity in water-scarce contexts; in California, groundwater regulation has increased attention to data-driven irrigation practices (Peddinti, 2025). A case example in almond and pistachio orchards suggests that precision irrigation can improve water-use efficiency, enhance tree health, and reduce production costs (Peddinti, 2025).

5.4 Policy Environment and Public Programs: Incentives, Infrastructure, and Evidence Capacity

Policy interest in PA has expanded because it is viewed as a lever for productivity, sustainability, and climate adaptation. GAO reports that between 2017 and 2021, approximately $200 million was allocated through USDA and NSF initiatives and competitive grants supporting automation, irrigation systems, sensor integration, and adoption research (GAO, 2024). Connectivity has also received legislative attention through provisions in the 2018 Farm Bill directing the FCC to map agricultural coverage gaps and prioritize rural broadband deployment (GAO, 2024). State policies can further shape adoption where water constraints and compliance pressures increase the value of precision irrigation and documentation.

A cross-cutting constraint is evidence capacity. Public datasets often lack granular measures of PA intensity and technology combinations, weakening inference about long-run economic and environmental performance and complicating evaluation of policy effectiveness (GAO, 2024). As a result, PA policy is not only an adoption-incentive problem but also a data and implementation problem, requiring investments in infrastructure, standards, and evaluation systems that enable programs to learn and adapt over time.

6. Research Gaps and Limitations: Decision-Relevant Uncertainties for Sustainability Policy

Although the PA literature has expanded rapidly, important uncertainties remain for sustainability-oriented policy design and evaluation. Evidence indicates that PA can improve operational efficiency and reduce some inputs, yet the magnitude, persistence, and distribution of economic and environmental benefits remain difficult to verify across diverse U.S. farming systems. A recurring constraint is measurement: widely used public datasets often lack the granularity needed to evaluate PA as an integrated information-and-control system, particularly with respect to adoption intensity, implementation quality, and technology "stacking."

6.1 Key Evidence Gaps and Limitations

First, long-run profitability remains uncertain. Longitudinal studies suggest PA can generate cost savings and sometimes recoup investment costs, but results do not consistently show sustained increases in long-run net returns once equipment, software, learning, and management costs are incorporated. Reported gains for early adopters are often small and context dependent, limiting generalizable ROI claims.

Second, diffusion remains uneven by farm size and capacity. While correlates such as scale, education, and financial resources are well established, the evidence base provides limited causal guidance on which scalable policy bundles—beyond subsidies—reduce adoption gaps and support durable, high-quality use among small and mid-sized farms. In practice, capital constraints, uncertain returns, limited training and technical support, and insufficient broadband frequently interact, implying that incentives alone may yield shallow adoption without complementary service and infrastructure investments.

Third, environmental performance is difficult to verify at scale. Many studies infer environmental gains from improved input-use efficiency, but translating reduced inputs into verified outcomes depends on local biophysical conditions and implementation quality. Most evaluations also lack robust measures of adoption intensity and technology "stacking," weakening inference about cumulative impacts and complicating linkage to monitoring, reporting, and verification (MRV) systems.

Finally, external validity is constrained by data coverage. Public datasets disproportionately reflect Midwest row-crop systems and frequently omit variables critical for specialty crops (e.g., labor intensity, water constraints, perennial cycles, and distinct pest and disease pressures). This limits credible assessment in regions such as California and increases the risk of one-size-fits-all policy conclusions.

6.2 Policy Implications

The literature supports four policy directions that address these limitations without assuming uniform returns or uniform environmental effects. First, shift from adoption-only incentives to integrated support for adoption and implementation quality. Because PA impacts depend on effective use—calibration, data interpretation, and incorporation into day-to-day management—programs should not treat adoption as a binary outcome. Cost-share incentives are more likely to yield durable gains when paired with technical assistance, standardized training, dealer and consultant capacity, and extension-led demonstrations that strengthen implementation quality and persistence.

Second, address equity and access constraints for small and mid-sized farms. The size-based adoption divide implies sustainability programs may unintentionally reinforce disparities when participation requires large up-front capital outlays or advanced data capacity. Targeted cost-share rates, low-interest financing, cooperative purchasing, and service-based models (e.g., custom application, "precision-as-a-service," shared data-management support) can reduce fixed-cost burdens. Where constraints differ from Midwest row crops (e.g., water scarcity, perennial systems), region- and commodity-specific program design is especially important.

Third, invest in connectivity, interoperability, and data governance as enabling infrastructure. PA increasingly relies on reliable broadband and interoperable data flows across equipment, sensors, and platforms. Rural connectivity remains foundational, but it should be complemented by measures that reduce transaction costs from data silos and vendor lock-in. Interoperability standards and clearer data-rights guidance can improve the usefulness of PA for both management and verification, while strengthening evaluation capacity through more consistent documentation.

Fourth, embed MRV and evaluation capacity into sustainability programs. If PA is to credibly support nutrient reduction, water conservation, and climate-smart initiatives, programs need scalable MRV frameworks that translate PA-generated records into reliable indicators of practice adoption and outcomes. Given heterogeneity and the evidence lag identified in our bibliometric analysis, adaptive designs—phased rollouts, learning pilots, and outcome-based benchmarking—can generate evidence while scaling.

6.3 Availability of Public Data

Strengthening public datasets and surveys to measure PA intensity and technology bundles would further improve causal inference and cost-effectiveness assessment. By searching government datasets, we document where state agencies publicly signal or support PA through programs, communications, research, or policy during 2016–2026. A state is coded as having PA data activity if its official government website contains at least one PA-relevant item dated 2016–2026 meeting our inclusion criteria: initiatives or programs (e.g., grants, cost-share, training, pilots, partnerships), research or technical reporting (methods, results, evaluation), publications or communications (fact sheets, guidance, reports, news posts), and/or policy content (plans, formal guidance, regulations, policy statements). Using these criteria, 22 states showed evidence of PA-related activity (Figure 2).

We used each website's internal search function (when available) and the keywords "precision agriculture," "ag tech," and "agriculture technologies." For each qualifying item, we recorded the title, URL, document type, year (when available), access date, and evidence type (initiative, research, publication, policy). Four states—California, Kansas, Maine, and Maryland—are classified as higher-evidence because they provide state-generated outputs beyond general references (e.g., datasets, evaluation results, or technical reports describing data collection or methods). This approach likely undercounts activity that is undocumented online or described using different terminology; Figure 2 should therefore be interpreted as a measure of public documentation and agency engagement.

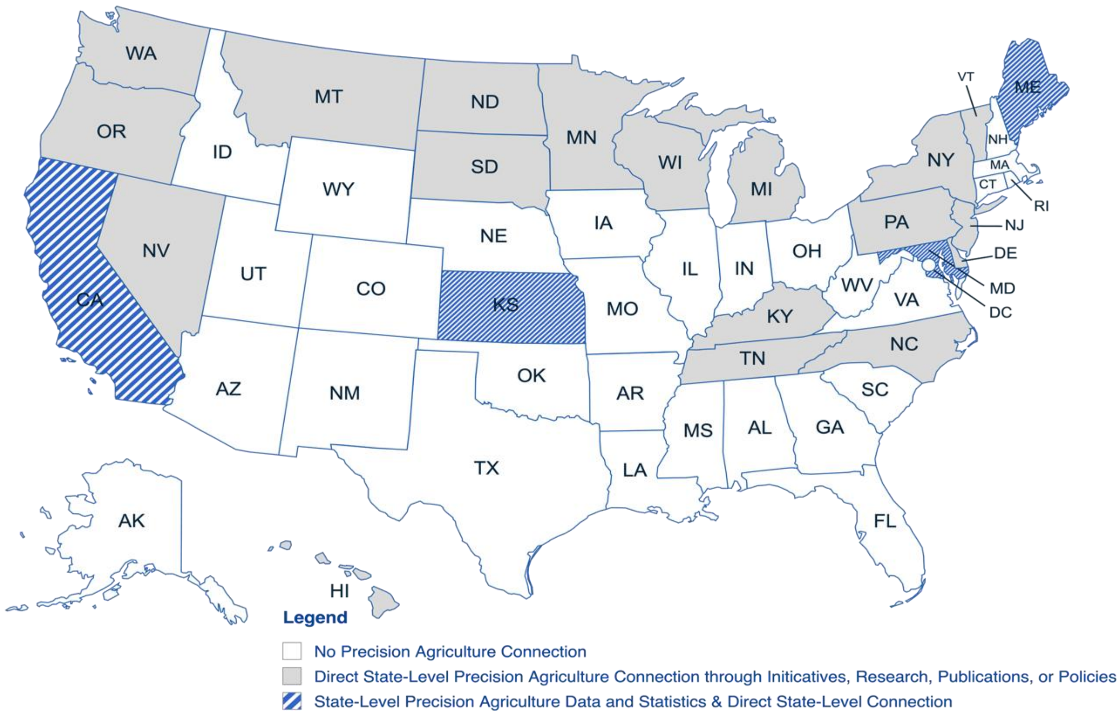

Figure 2: United States Map Highlighting States with Precision Agriculture (PA) Initiatives, Research, Publications, or Policies (2016–2026)

Data Source: Author collected from various states' official government websites

7. Concluding Remarks

Precision agriculture (PA) is increasingly central to modern agricultural production and sustainability policy. Our review indicates that PA's core contribution is improving how farms measure and manage heterogeneity in production conditions, enabling more targeted input use, greater operational precision, and stronger documentation of management practices. These capabilities position PA as a potential bridge between farm-level efficiency objectives and public sustainability goals, particularly for nutrient management, water conservation, and climate resilience.

Three conclusions follow from the evidence we synthesize. First, PA most consistently creates value through operational efficiencies and targeted input reductions, while average gains in net profitability are often modest and heterogeneous once fixed costs, learning, and management complexity are included. Second, diffusion remains uneven. Adoption is concentrated among larger operations and major field crops, while smaller farms and some production systems face binding constraints related to capital costs, connectivity, technical support, and human capital. These constraints matter for equity and competitiveness, especially as PA becomes more closely tied to compliance, sustainability certification, or buyer requirements. Third, environmental benefits are plausible—often discussed in terms of reduced fertilizer, chemical, and water use—but verifying these benefits at scale remains difficult because outcomes depend on implementation quality, local biophysical conditions, and credible monitoring, reporting, and verification (MRV).

A central contribution of this paper is bibliometric evidence that economic evaluation tends to lag technological and agronomic innovation. Using two Web of Science datasets—PA General and PA & Econ—and mapping keyword co-occurrence and timing patterns with VOSviewer, we identify three dominant thematic clusters (input optimization; information and externalities; predictive analytics) and document an average delay of approximately 2.25 years between the emergence of topics in the general PA literature and their appearance in economic assessment. We interpret this pattern as an economic verification gap: technologies and themes may be promoted, adopted, and sometimes subsidized before credible estimates of profitability, risk, and public benefits are available. This lag helps explain why policy can move ahead of mature evidence and why reported returns remain heterogeneous across contexts.

The policy implications are practical. Sustainability programs should anticipate heterogeneity and avoid assuming uniform private ROI or uniform environmental benefits. Adoption interventions are more likely to succeed when they support implementation quality, not just equipment purchase, through training and advisory capacity that helps producers translate data into decisions. Connectivity and interoperability remain enabling infrastructure; reducing data silos and strengthening documentation standards can lower transaction costs and improve the feasibility of MRV. Because evidence develops with a lag, programs should embed evaluation capacity through adaptive designs such as phased rollouts and learning pilots that generate credible performance evidence while scaling.

Finally, our state-level documentation suggests that public engagement with PA is broad but uneven. Documentation of PA-related initiatives, research, and policy varies across states, and online records likely undercount activity in some cases. This reinforces the need for more consistent data systems and reporting if PA is expected to play a measurable role in sustainability governance.

Overall, PA can contribute to sustainability by improving measurement, targeting, and documentation, but realized benefits depend on context, implementation quality, and access to complementary infrastructure and support. Treating PA as part of an institutional and data-enabled transition—supported by standards, connectivity, and evaluation—offers a more credible path to cost-effective policy than relying on technology promotion alone.

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Appendix

From Efficiency to Sustainability Governance: A Bibliometric and Critical Review of Precision Agriculture's Economic and Policy Impacts

Table A1. Search strategy and dataset construction parameters.

Parameter	**Details**
Database	Web of Science (WoS) Core Collection
Date of Search	[Insert Date, e.g., December 15, 2024]
Time Span	1990 – 2024 (or "All years available")
Document Types	Articles, Review Articles
Language	English
Query Set 1: PA General	**TS=**("Precision Agriculture" OR "Precision Farming" OR "Smart Farming" OR "Site-specific crop management" OR "Variable rate technology")
Selection Criteria (Set 1)	Sorted by "Citations: highest first"; Top 2,000 records selected.
Query Set 2: PA & Econ	**TS=**("Precision Agriculture" OR "Precision Farming" OR "Smart Farming") **AND** **TS=**("Economic*" OR "Cost-benefit" OR "Profit*" OR "Business" OR "Return on Investment" OR "Financial feasibility" OR "Adoption")
Selection Criteria (Set 2)	All retrieved records included (approx. 1,600).

Table A2. Top Key Words of PA & Econ Literature

Key Word	**cluster**	**Avg. pub. year**	**Avg. citations**	**Avg. norm. citations**
vegetation indexes	1	2020.4667	53.2667	1.9033
water	1	2017.4167	45.9792	1.1055
use efficiency	1	2019.3421	44.2105	1.0746
remote sensing	1	2019.8111	42.6667	1.1672
site-specific management	1	2015.8158	42.1842	0.9213
management	1	2018.851	41.899	1.2276
growth	1	2018.96	40.54	1.1755
maize	1	2018.55	38.325	0.91
wheat	1	2018.6912	37.0441	1.1529
crop	1	2020.44	34.78	1.1905
precision agriculture	1	2019.3465	32.2775	0.9703
soil	1	2015.859	31.8846	0.8888
economics	1	2015.3	31.55	0.8265
corn	1	2016.0571	31.1429	0.7148

nitrogen	1	2016.3229	30.8021	0.8121
precision farming	1	2015.0476	30.7143	0.9283
variability	1	2015.7971	29.4058	0.7684
yield	1	2018.3393	24.9643	0.7467
management zones	1	2018.8837	22.5814	0.502
spatial variability	1	2015.2105	21.5263	0.5787
quality	1	2020.2245	18.898	0.7286
internet	2	2021.9778	67.7778	1.6917
big data	2	2021.8971	63.3529	2.1268
technology	2	2020.25	61.65	1.5504
irrigation	2	2021.0976	58.3902	1.5787
model	2	2018.2152	58.1266	1.2574
iot	2	2022.4565	50.8696	1.7481
technologies	2	2021.6071	47.6071	1.6962
climate-change	2	2021.1111	44.9444	1.4188
internet of things	2	2022.3269	41.0769	1.6733
information	2	2020.5833	36.1111	1.2921
sensors	2	2020.65	35.2	1.2441
adoption	2	2020.3298	35.0532	1.2414
food security	2	2022.2766	34.5745	1.9406
smart farming	2	2022.6	33.2571	1.3908
smart agriculture	2	2023.0488	28.4878	1.5352
sustainability	2	2022.1408	28.3944	1.3682
digital agriculture	2	2022.7465	27.5634	1.1583
sustainable agriculture	2	2022.8095	26.5714	1.9631
impact	2	2021.5625	25.4167	1.3329
productivity	2	2019.5405	21.5135	0.9472
prediction	3	2020.9423	48.9038	1.5865
classification	3	2020.4217	37.253	1.205
artificial intelligence	3	2023.2	30.4545	1.6861
machine learning	3	2023.043	25.043	1.3308
deep learning	3	2023.4433	24.268	1.3135
computer vision	3	2023.425	18.35	1.2932

Table A3. Top Keywords of the Most Recent 2,000 PA General Publications

label	**Avg. pub. Year**	**Avg. norm. citations**
challenges	2025.1	3.871
identification	2025.0	2.782
sustainable agriculture	2025.0	2.351
hyperspectral imaging	2025.1	2.192

big data	2025.0	2.085
regression	2025.1	2.078
classification	2025.0	1.941
irrigation	2025.0	1.820
internet	2025.1	1.813
prediction	2025.0	1.804
crops	2025.0	1.736
internet of things (iot)	2025.0	1.698
smart agriculture	2025.0	1.596
remote sensing	2025.1	1.685
computer vision	2025.0	1.522
performance	2025.1	1.455
management	2025.1	1.452
internet of things	2025.1	1.439
object detection	2025.0	1.437
leaf	2025.1	1.417
unmanned aerial vehicle	2025.1	1.413
wheat	2025.0	1.379
resistance	2025.0	1.357
sustainability	2025.1	1.353
artificial intelligence	2025.1	1.346
climate change	2025.0	1.339
smart farming	2025.1	1.301
winter-wheat	2025.1	1.259
semantic segmentation	2025.0	1.243

Notes: As of December 29, 2025.

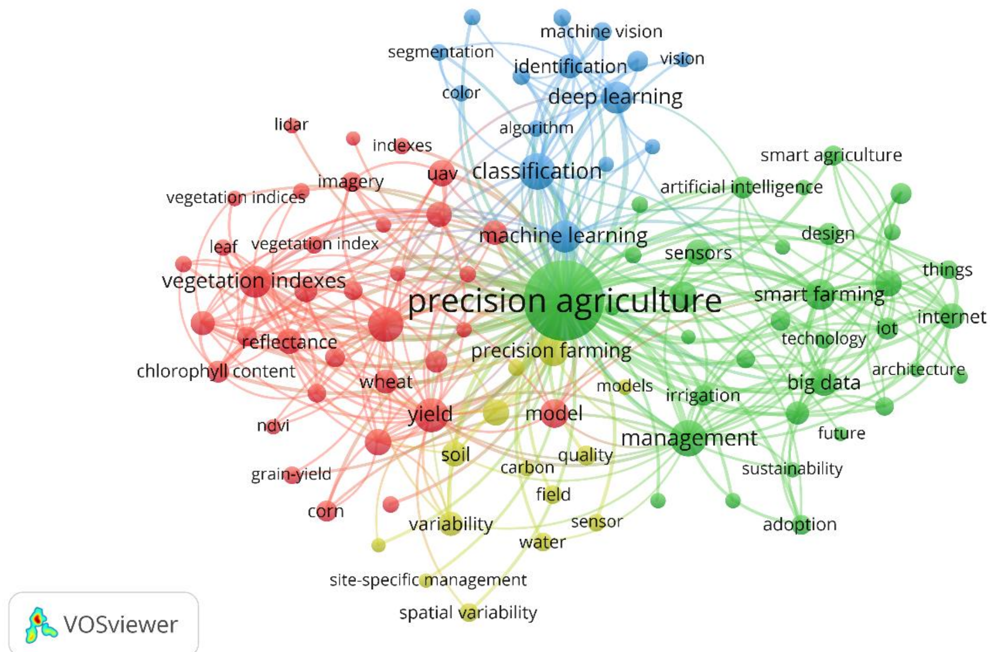

Figure A1(a). Network Visualization of keywords in PA General Literature

Key parameters: see Appendix Table 1.

Only the lines with minimum connection strength of 10 are displayed.

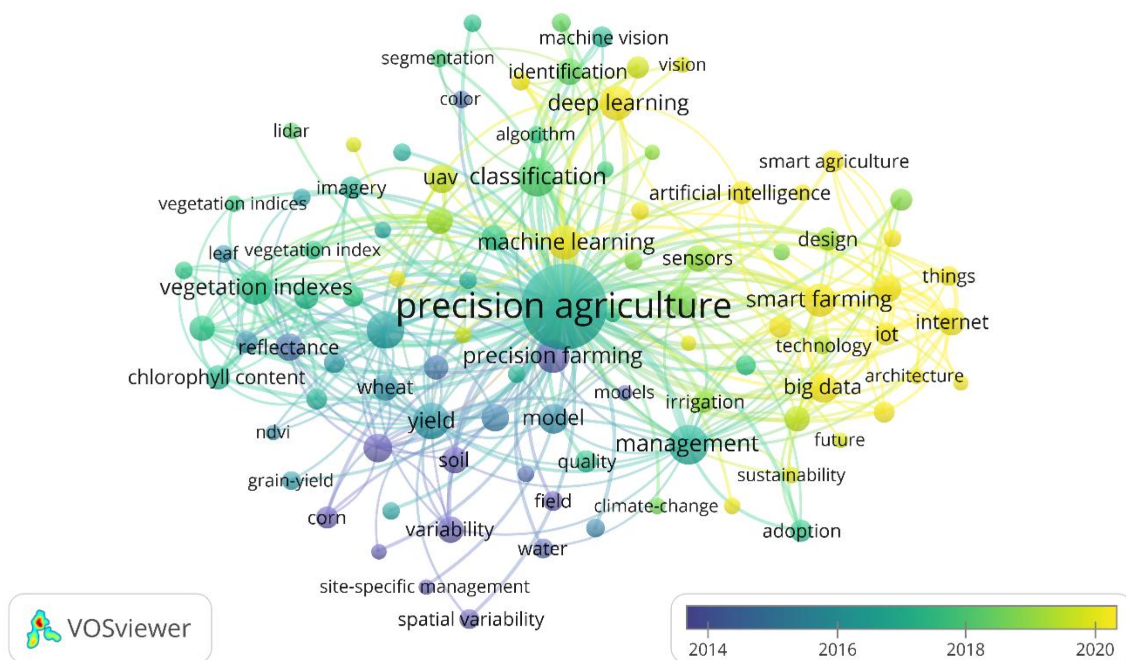

Figure A1(b). Overlay Visualization of keywords in PA General Literature

Key parameters: see Appendix Table 1.

Only the lines with minimum connection strength of 10 are displayed.