Machine Learning for Sustainable Agriculture and Precision Farming: A Systematic Review of Predictive Models, Resource Optimization, and Implementation Barriers

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Abstract

The imperative to increase global food production by fifty percent before 2050, coupled with the urgent need to reduce agriculture's environmental footprint, has positioned machine learning as a transformative technology for sustainable farming systems. This paper presents a systematic review of machine learning applications in sustainable agriculture and precision farming, synthesizing peer-reviewed literature published between 2018 and 2026 across computer science, agronomy, and environmental science disciplines. Through analysis of 124 relevant studies identified via the PRISMA framework, we examine three primary domains of ML application: crop yield prediction, resource optimization (irrigation and nutrient management), and crop health monitoring. The findings reveal that ensemble methods, particularly random forest and gradient boosting architectures, consistently outperform single-model approaches for yield prediction, achieving R^2 values between 0.82 and 0.92 in validation studies. However, the literature demonstrates pronounced heterogeneity in data collection protocols, feature selection methods, and performance reporting standards, which substantially limits cross-study comparability and generalizability. Furthermore, implementation research reveals significant barriers related to data infrastructure, model interpretability, and smallholder farmer accessibility that remain underexplored. The paper advances a conceptual framework linking ML technical capabilities to sustainability outcomes and identifies critical research priorities for translating algorithmic advances into field-level impact.

Keywords: Machine learning, precision agriculture, sustainable farming, crop yield prediction, resource optimization, systematic review.

Journal of Science, Technology and Social Transformation (2026) Doi: 10.64235/584snk91

Introduction

The convergence of climate volatility, soil degradation, water scarcity, and population growth has produced what many agricultural scientists characterize as the most formidable food production challenge since the Green Revolution. Global food systems must increase output by an estimated fifty percent by 2050 while simultaneously reducing greenhouse gas emissions, fertilizer runoff, and freshwater withdrawal—objectives that appear fundamentally contradictory under conventional farming paradigms . This tension has driven intensifying interest in precision agriculture, an approach that substitutes blanket input applications with data-driven, site-specific management. Yet precision agriculture generates data volumes far exceeding human analytical capacity, creating both the necessity and the opportunity for machine learning intervention.

Machine learning has emerged as a central enabling technology for sustainable precision agriculture, offering capabilities that directly address the sector's core challenges.

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How to cite this article: James, C. (2026). Machine Learning for Sustainable Agriculture and Precision Farming: A Systematic Review of Predictive Models, Resource Optimization, and Implementation Barriers. *Journal of Science, Technology and Social Transformation* 2(3), 1-8.

Source of support: Nil

Conflict of interest: None

Unlike traditional statistical methods constrained by linear assumptions and predefined functional forms, ML algorithms can discover complex, nonlinear relationships among weather variables, soil properties, crop genetics, and management practices. They integrate heterogeneous data sources—satellite imagery, in situ sensors, weather forecasts, and historical yield records—into unified predictive

frameworks. Moreover, ML systems improve with additional data, creating the potential for adaptive management tools that become more accurate over time.

The research landscape has expanded dramatically. Publications on ML in sustainable agriculture have grown at rates approaching ninety-one percent annually, with the most productive years concentrated between 2022 and 2025 . This growth reflects not merely academic interest but genuine technological maturation; models have progressed from proof-of-concept demonstrations to deployment-ready systems achieving impressive accuracy metrics. Convolutional neural networks identify crop diseases with accuracy exceeding ninety percent . Ensemble methods predict yields with R^2 values surpassing 0.88 . Decision support systems integrate multiple ML modules—yield forecasting, irrigation scheduling, pest identification—into unified platforms .

Yet beneath this impressive technical progress lie concerning gaps. The literature is fragmented across disciplinary silos: computer scientists publish sophisticated models validated on laboratory or controlled environment data, while agronomists document field conditions that systematically violate model assumptions. Performance metrics are inconsistently reported; many papers claim high accuracy without specifying whether this reflects cross-validation, holdout testing, or external validation . Furthermore, the vast majority of research originates from industrialized agricultural contexts, raising fundamental questions about applicability to smallholder systems where sustainability interventions are most urgently needed.

This paper addresses three central research questions. First, what ML architectures and modeling approaches have demonstrated effectiveness for yield prediction, resource optimization, and crop health monitoring in sustainable agriculture contexts? Second, what evidence exists linking ML implementation to measurable sustainability outcomes—reduced input use, improved resource efficiency, or decreased environmental impact? Third, what barriers currently limit the translation of ML models from research settings to field deployment, particularly in resource-constrained agricultural systems?

The theoretical framework guiding this review integrates concepts from precision agriculture systems theory, socio-technical transitions, and critical data studies. Precision agriculture is understood not merely as a set of technical tools but as a system linking data collection, analysis, decision-making, and field action—each component presenting potential failure points. Sustainability is operationalized across three dimensions: environmental (reduced input intensity, lower emissions), economic (improved profitability, risk reduction), and social (accessibility, labor implications). This multi-dimensional framing prevents the techno-centric reductionism that characterizes much ML-for-agriculture research.

The paper proceeds as follows. Section two presents a synthesized literature review organized around the three application domains, identifying key debates and gaps. Section three describes the systematic review methodology, including search protocols, inclusion criteria, and analytical procedures. Section four reports findings on model performance, sustainability evidence, and implementation barriers. Section five discusses implications for research and practice, including a proposed research agenda. Section six concludes with recommendations for policy, practice, and future investigation.

Literature Review

Crop Yield Prediction: From Statistical Models to Ensemble Architectures

Crop yield prediction represents the most extensively researched ML application in sustainable agriculture, with good reason. Accurate pre-harvest yield estimates enable optimized storage allocation, forward contracting, supply chain coordination, and risk management—interventions that reduce both economic waste and post-harvest losses. The evolution of prediction methodologies reflects broader trends in applied machine learning, from simple regression toward sophisticated ensemble and deep learning architectures.

Early ML approaches relied on linear regression and support vector regression using limited feature sets—typically historical yield, seasonal rainfall, and average temperature . These models achieved modest accuracy (R^2 values between 0.45 and 0.65) but suffered from high spatial and temporal variability. Their fundamental limitation was architectural: by assuming linearity or relying on manually specified feature spaces, they could not capture the complex interactions among weather, soil, genetics, and management that determine actual yield.

The introduction of ensemble methods, particularly random forest and gradient boosting machines, marked a significant advancement. These algorithms combine multiple decision trees trained on bootstrap samples and random feature subsets, producing predictions that average over individual model variance while preserving the capacity to model nonlinear relationships and interaction effects. Sree and colleagues documented that gradient boosting architectures achieve R^2 values of approximately 0.89 for yield prediction across diverse crop types and growing conditions, substantially outperforming both traditional regression ($R^2 \approx 0.62$) and single decision tree approaches ($R^2 \approx 0.71$) .

Recent research has demonstrated that deep learning approaches, particularly long short-term memory networks designed for sequential data, can further improve prediction accuracy by explicitly modeling temporal dependencies in weather and crop development trajectories . A deep learning-based decision support system developed for rice, maize, and wheat achieved yield prediction R^2 values of 0.888 using decision tree architectures, with convolutional neural networks for associated disease identification reaching

validation accuracies of 92 percent . The MobileNetV2-based CNN architecture reported by another research group achieved 90 percent accuracy for disease classification and R^2 of 0.92 for yield prediction, though the authors note substantial performance variation across crop types and geographic regions .

Despite these technical advances, critical debates persist regarding model evaluation standards. A systematic literature review of AI in precision agriculture identified significant heterogeneity in validation approaches across 76 studies; fewer than thirty percent reported external validation on geographically distinct datasets, and only twelve percent made their code or data available for replication . This lack of standardization severely limits the field's cumulative progress, as claims of superior performance cannot be meaningfully compared across methodologically incommensurable studies.

Resource Optimization: Irrigation, Nutrients, and the Efficiency Frontier

The second major ML application domain addresses resource optimization—specifically, the efficient allocation of water and nutrients. Agriculture accounts for approximately seventy percent of global freshwater withdrawals and is the dominant source of nitrogen and phosphorus pollution in freshwater systems. ML optimization offers the prospect of maintaining or increasing yields while substantially reducing input intensity.

ML-based irrigation scheduling represents a mature application area. These systems integrate soil moisture sensors, weather forecasts, evapotranspiration models, and crop-specific water requirement functions within optimization frameworks that recommend irrigation timing and volume. A comprehensive review identified that ML approaches reduce water consumption by twenty to forty percent compared to schedule-based irrigation, with no significant yield reduction, though performance varies substantially with soil type, crop species, and climate regime . The underlying mechanism is straightforward but powerful: by learning the relationship between soil moisture dynamics, weather variables, and crop water stress, ML models can predict the minimum irrigation required to maintain yield.

Nutrient management has received comparatively less research attention, a gap that several review articles highlight as a priority for future investigation . The available literature indicates that ML approaches for fertilizer recommendation typically employ similar architectures to yield prediction models, using soil test data, crop type, and target yield to recommend nitrogen, phosphorus, and potassium application rates. A decision support system incorporating nutrient management modules demonstrated that ML-based recommendations reduced nitrogen over-application by an average of thirty-two percent compared to standard extension recommendations, with equivalent or slightly higher yields .

However, the resource optimization literature reveals a critical tension between algorithmic efficiency and field applicability. Many optimization models assume that farmers can implement variable-rate applications with fine spatial resolution, an assumption that requires expensive precision application equipment and digital infrastructure. A systematic review of AI in transforming precision agriculture notes that "challenges include managing large volumes of data and adequate infrastructure," yet few studies explicitly address the infrastructure requirements of proposed solutions . This creates a troubling dynamic: the most resource-efficient models are often the least accessible to the farmers who could benefit most from input reduction.

Crop Health Monitoring: Computer Vision for Disease and Pest Detection

The third major application domain involves crop health monitoring via computer vision and deep learning. Early detection of disease, nutrient deficiency, or pest infestation enables targeted intervention before significant yield loss occurs, potentially reducing pesticide use through precision application.

Convolutional neural networks dominate this literature, given their proven effectiveness for image classification tasks. The typical pipeline involves training a CNN on labeled images of healthy and diseased plant tissue, then deploying the trained model to classify new images captured by drones, ground-based vehicles, or farmer smartphones. A CNN-based disease prediction module achieved training and validation accuracies of 96.6 percent and 91.8 percent, respectively, for rice, maize, and wheat disease identification . The MobileNetV2 architecture, designed for computational efficiency on mobile devices, achieved 90 percent disease classification accuracy while requiring substantially less memory and processing power than larger architectures .

A significant debate concerns the generalizability of disease detection models. Models trained on images captured under controlled lighting conditions with high-resolution cameras perform markedly worse when applied to farmer-captured images with variable lighting, angles, and resolution. This domain shift problem is not merely technical but practical: if disease detection models cannot operate reliably under field conditions, their utility for smallholder farmers is severely limited. Some researchers have advocated for training augmentation strategies that deliberately introduce variability—random rotations, brightness adjustments, simulated noise—to improve robustness, but systematic evidence on optimal augmentation approaches remains limited.

Implementation Barriers and the Smallholder Challenge

The literature on ML for sustainable agriculture is overwhelmingly oriented toward technical development rather than implementation. However, a smaller but growing

body of research examines the barriers that prevent field deployment, particularly in smallholder systems where sustainability interventions could have the greatest impact.

Data infrastructure represents the most frequently cited barrier . ML models require large quantities of labeled training data, yet such data rarely exists for smallholder contexts. Even when data exists, it may be stored in incompatible formats, lack standardized metadata, or be inaccessible due to proprietary restrictions. The systematic review by Botero-Valencia and colleagues explicitly notes that "managing large volumes of data and adequate infrastructure" remains an unresolved challenge .

Model interpretability presents a distinct but related barrier. Farmers and agricultural extension agents are understandably reluctant to implement recommendations from models they cannot understand or trust. While certain ML architectures—decision trees, logistic regression—are inherently interpretable, the most accurate models (deep neural networks, gradient boosting ensembles) operate as black boxes. Research on explainable AI for agriculture is nascent; few studies have evaluated whether providing explanation interfaces actually increases farmer trust or adoption.

Finally, the economic barriers to ML adoption are substantial. Precision agriculture technologies typically require capital investment in sensors, connectivity, and processing infrastructure that smallholder farmers cannot afford. Moreover, the benefits of ML optimization—input reduction, yield improvement—accrue over multiple seasons, while costs are incurred upfront. Without financing mechanisms or subsidy programs, adoption will likely remain concentrated among large-scale commercial operations.

Gaps in Existing Research

Synthesizing the literature reviewed above reveals three critical gaps that motivate the present study. First, the field lacks standardized evaluation protocols that would enable meaningful cross-study comparison of model performance. Second, the evidence linking ML implementation to measurable sustainability outcomes remains sparse and methodologically weak; most studies report technical metrics (accuracy, R^2) rather than agronomic or environmental outcomes (water saved, fertilizer reduced, emissions avoided). Third, the implementation literature is disproportionately focused on high-income, large-farm contexts, with limited attention to smallholder systems where sustainability interventions are most urgently needed.

Methodology

Research Design

This study employs a systematic literature review design following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, as recommended by recent methodological guidance for agricultural AI research . The systematic review approach is appropriate given our research questions, which require comprehensive identification, appraisal, and synthesis of existing evidence rather than primary data collection.

Search Strategy

A systematic search was conducted across three academic databases: Scopus, Web of Science, and IEEE Xplore. The search string combined terms related to machine learning ("machine learning" OR "deep learning" OR "neural network" OR "random forest" OR "gradient boosting" OR "support vector machine"), agriculture ("agriculture" OR "farming" OR "precision agriculture" OR "sustainable agriculture"), and application domains ("yield prediction" OR "crop monitoring" OR "irrigation" OR "nutrient management" OR "disease detection").

Additional records were identified through reference list screening of included studies and relevant review articles. The search was limited to peer-reviewed journal articles and conference proceedings published between January 2018 and March 2026. English language publication was required.

Inclusion and Exclusion Criteria

Studies were included if they: (1) described original empirical research applying machine learning to an agricultural problem; (2) reported quantitative performance metrics; (3) addressed at least one sustainability outcome (environmental, economic, or social); and (4) provided sufficient methodological detail to enable evaluation. Studies were excluded if they: (1) were theoretical or methodological without empirical application; (2) focused exclusively on post-harvest or supply chain applications; (3) used only traditional statistical methods without ML components; or (4) lacked original data.

The initial search yielded 8145 potentially relevant records, consistent with prior systematic reviews in this domain . After duplicate removal, 6124 records proceeded to title and abstract screening, which excluded 5788 records that clearly did not meet inclusion criteria. The remaining 336 records underwent full-text assessment, resulting in 124 studies included in the final synthesis.

Data Extraction and Synthesis

Data were extracted from included studies using a standardized form capturing: (1) bibliographic information; (2) ML architecture and algorithms; (3) application domain; (4) dataset characteristics (size, source, features); (5) performance metrics reported; (6) sustainability outcomes; (7) implementation barriers noted; and (8) study limitations acknowledged.

Synthesis proceeded through thematic analysis, with studies grouped by application domain and ML architecture. For quantitative synthesis, performance metrics were extracted where reported in comparable form.

Table 1: Summary of ML Performance by Application Domain

Application domain	*Number of studies*	*Median reported metric*	*Range*	*Most common architecture*
Yield Prediction	52	$R^2 = 0.84$	0.62-0.94	Random Forest / Gradient Boosting
Disease Detection	28	Accuracy = 89%	71-97%	CNN (MobileNetV2, ResNet, Xception)
Irrigation Optimization	14	Water savings = 28%	12-44%	Reinforcement Learning
Nutrient Management	9	Fertilizer reduction = 31%	18-45%	Decision Tree/Random Forest

Quality Assessment

Study quality was assessed using adapted criteria from existing agricultural AI systematic reviews . Criteria included: clear problem definition (present/absent); appropriate ML architecture justification (present/absent); adequate dataset description (present/absent); appropriate validation method (cross-validation/external/holdout); reporting of uncertainty metrics (present/absent); and discussion of limitations (present/absent). Each study received a quality score from 0 to 6.

Results

ML Architectures and Performance

The 124 included studies employed diverse ML architectures. Ensemble methods—random forest and gradient boosting—were most common for yield prediction (47 studies), followed by deep learning architectures including CNNs and LSTM networks (31 studies). For crop health monitoring, CNNs dominated (28 studies). For resource optimization, reinforcement learning and decision tree approaches were most frequent (18 studies).

Performance varied substantially by application domain and crop type. Across yield prediction studies reporting R^2, the median value was 0.84 (interquartile range 0.76 to 0.91). Ensemble methods outperformed single-model approaches in 78 percent of direct comparisons. Deep learning achieved higher maximum performance (R^2 up to 0.94) but also greater variability (standard deviation 0.11 versus 0.07 for ensemble methods), suggesting sensitivity to dataset characteristics.

Evidence for Sustainability Outcomes

Linking ML implementation to sustainability outcomes proved challenging, as only 34 studies (27 percent) directly measured agronomic or environmental outcomes rather than technical performance metrics. Among these, the most frequently documented outcomes were water use reduction (median 28 percent, range 12 to 44 percent from 14 studies), fertilizer reduction (median 31 percent, range 18 to 45 percent from 9 studies), and yield increase (median 12 percent, range 4 to 28 percent from 22 studies).

However, the quality of outcome evidence was concerning. Only 8 studies employed randomized controlled designs comparing ML-based management to counterfactual conditions. The remainder used pre-post comparisons, simulation-based counterfactuals, or uncontrolled field demonstrations, all of which are vulnerable to confounding and selection bias. Moreover, the duration of outcome measurement was typically a single growing season; multi-year studies were extremely rare (3 studies total). This temporal limitation is significant because the benefits of precision agriculture often accumulate over multiple seasons, while year-to-year climate variability can obscure treatment effects in single-season studies.

Implementation Barriers

Implementation barriers were explicitly discussed in 71 studies (57 percent). Data-related barriers were most frequently mentioned (63 studies), including insufficient training data (47 studies), poor data quality (31 studies), and lack of data standardization (28 studies). Infrastructure barriers followed (42 studies), including inadequate connectivity (34 studies), lack of sensor deployment (29 studies), and insufficient computing capacity (18 studies). Economic barriers were noted in 38 studies, primarily regarding technology cost (35 studies) and return on investment uncertainty (22 studies).

Notably, only 12 studies discussed barriers specifically relevant to smallholder farmers, despite the global importance of smallholder systems for food security and environmental outcomes. This represents a significant gap in the literature.

Discussion

The findings of this systematic review reveal a field at an important inflection point. ML models for sustainable agriculture have achieved impressive technical performance, with ensemble and deep learning architectures consistently outperforming traditional approaches across yield prediction, disease detection, and resource optimization. The best-performing models achieve accuracy metrics—R^2 values

above 0.90, classification accuracies above 95 percent—that would have seemed implausible a decade ago. This technical progress is real and should not be dismissed.

However, the gap between technical capability and practical impact remains substantial and, in some respects, widening. The models that achieve the highest accuracy in research settings are often those that require precisely the data and infrastructure that are unavailable in the agricultural contexts where sustainability improvements are most needed. A CNN that achieves 96 percent validation accuracy on a curated dataset of high-resolution images captured under controlled lighting will perform substantially worse on farmer-captured images from a smartphone in variable field conditions—yet this performance degradation is rarely quantified or addressed.

The evidence base for sustainability outcomes is weaker than commonly acknowledged. Despite extensive claims about ML's potential to reduce environmental impact, rigorous evidence from randomized controlled trials or quasi-experimental designs is extremely limited. Most studies report technical metrics rather than agronomic or environmental outcomes, and even when outcomes are reported, study designs are typically inadequate for causal inference. This does not mean ML does not work; it means the field has not yet met evidentiary standards that would be considered minimal in medicine, public health, or development economics.

Several limitations of this review warrant acknowledgment. First, despite systematic search protocols, relevant studies may have been missed, particularly those published in non-English languages or in regional journals not indexed in major databases. Second, publication bias toward positive results likely inflates reported performance metrics; studies finding null or negative results are systematically less likely to be published. Third, the rapid pace of ML development means that findings from even recent studies may not reflect current state-of-the-art.

Future research must prioritize three directions. First, the field urgently needs standardized evaluation protocols that enable meaningful cross-study comparison and require reporting of agronomic or environmental outcomes alongside technical metrics. Second, implementation research in smallholder contexts must expand dramatically; the current geographic and economic concentration of ML-for-agriculture research is incompatible with global sustainability goals. Third, multi-year randomized trials evaluating ML-based management against counterfactuals are needed to establish causal evidence for sustainability outcomes.

Conclusion

Machine learning holds genuine promise for sustainable agriculture, offering the capacity to optimize input use, monitor crop health, and predict yields with unprecedented accuracy. This systematic review documents substantial technical progress across ensemble and deep learning architectures, with performance metrics that would have seemed aspirational a decade ago.

Yet promise is not proof, and technical accuracy is not practical impact. The field's most significant challenge is no longer algorithmic; it is translational. The models that achieve the highest research accuracy are often the least deployable in the agricultural contexts where they are most needed. Data infrastructure gaps, economic barriers, and the specific challenges of smallholder systems remain systematically underexplored. Rigorous evidence linking ML implementation to measurable sustainability outcomes—water saved, fertilizer reduced, emissions avoided—remains remarkably sparse.

The path forward requires recalibrating research priorities. Accuracy maximization cannot remain the sole or primary objective. Future work must prioritize external validation across diverse contexts, standardized outcome reporting, implementation science in smallholder systems, and rigorous causal evaluation designs. Without these shifts, ML for sustainable agriculture risks becoming a technically impressive solution in search of a problem it can actually solve.

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