



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(5): 383-388
Received: 13-02-2026
Accepted: 21-03-2026

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Emerging trends in precision agriculture and machine learning for rice production enhancement

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DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i5Se.5596>

Abstract

Rice is one of the most important staple crops worldwide, playing a critical role in global food security and rural livelihoods. However, increasing population pressure, climate variability, water scarcity, declining soil fertility, and labor shortages continue to challenge sustainable rice production. In recent years, precision agriculture combined with artificial intelligence (AI) and machine learning (ML) has emerged as a transformative approach for improving productivity, resource-use efficiency, and environmental sustainability in rice farming systems. Machine learning-based yield prediction models achieve R^2 values ranging from 0.65 to 0.95, with random forest and deep learning models consistently outperforming traditional approaches. Disease detection models, particularly those based on convolutional neural networks (CNNs), report classification accuracies between 82per cent and 98per cent, while remote sensing-driven nutrient and water management approaches demonstrate input-use efficiency improvements of 15-35per cent. Despite these advances, critical gaps persist, including limited model generalizability across agro-ecological regions and lack of standardized datasets. Overall, the convergence of precision agriculture and machine learning technologies represents a promising pathway toward achieving higher productivity, improved resource efficiency, and sustainable rice production under evolving global agricultural challenges.

Keywords: Precision agriculture, Artificial intelligence, machine learning, remote sensing, yield prediction and crop management

1. Introduction

Rice (*Oryza sativa* L.) is a foundational staple crop cultivated across diverse agro-ecological zones and sustains more than half of the global population. With rising demand driven by population growth and dietary transitions, enhancing rice productivity while minimizing environmental impacts has become a critical scientific and policy priority (Alexandratos *et al.*, 2012; Tilman *et al.*, 2011) ^[1, 30]. Conventional rice production systems have historically relied on empirical field practices, periodic sampling, and labor-intensive management. However, increasing climatic variability, declining labor availability, and resource constraints necessitate the adoption of more efficient and adaptive approaches. Precision agriculture (PA) has emerged as a transformative paradigm that enables site-specific, data-driven crop management through the integration of sensors, remote sensing, geospatial tools, and automation technologies (Lobell *et al.*, 2011) ^[19]. In parallel, advances in artificial intelligence (AI) and machine learning (ML) have significantly enhanced the ability to process large, complex agricultural datasets and generate actionable insights. AI broadly refers to computational systems capable of performing tasks that typically require human intelligence, including pattern recognition, decision-making, and predictive analytics (Russell *et al.*, 2020) ^[26]. Within this domain, most agricultural applications fall under narrow (applied) AI, which is designed to perform specific tasks (e.g., disease classification or yield prediction), as opposed to general AI, which aims to replicate broader human cognitive abilities. ML, a subset of AI, enables systems to learn from data and improve performance without explicit programming, making it particularly suitable for dynamic and data-intensive agricultural systems (Mitchell, 1997) ^[20]. The integration of AI/ML within PA frameworks facilitates real-time monitoring, predictive modeling, and decision support,

thereby improving crop productivity, resource-use efficiency, and resilience to environmental stressors (Liakos *et al.*, 2018)^[18]. Applications in rice systems include yield estimation, pest and disease detection, water and nutrient management, and automated advisory systems. Despite rapid advancements, the field remains fragmented, with variability in data sources, model performance, and scalability across regions.

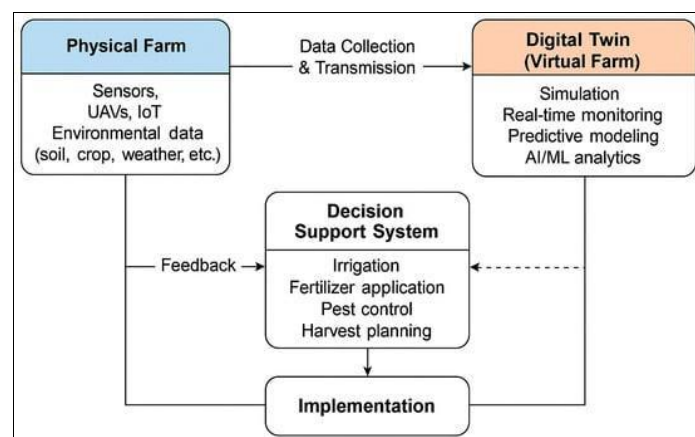
2. Definitions and Evolution of Precision Agriculture

Precision agriculture (PA) is broadly defined as the management of spatial and temporal variability in crop production systems to optimize productivity, resource-use efficiency, and environmental sustainability (Stafford, 2000)^[29]. The concept emerged in the early 1990s, driven by the adoption of Global Positioning System (GPS) technologies and yield monitoring tools, which enabled site-specific field management for the first time (Pierce *et al.*, 1999)^[24]. Over the past three decades, PA has evolved significantly, transitioning from basic geospatial mapping to advanced, data-driven systems integrating remote sensing, Internet of Things (IoT), automation, and artificial intelligence. In rice-based systems, PA is particularly relevant due to the crop's sensitivity to water management, nutrient cycling, and biotic stresses. Flooded rice ecosystems require precise irrigation control to balance yield, methane emissions, and labor requirements (Bouman *et al.*, 2007)^[2], while dynamic redox conditions influence nutrient transformations, necessitating site-specific nutrient management strategies (Fageria *et al.*, 2011)^[8].

Evolution of Precision Agriculture Technologies- A conceptual evolution of PA technologies can be summarized as follows:

- 1990s: Introduction of GPS-based yield monitoring and soil mapping
- 2000s: Expansion of Geographic Information Systems (GIS) and satellite-based remote sensing
- 2010s: Emergence of UAVs (drones), proximal sensors, and early machine learning applications
- 2020s: Integration of AI/ML, IoT-enabled smart farming, cloud computing, and digital twin systems

This progression highlights a shift from data collection toward intelligent, automated decision-support systems, enabling real-time and predictive farm management.



Data source: IoT soil moisture sensors, TDR probes, Automatic weather stations (AWS), meteorological APIs, Landsat-8/9 (NASA/USGS), IoT gateways

Fig 1: IoT- and Machine Learning-Based Digital Twin Model for Rice Production Management

2.1. Core Components of Precision Agriculture

Precision agriculture systems are commonly structured around

four interrelated core components, which together enable data-driven and site-specific crop management:

2.1.1. Data Acquisition and Sensing Technologies

This component involves the collection of high-resolution spatial and temporal data using tools such as satellites, UAVs (drones), ground-based sensors, and IoT devices. These technologies capture critical information on soil properties, crop health, weather conditions, and water status. In rice systems, remote sensing indices (e.g., NDVI), soil moisture sensors, and water level monitoring are widely used to assess crop conditions and guide management decisions (Fountas *et al.*, 2015)^[9].

2.1.2. Data Processing and Analytical Modeling

Collected data are processed and analyzed using statistical models, geospatial tools, and increasingly, AI/ML algorithms. Techniques such as machine learning, deep learning, and geostatistical analysis enable pattern recognition, yield prediction, disease detection, and stress classification. This component transforms raw data into actionable insights, forming the backbone of decision-support systems.

2.1.3. Decision-Making and Variable Rate Application (VRA)

Based on analytical outputs, site-specific management decisions are implemented through technologies such as variable rate application of fertilizers, irrigation, and pesticides. In rice cultivation, this includes precision nitrogen management, controlled irrigation scheduling, and targeted pest control. Automated machinery and smart irrigation systems play a critical role in executing these decisions efficiently.

2.1.4. Evaluation, Feedback, and Optimization

The final component involves assessing the outcomes of implemented strategies through yield monitoring, environmental impact assessment, and economic analysis. Feedback loops allow continuous system improvement by refining models and management practices. This iterative process is essential for adapting PA systems to varying agro-ecological conditions and improving long-term sustainability.

2.2. Sensing Technologies in Precision Rice Systems

2.2.1. Satellite Remote Sensing

Satellite imagery (e.g., Landsat, Sentinel-2) provides multispectral, large-scale, and temporally consistent data, making it highly suitable for monitoring crop phenology, vigor, and biomass across field to regional scales (Wulder *et al.*, 2019)^[33]. Vegetation indices such as NDVI (Normalized Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index), and EVI (Enhanced Vegetation Index) are widely applied to estimate crop health and biomass (Huete *et al.*, 2002)^[12]. In rice systems, spectral responses are strongly correlated with canopy structure and chlorophyll content, enabling early detection of stress conditions such as nutrient deficiency and drought at large spatial scales (Gnyp *et al.*, 2014)^[11].

2.2.2. Unmanned Aerial Systems (UAS)

Unmanned Aerial Systems (UAS), commonly referred to as drones, provide ultra-high spatial resolution data through sensors such as multispectral, hyperspectral, thermal, and LiDAR systems. These platforms can detect within-field variability at centimeter-level resolution, enabling precise identification of micro-scale stress patterns, including waterlogging, lodging, and nutrient deficiencies (Zhang and Kovacs, 2012)^[35]. The

integration of UAS data with AI/ML models has significantly enhanced precision in rice systems by capturing fine-scale canopy heterogeneity that is not detectable through satellite imagery alone (Zheng *et al.*, 2018) ^[36].

2.2.3. Ground Sensors and IoT Networks

Ground-based (proximal) sensors and Internet of Things (IoT)

networks enable continuous, real-time monitoring of soil and environmental parameters, including soil moisture, electrical conductivity, temperature, and nutrient dynamics (Ojha *et al.*, 2015) ^[22]. In rice cultivation, IoT-enabled systems are particularly valuable for automated irrigation management and nutrient optimization, improving both efficiency and sustainability (Tzounis *et al.*, 2017) ^[31].

Table 1: Comparison of Sensing Technologies for Rice Precision Agriculture Systems

Parameter	Satellite Remote Sensing	UAS (Drones)	Ground Sensors and IoT	References
Spatial Resolution	Moderate (10-30 m)	Very high (cm-level)	Point-based (highly localized)	Zhang and Kovacs (2012) ^[35] ; Mulla (2013) ^[21] ; Tzounis <i>et al.</i> , 2017 ^[31]
Temporal Resolution	Medium to high (5-16 days revisit)	Flexible (on-demand flights)	Continuous (real-time)	Xue and Su (2017); Wolfert <i>et al.</i> , 2017 ^[32]
Data Types	Multispectral, temporal imagery	Multispectral, hyperspectral, thermal, LiDAR	Soil moisture, nutrients, temperature, EC	Liakos <i>et al.</i> , 2018 ^[18] ; Kamilaris and Prenafeta-Boldú (2018) ^[16] ; Zhang and Kovacs (2012) ^[35]
Cost	Low to moderate (often free data)	Moderate to high (equipment and operation)	Moderate (installation + maintenance)	Mulla (2013) ^[21] ; Tzounis <i>et al.</i> , 2017 ^[31]
Scalability	High (regional to global coverage)	Medium (field-scale applications)	Low to medium (field-specific deployment)	Wolfert <i>et al.</i> , 2017 ^[32]
Suitability	Large-scale and regional monitoring	Field-level precision farming	Site-specific monitoring and automation	Liakos <i>et al.</i> , 2018 ^[18]

2.3. Integration of Data and Decision Support Systems

The integration of multi-source data is central to the effectiveness of precision agriculture. Geographic Information Systems (GIS) provide a spatial framework for combining heterogeneous datasets, including satellite imagery, UAS observations, soil maps, and in-situ sensor data. When coupled with temporal datasets such as weather variables and crop phenology, these integrated data streams form the foundation for predictive AI/ML models (Mulla, 2013) ^[21]. Decision Support Systems (DSS) built on these integrated datasets enable stakeholders to make data-driven, site-specific management decisions. In rice systems, DSS applications include optimizing irrigation scheduling, fertilizer application, and pest management strategies at field or sub-field scales (Sørensen *et al.*, 2011) ^[28]. Increasingly, DSS platforms are incorporating AI-driven analytics and cloud-based architectures, allowing real-time recommendations and improved accessibility for farmers and agronomists.

3. Overview of AI/ML Techniques in Agriculture

AI and ML encompass a wide spectrum of computational techniques that extract patterns from data and generate predictive insights. In rice production, popular AI/ML methods include:

Supervised learning algorithms

- Linear and logistic regression
- Support Vector Machines (SVM)
- Random Forests (RF)
- Gradient Boosting Machines (GBM)
- Deep learning and neural networks:
- Convolutional Neural Networks (CNN) for image classification
- Recurrent Neural Networks (RNN)
- Long Short-Term Memory (LSTM) for time series analysis
- Unsupervised learning: Clustering methods (k-means, hierarchical clustering) for identifying patterns in unlabeled data
- Reinforcement learning: Optimization of sequential decision processes (e.g., irrigation scheduling)

These techniques can model non-linear and complex relationships in agricultural datasets, making them particularly useful for predicting yield, detecting stress, and guiding field management.

3.1. Feature Engineering and Data Preprocessing

A critical step in ML workflows is feature engineering—transforming raw sensor and environmental data into meaningful predictors for models. Common features include spectral indices (NDVI, PRI, MSAVI) texture measures from imagery, soil nutrient indices, and weather variables such as cumulative growing degree days (Delegido *et al.*, 2011) ^[6]. Preprocessing steps such as data cleaning, normalization, and gap filling are essential to ensure model robustness and generalization (García *et al.*, 2015) ^[10].

3.2. Model Training and Validation

Model development typically follows a supervised learning pipeline:

- **Dataset Splitting:** Training, validation, and testing subsets
- **Cross-validation:** Ensuring model generalizability
- **Hyperparameter Optimization:** Using grid search, Bayesian optimization, or genetic algorithms to tune model parameters

Proper validation is vital, especially in rice systems where spatial and temporal heterogeneity can bias model performance if not properly addressed (Roberts *et al.*, 2017) ^[25].

4. Yield Prediction and Forecasting

Yield estimation is one of the most widely studied applications of AI/ML in rice production given its importance for food security and market planning.

4.1. Traditional Approaches vs. AI/ML

Traditional yield models rely on crop growth simulation or empirical regression based on field trials (Jones *et al.*, 2003) ^[15]. While useful, these models often require extensive parameterization and may not capture complex environmental

interactions. AI/ML models can learn directly from multi-dimensional datasets without explicit assumptions about underlying physiological processes. Studies have shown that ML models can outperform traditional statistical models in predicting rice yield using combined inputs from satellite imagery, weather data, and soil properties (Jeong *et al.*, 2016) ^[14].

4.2. Satellite Data Based Yield Prediction

Satellite time series (e.g. Sentinel-2) provide periodic coverage of crop growth stages. When combined with weather and soil data, ML models such as Random Forest and Gradient Boosting have been used to predict rice yield with high accuracy ($\sim R^2 > 0.8$) weeks before harvest (Cao *et al.*, 2021) ^[3].

Data Sources: (MODIS, 2025); (FAOSTAT, 2025), (IRRI Rice Knowledge Bank); (NOAA Climate Data)

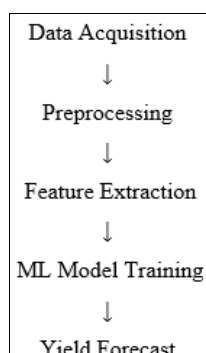


Fig 2: Framework for Satellite Remote Sensing-Based Crop Yield Prediction

4.3. UAV and Proximal Sensor Based Yield Models

High-resolution UAS data capture in-field variability of canopy structure and biomass. CNN and LSTM models trained on UAS imagery have been shown to accurately estimate rice biomass and yield at critical phenological stages, enabling within-season decision support.

4.4. Time Series and Deep Learning Models

LSTM and Temporal Convolutional Networks (TCN) are particularly suited for modeling sequential crop growth patterns. These models capture temporal dynamics of vegetation indices and weather sequences to improve yield forecasting across growing seasons (Khaki and Wang, 2019) ^[17].

5. Disease, Pest, and Stress Detection

Timely detection of diseases, pests, and abiotic stresses is essential for effective management in rice systems.

5.1. Image-Based Disease Recognition

Diseases such as rice blast, bacterial leaf blight, and sheath blight significantly impact yield and quality. Imaging (RGB, multispectral, hyperspectral) of leaves and canopy combined with ML classifiers (SVM, RF) or deep CNNs can distinguish healthy from diseased plants (Chen *et al.*, 2020) ^[5]. CNN based models achieve high classification accuracy (>90per cent) in controlled datasets. Hyperspectral imaging improves detection sensitivity across stress gradients

5.2. UAV-enabled Stress Mapping

UAS mounted thermal and multispectral sensors can detect water stress and nutrient deficiencies before visual symptoms

appear, enabling early intervention (Shi *et al.*, 2016) ^[27]. Indices such as the Crop Water Stress Index (CWSI) derived from thermal imagery serve as inputs to ML models to classify stress levels (Jackson *et al.*, 1981) ^[13].

5.3. Integrated Pest Management (IPM)

AI models can integrate pest trap counts, weather data, and crop phenology to forecast pest outbreaks. For example, decision trees and Bayesian networks predict rice stem borer outbreaks with lead time sufficient for targeted interventions (Peng and Liu, 2021) ^[23].

6. Resource Optimization and Decision Support

Precision management aims to optimize resource use (water, fertilizer, pesticides) while maintaining or increasing yield.

6.1. Irrigation Management

Rice is traditionally grown under flooded conditions, which demands significant water and contributes to methane emissions. PA systems using soil moisture sensors and weather forecasts, combined with AI/ML controllers, enable alternate wetting and drying (AWD) regimes that save water and reduce emissions (Carrijo *et al.*, 2017) ^[4]. Reinforcement learning models have been developed to optimize irrigation schedules under varying climatic conditions.

6.2. Fertilizer Management

Variable rate fertilizer application guided by soil property maps, crop growth status, and ML-based nutrient response models can improve fertilizer use efficiency and reduce environmental losses (Yao *et al.*, 2013) ^[34]. Spatially resolved management zones derived from clustering approaches support targeted nitrogen applications that enhance yield while minimizing runoff.

6.3. Autonomous Machinery and Robotics

Autonomous tractors, robotic weeders, and variable rate applicators equipped with AI perception systems are increasingly used in rice production. Vision-based weed detection systems (e.g., using YOLO, Faster-R CNN) enable selective herbicide application, reducing chemical use and labor (Kamilaris and Prenafeta-Boldú, 2018) ^[16].

7. Data Ecosystems and Integration Frameworks

7.1. Big Data Architectures

Modern PA systems generate large volumes of data across temporal and spatial scales. Cloud computing, edge analytics, and distributed databases are required to manage these datasets. Data standards, interoperability, and semantic data models are crucial for integrating sensor streams, imagery, and farm records (Wolfert *et al.*, 2017) ^[32].

7.2. Digital Twins and Simulation

Digital twin frameworks virtual representations of rice fields that mirror real-time conditions can simulate responses to management scenarios using AI-enhanced crop models. These systems support scenario analysis for irrigation, fertilization, and harvesting decisions.

7.3. Farmer Platforms and Mobile Apps

User-centric applications that provide actionable recommendations based on AI/ML analytics are essential for adoption. Mobile decision support apps that translate sensor data into fertilizer schedules, disease alerts, and irrigation advisories

support farmer decision making in real time (Eastwood *et al.*, 2019) [7].

8. Challenges and Limitations

8.1. Data Availability and Quality

AI/ML models are highly data dependent. In many rice-growing regions, there is a lack of high-quality, labeled datasets that capture phenological, environmental, and management variability. Data gaps, inconsistencies, and sensor noise can undermine model performance.

8.2. Model Interpretability

Complex AI/ML models, particularly deep learning systems, can be “black boxes,” making it difficult for farmers and agronomists to understand why specific recommendations are made. This limits trust and adoption. Explainable AI (XAI) methods are needed to provide transparent insights into model outputs.

8.3. Scalability and Computational Resources

Processing high-resolution imagery and training complex models require substantial computational resources that may be inaccessible to smallholder farmers and institutions in developing regions.

8.4. Adoption Barriers

Socio-economic factors, digital literacy, cost of technology, and infrastructure (e.g., connectivity) constrain adoption of PA and AI/ML solutions in many rice communities. Extension services, capacity building, and public-private partnerships play a critical role in bridging these gaps.

9. Future Research Directions

9.1. Explainable and Trustworthy AI

Developing AI systems that are interpretable and provide rationale for decisions can foster adoption among stakeholders. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can be adapted for agricultural models.

9.2. Transfer Learning and Low-Data Models

Many rice growing regions lack large datasets. Transfer learning enables models trained in data-rich contexts to be adapted to new regions with limited data. Few-shot learning methods and synthetic data generation can further address data scarcity.

9.3. Multi-Modal Data Fusion

Integration of multi-source data- satellite, UAS, proximal sensors, weather data, and farmer records using advanced data fusion frameworks can improve predictive accuracy and resilience.

9.4. Integration with Climate Risk Models

Linking AI/ML models with climate projections can help forecast yield under future climate scenarios and support long-term planning for climate-smart rice systems.

9.5. Socio-Economic and Policy Research

Studying the socio-economic impact of PA and AI/ML adoption, including labor implications, equity, and market integration, can inform policies that support sustainable and inclusive innovation.

10. Conclusion

Precision agriculture, empowered by artificial intelligence and machine learning, represents a paradigm shift in rice production. Through high-resolution sensing, data integration, predictive analytics, and automated control, these technologies enable enhanced monitoring, diagnosis, and decision support that can improve resource efficiency, yield, and sustainability. While significant progress has been made, key challenges remain in data quality, model interpretability, infrastructure, and adoption. Addressing these challenges requires interdisciplinary research, inclusive frameworks, and collaborative innovation between researchers, technology developers, policymakers, and farming communities. With strategic investment and continued advancement, AI-enhanced PA can play a pivotal role in building resilient and sustainable rice production systems for the future.

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