



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(7): 121-128
Received: 11-05-2026
Accepted: 15-06-2026

E Priyankabai
Research Associate, Department of
Agronomy, Agricultural Research
Station, Kadiri, ANGRAU, Sri Sathya
Sai, Andhra Pradesh, India

M Bhanu Soumya
Assistant Professor, Department of
Agronomy, College of Agriculture,
Annamacharya University, Rajampet,
Kadapa, Andhra Pradesh, India

Dr. Manish Kushwaha
Assistant Professor, Department of
Agricultural Engineering and Food
Technology, AKS University, Satna,
Madhya Pradesh, India

Vikash Singh
Assistant Professor, Department of
Agricultural Engineering and Food
Technology, AKS University, Satna,
Madhya Pradesh, India

S Glory Madhuri
M.Sc. (Ag), Department of Agronomy,
S. V. Agricultural College, Tirupati,
Acharya N G Ranga Agricultural
University, Guntur, Andhra Pradesh,
India

Abhinish Kumar
Research Consulate, International
Water Management Institute, New
Delhi, India

A Ajay Raja
Research Scholar, Department of
Vegetable Science, Horticultural College
and Research Institute, Tamil Nadu
Agricultural University, Coimbatore,
Tamil Nadu, India

Battala Sheshagiri
MBA Agribusiness, Department of
Agricultural Economics, Naini
Agricultural Institute, Sam
Higginbottom University of
Agriculture, Technology and Sciences,
Prayagraj, Uttar Pradesh, India

Corresponding Author:
E Priyankabai
Research Associate, Department of
Agronomy, Agricultural Research
Station, Kadiri, ANGRAU, Sri Sathya
Sai DIST, Andhra Pradesh, India

Artificial intelligence technologies in agronomy: Current trends and future perspectives: A review

E Priyankabai, M Bhanu Soumya, Manish Kushwaha, Vikash Singh, S Glory Madhuri, Abhinish Kumar, A Ajay Raja and Battala Sheshagiri

DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i7Sb.5934>

Abstract

The global agricultural sector faces mounting pressures from climate variability, resource scarcity, and the imperative to feed a projected population of nearly ten billion by 2050. Conventional agronomic practices have proven increasingly insufficient in addressing the spatial and temporal heterogeneity inherent in agricultural systems. Artificial intelligence (AI) has emerged as a transformative paradigm, offering data-driven methodologies that span from predictive crop modelling to autonomous field management. This critical review synthesizes the current landscape of AI applications in agronomy, examining the scientific foundations of machine learning, deep learning, computer vision, and emerging generative architectures. The manuscript critically evaluates the deployment of Random Forest, CNN, YOLO, reinforcement learning, and IoT-integrated systems across seven major application domains, including yield prediction, precision nutrient management, irrigation scheduling, weed and pest surveillance, climate-smart agronomy, and decision support systems. The review specifically examines why high reported accuracies on benchmark datasets frequently fail to translate into reliable field performance, analyzing the technical, economic, and social barriers that constrain adoption. While significant advances have been demonstrated in controlled environments, persistent challenges including data scarcity, model generalization failures, high infrastructure costs, farmer trust deficits, and algorithmic opacity continue to impede widespread deployment. The review identifies six transformative research trends, from edge computing and explainable AI to digital twin architectures and federated learning and proposes a strategic roadmap for transitioning AI from experimental promise to agronomic practice. The findings underscore that realizing the full potential of AI in agronomy demands not merely algorithmic innovation but interdisciplinary collaboration, farmer-centric design, and policy frameworks that address data governance, ethical considerations, and equitable access across diverse agricultural systems.

Keywords: Artificial intelligence, precision agriculture, machine learning, deep learning, computer vision, decision support systems, smart farming

Introduction

Global agriculture confronts a convergence of unprecedented challenges that threaten the sustainability and productivity of food systems worldwide. Projections indicate that agricultural output must increase by approximately 70 percent over the next three decades to meet the nutritional demands of a growing population, yet this expansion must occur within planetary boundaries that constrain water use, nutrient fluxes, and greenhouse gas emissions^[47]. The yield gaps the difference between realized and attainable yields remains substantial across both developed and developing regions, driven by suboptimal management decisions, climate variability, and the inherent complexity of biological systems^[56]. Traditional agronomic decision-making, relying on empirical observation, static fertiliser recommendations, and calendar-based irrigation schedules, lacks the precision required to manage spatially variable field conditions at the scale demanded by sustainable intensification^[52].

The emergence of digital agriculture, underpinned by advances in sensing technologies, computational infrastructure, and algorithmic sophistication, has catalyzed a fundamental rethinking of how agronomic knowledge is generated and applied^[13]. Within this paradigm, AI represents the most disruptive technology, enabling systems that can learn from historical data,

recognize complex patterns in images and time series, and generate recommendations that adapt dynamically to changing conditions ^[1]. Early applications of AI in agriculture were limited by computational constraints and the absence of structured data repositories; however, the proliferation of Internet of Things (IoT) devices, unmanned aerial vehicles (UAVs), and open satellite missions has created an ecosystem in which data-driven agronomy is increasingly necessary ^[17].

Despite the rapid expansion of AI research in agronomy, a critical gap persists between algorithmic performance in controlled settings and practical utility under field conditions ^[6], ^[11]. Many published studies report accuracies exceeding 90 percent on benchmark datasets, yet these models frequently fail when confronted with the biological variability, environmental noise, and management heterogeneity characteristic of commercial farming ^[49]. This discrepancy raises fundamental questions about the robustness, interpretability, and scalability of AI systems designed for agricultural deployment. Furthermore, the ethical dimensions of algorithmic decision-making in food systems including questions of data ownership, algorithmic bias, and the displacement of agronomic expertise remain insufficiently addressed in the technical literature ^[54].

The present review offers a critical examination of AI technologies in agronomy, moving beyond descriptive summaries to evaluate the comparative strengths and limitations of methodological approaches, identify structural barriers to adoption, and articulate actionable directions for future research. The manuscript distinguishes itself through its emphasis on the gap between experimental performance and field-scale utility, its analysis of emerging generative AI applications, and its integration of technical, economic, and ethical perspectives. The scope encompasses peer-reviewed literature from 2014 to 2026, with particular attention to systematic reviews and comparative studies that provide meta-level insights into the trajectory of the field.

Conceptual Foundation of AI in Agronomy

Artificial Intelligence

Artificial intelligence, broadly defined as the capacity of computational systems to perform tasks that typically require human cognition, encompasses methodologies ranging from rule-based expert systems to sophisticated neural architectures ^[12]. In the agronomic context, AI systems process heterogeneous data streams including spectral imagery, soil profiles, meteorological records, and crop phenological observations to derive actionable insights that would be infeasible through manual analysis ^[1]. The evolution of AI in agriculture has progressed through distinct phases, from early expert systems that encoded heuristic agronomic knowledge, through statistical learning approaches, to the current era of deep learning and foundation models ^[47].

Machine Learning

Machine learning (ML) constitutes the dominant methodological paradigm within agronomic AI research, providing algorithms that improve performance through exposure to training data ^[2]. Supervised learning approaches, in which models are trained on

labelled datasets to predict outcomes such as yield, disease incidence, or nutrient status, account for the majority of published applications ^[3]. Algorithms including Random Forest, Support Vector Machines (SVM), and gradient boosting frameworks have demonstrated efficacy in agronomic prediction due to their capacity to handle high-dimensional, nonlinear relationships ^[9]. Unsupervised learning techniques, including clustering and dimensionality reduction, have found application in delineating management zones without the requirement for ground-truth labels ^[20]. Reinforcement learning, though less extensively explored, offers a promising framework for sequential decision-making in contexts such as irrigation scheduling and autonomous navigation ^[35].

Deep Learning

Deep learning represents a subfield of ML characterized by neural networks with multiple layers of abstraction, enabling automatic extraction of hierarchical features from raw data ^[4]. Convolutional Neural Networks (CNNs) have become the architecture of choice for image-based agronomic tasks, achieving state-of-the-art performance in plant disease detection, weed identification, and crop phenotyping ^[43]. Recurrent Neural Networks (RNNs) and their Long Short-Term Memory (LSTM) variants excel in processing sequential data such as time-series weather records and sensor measurements ^[26]. More recently, Vision Transformers (ViTs) have emerged as alternatives to CNNs for image classification, leveraging self-attention mechanisms to capture global spatial relationships; however, their computational demands limit applicability in resource-constrained agricultural settings ^[41].

Computer Vision

Computer vision constitutes a critical interface between physical crop conditions and digital agronomic systems, enabling automated interpretation of visual information from RGB, multispectral, and hyperspectral imagery ^[44]. Image-based diagnostics have advanced from simple vegetation index computation to sophisticated semantic segmentation models that can localize and classify individual plants and pathological symptoms at pixel-level resolution ^[59]. The integration of computer vision with UAV platforms has revolutionized field-scale crop monitoring, providing centimetre-resolution data that capture spatial variability inaccessible from satellite observation alone ^[42].

Generative AI and Large Language Models

The emergence of generative AI and Large Language Models (LLMs) represents a nascent but potentially transformative frontier in agronomic advisory systems. These architectures, originally developed for natural language processing, are increasingly being adapted for multimodal applications that combine textual agronomic knowledge with visual and sensor data ^[14]. While current implementations remain largely experimental, the capacity of LLMs to synthesize complex information positions them as promising components of next-generation decision support systems ^[8].

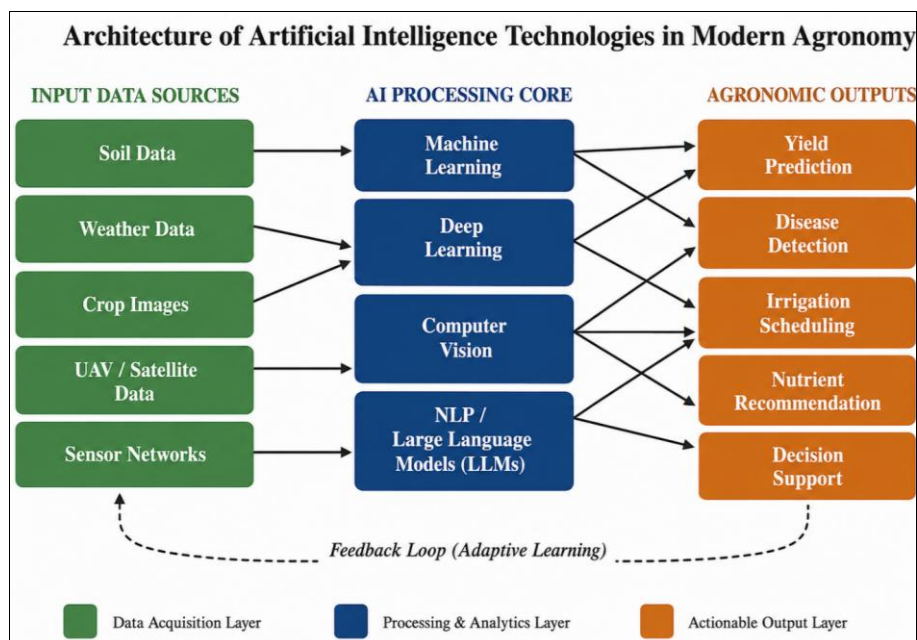


Fig 1: Conceptual architecture illustrating the flow of information from heterogeneous input data sources (soil, weather, imagery, sensor networks) through AI processing layers (machine learning, deep learning, computer vision, natural language processing) to actionable agronomic outputs including yield prediction, disease detection, irrigation scheduling, nutrient recommendation, and integrated decision support. The feedback loop represents adaptive model refinement through continuous field data acquisition.

Major AI Technologies Used in Agronomy

Machine Learning Models

Traditional ML algorithms continue to occupy a significant position in agronomic research, particularly in applications where interpretability, computational efficiency, and limited training data constrain the feasibility of deep learning [10]. Random Forest algorithms have demonstrated robust performance across diverse crop yield prediction tasks, exhibiting lower sensitivity to hyperparameter configuration and reduced tendency toward overfitting [24], [37]. SVM classifiers have proven effective in soil type classification and crop mapping, though their computational cost scales poorly with large datasets [29]. Gradient boosting frameworks, particularly XGBoost, have achieved competitive accuracy in yield forecasting, often outperforming neural network approaches when training data are sparse [25]. A critical limitation across all traditional ML approaches is their reliance on manually engineered features, which demands substantial domain expertise and may inadvertently discard informative signal components [32], [36].

Deep Learning Architectures

Deep learning has catalyzed transformative advances in image-intensive agronomic applications. CNN architectures including VGG, ResNet, and EfficientNet have established benchmarks for plant disease classification, frequently achieving diagnostic accuracies exceeding 95 percent on curated datasets [46]. Object detection frameworks such as YOLO and Faster R-CNN enable real-time localization of weeds, pests, and diseased tissues, supporting precision intervention systems [41]. U-Net and its variants have become standard architectures for semantic segmentation tasks including crop row detection and canopy cover estimation [59]. The computational demands of these architectures present a significant barrier to field deployment, particularly in resource-constrained settings where inference must occur on edge devices [15]. Vision Transformers have demonstrated superior accuracy on several benchmarks but

require substantially larger training datasets and computational resources, limiting their current practical applicability [21].

IoT and Sensor Integration

The Internet of Things has emerged as a critical infrastructure layer for AI-enabled agronomy, providing continuous streams of in-situ data that complement remote sensing observations [16], [61]. Soil moisture sensors, weather stations, and leaf wetness monitors generate high-frequency temporal data that enable AI systems to detect crop stress conditions in near real-time [42]. Smart irrigation systems incorporating AI-driven control algorithms have demonstrated water savings of 20-40 percent compared to schedule-based approaches, though performance depends critically on sensor calibration and communication reliability [5]. The integration of IoT data streams with ML models presents significant engineering challenges, including data synchronization across heterogeneous networks and the computational burden of processing high-velocity data at the edge [44].

Remote Sensing and Satellite Analytics

Remote sensing platforms provide the spatial coverage necessary for regional-scale agronomic monitoring, with multispectral and hyperspectral instruments capturing vegetation characteristics that correlate with crop health and yield potential [57], [39]. The Normalized Difference Vegetation Index (NDVI) and its derivatives remain the most widely employed spectral metrics for crop condition assessment, though their saturation at high biomass levels limits diagnostic precision [58]. Hyperspectral imaging offers enhanced capacity for detecting early-stage nutrient deficiencies, but the dimensionality of hyperspectral data poses substantial challenges for storage, transmission, and analysis [57]. UAV-based imaging bridges the spatial resolution gap between ground sensors and satellite platforms; nevertheless, regulatory restrictions, battery limitations, and orthomosaic processing requirements constrain operational scalability [60].

Robotics and Autonomous Systems

Agricultural robotics represents the physical manifestation of AI in agronomy, translating algorithmic decisions into mechanical actions [23]. Weeding robots equipped with computer vision and precision actuation can identify and remove individual weeds without broadcast herbicide application [55]. Autonomous harvesting systems have advanced significantly for structured orchard and greenhouse environments, though handling of delicate produce under variable conditions remains an active challenge [59]. The feasibility of robotic systems in developing countries is constrained by capital costs, maintenance infrastructure, and the prevalence of smallholder farm geometries that limit operational efficiency [55].

Application Areas in Agronomy

Yield Prediction and Crop Modeling

Accurate yield prediction underpins supply chain planning, food security assessment, and insurance risk evaluation. AI-based yield models integrate multi-source data including weather records, soil properties, remote sensing observations, and management practices to generate predictions at scales ranging from individual fields to regional agro-ecological zones [24], [30]. ML approaches, particularly ensemble methods combining Random Forest and gradient boosting, have demonstrated R^2 values exceeding 0.8 for regional maize and wheat yield forecasting [26]. Deep learning architectures that process spatiotemporal sequences of satellite imagery have achieved state-of-the-art performance, capturing phenological dynamics that simpler models miss [27], [28].

A critical limitation of current yield prediction systems is their tendency to perform well under average conditions while failing to anticipate extreme weather events the scenarios in which accurate forecasting is most valuable [33]. The generalizability of yield models across cultivars, soil types, and climatic zones remains limited, with models trained in one agro-ecological region experiencing substantial accuracy degradation when transferred to new environments [34]. This domain transfer failure reflects the context-dependent nature of yield-determining processes and the insufficient representation of biological diversity in training datasets [40].

Precision Nutrient Management

Precision nutrient management aims to match fertiliser application with spatially variable crop requirements, simultaneously optimising economic returns and minimizing environmental losses [49]. AI systems contribute through two complementary pathways: image-based nutrient deficiency detection and model-driven fertiliser recommendation. Spectral indices derived from UAV and satellite imagery can detect nitrogen stress several weeks before visible symptoms manifest, enabling corrective interventions during the critical growth window [58]. ML models trained on soil test data and yield maps generate site-specific fertiliser prescriptions; compared with conventional uniform-rate fertilization, AI-guided variable-rate application has demonstrated nitrogen use efficiency improvements of 15-30 percent [18]. However, the accuracy of image-based nutrient diagnostics is sensitive to growth stage, cultivar, and environmental conditions, and calibration of spectral-nutrient relationships requires destructive sampling that limits scalability [58].

Irrigation Scheduling and Water Management

Water scarcity affects over 40 percent of the global population and poses a critical constraint to agricultural production in arid

and semi-arid regions. AI-based irrigation scheduling systems integrate soil moisture dynamics, weather forecasts, crop evapotranspiration models, and plant stress indicators to generate water application recommendations [5], [38]. Reinforcement learning frameworks have demonstrated particular promise for adaptive irrigation control, learning optimal watering policies through interaction with crop simulation environments [35]. Despite these advances, adoption of AI-based irrigation systems remains limited by the high capital cost of sensor infrastructure, system calibration complexity, and farmer risk aversion [6].

Weed Detection and Smart Weed Management

Weed competition reduces global crop yields by an estimated 10-15 percent, and the evolution of herbicide resistance has intensified the need for non-chemical management approaches [41]. Computer vision systems employing CNN and YOLO architectures can distinguish crop plants from weeds with accuracies exceeding 90 percent under controlled conditions, enabling targeted mechanical or thermal removal [4]. The transition from laboratory to field deployment has exposed significant robustness challenges, including performance degradation under variable lighting, canopy occlusion, and unrepresented weed species [44]. Manual identification by experienced agronomists remains more reliable under highly variable conditions, though AI systems offer decisive advantages in speed and the capacity to operate continuously over large areas [55].

Pest and Disease Surveillance

Early detection of pest and disease outbreaks is critical for effective crop protection, as intervention efficacy declines exponentially with infestation progression. AI-based diagnostic systems process leaf and canopy imagery to identify pathological symptoms, pest damage patterns, and vector presence [43]. Deep learning models trained on large plant pathology datasets have achieved diagnostic accuracies comparable to experienced plant pathologists for common diseases of major crops [46]. The reliability of AI diagnostic systems is constrained by the diversity of pathogen strains, the similarity of symptoms across different diseases, and the confounding effects of abiotic stress factors that mimic biotic damage [43]. False positive diagnoses carry significant economic costs through unnecessary pesticide applications, while false negatives can result in epidemic establishment.

Climate-Smart Agronomy

Climate change is increasing the frequency of extreme weather events and introducing novel stress combinations that challenge historical management experience. AI systems contribute to climate adaptation through stress prediction models that anticipate crop responses to heat, drought, and salinity based on genomic, environmental, and management data [15]. Crop advisory platforms leveraging ML integrate seasonal climate forecasts with crop simulation models to generate variety selection and planting date recommendations [19]. The development of AI tools for climate-smart agronomy must address the challenge of extrapolating from historical climate-crop relationships to novel conditions that have no direct precedent in training data [45].

Decision Support Systems

Decision Support Systems (DSS) represent the integration layer through which AI technologies deliver actionable

recommendations to agricultural practitioners [53]. Modern AI-driven DSS combine predictive models, optimization algorithms, and user interfaces to support complex management decisions [14]. Mobile-based advisory systems have proliferated in developing regions, delivering AI-generated recommendations through low-bandwidth interfaces [16]. The effectiveness of DSS depends critically on their capacity to accommodate farmer knowledge, local contextual factors, and risk preferences that are difficult to formalize algorithmically [48]. Adoption barriers include digital literacy requirements, the mismatch between algorithmic recommendations and farmer risk tolerance, and the absence of trust-building mechanisms that would enable farmers to verify AI-generated advice [54].

Current Research Trends

The AI-agronomy research frontier is characterized by several converging trends that promise to reshape the technological landscape. Multimodal AI architectures that integrate visual, textual, and sensor data streams are advancing rapidly, offering more holistic crop assessment capabilities than unimodal approaches [21]. Edge AI the deployment of compressed models on low-power field devices addresses the latency, connectivity, and privacy limitations of cloud-based inference [15]. Explainable AI (XAI) has gained substantial traction in response to the opacity of deep learning models, developing techniques that render decisions interpretable to agronomists and farmers [31]. Federated learning enables collaborative model training across multiple farms without centralizing sensitive production data [14]. Digital twin architectures virtual replicas of agricultural systems offer powerful platforms for scenario testing and prescriptive optimization [42]. Among these trends, explainable AI and edge computing appear most immediately transformative, while digital twins and foundation models represent longer-term horizons with substantial potential [22].

Major Challenges and Limitations

Technical Challenges

The technical barriers to effective AI deployment in agronomy are substantial and interconnected. Data scarcity represents the most fundamental constraint: while sensor and imaging data are proliferating, high-quality labelled datasets pairing ground-truth observations with sensor measurements remain rare [1]. The labor-intensive nature of agronomic data collection limits dataset size and diversity compared with domains such as natural language processing [7]. Poor data labelling practices propagate through training pipelines to degrade model performance in subtle ways [20]. Model drift the gradual degradation of accuracy as environmental conditions evolve beyond the training distribution poses a persistent challenge in agricultural systems characterized by non-stationary climate and pest populations [49]. Domain transfer failure, in which models trained in one agro-ecological context fail when deployed in another, reflects the site-specific nature of crop-environment interactions and insufficient diversity in training datasets [40].

Agronomic Challenges

Agricultural systems exhibit biological and environmental heterogeneity that exceeds the complexity of most industrial AI applications. Within-field variability in soil properties, microclimate, and pest pressure creates conditions that challenge the assumption of spatial stationarity underlying most ML models [18]. Biological variability including phenotypic plasticity and genotype-by-environment interactions introduces irreducible uncertainty that no algorithmic sophistication can fully eliminate

[56]. The temporal dynamics of crop growth, with critical developmental windows and irreversible stress responses, impose constraints on the value of AI interventions that are not captured by static accuracy metrics [33].

Economic and Social Challenges

The economic barriers to AI adoption are substantial, particularly for smallholder farmers who cultivate the majority of global agricultural land. Precision agriculture technologies entail capital investments that exceed the financial capacity of most farming operations in developing countries [52]. The digital literacy gap between AI developers and agricultural practitioners impedes effective technology transfer [54]. Trust deficits represent a significant barrier: farmers who have developed expertise through decades of experiential learning may reasonably resist delegating critical decisions to opaque algorithmic systems [48].

Ethical Issues

The ethical dimensions of AI in agronomy extend beyond privacy concerns to encompass fundamental questions about the governance of food systems [50]. Data ownership remains contested, with farmers frequently lacking clear rights to data generated on their farms by embedded sensors and third-party services [13]. Algorithmic bias stemming from training datasets that underrepresent certain crop types, farming systems, or geographic regions risks reinforcing existing inequities [54]. The potential displacement of agronomic expertise by automated systems raises concerns about the devaluation of traditional ecological knowledge [55]. These challenges demand proactive governance frameworks that prioritise farmer agency, equitable access, and the preservation of diverse agricultural knowledge systems [51].

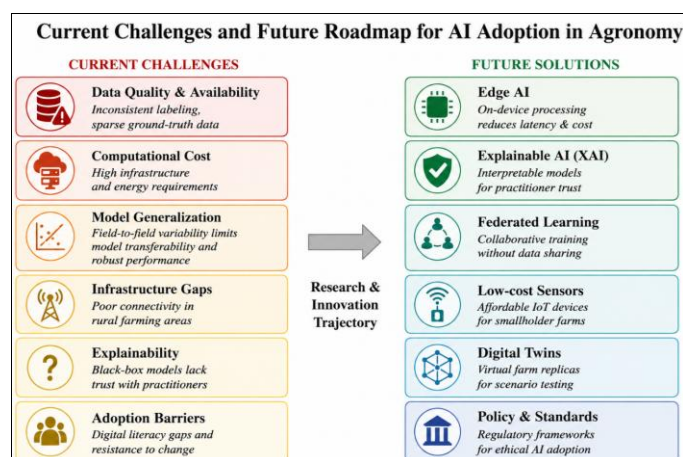


Fig 2: Two-panel conceptual framework illustrates the transition from current barriers to AI adoption in agronomy (left panel) to prospective solutions and research directions (right panel). The six challenge-solution pairings represent interconnected domains where targeted innovation and policy intervention can accelerate the practical deployment of AI in agricultural systems.

Future Perspectives

The trajectory of AI in agronomy will be shaped by advances in algorithmic methodology, sensing technology, and governance frameworks that determine whether current innovation translates into durable improvements in productivity and sustainability. Explainable agronomic AI represents a critical priority: future systems must move beyond black-box predictions to provide transparent reasoning that enables farmers and advisors to

understand, validate, and contextualize algorithmic recommendations^[31]. The development of attention-based architectures that highlight the features driving specific predictions will be essential for building trust^[14].

Autonomous agronomic ecosystems, in which AI-powered sensing, decision-making, and actuation operate in closed-loop configurations, represent a longer-term vision already emerging in controlled-environment agriculture^[23]. The integration of AI-driven phenotyping with genomic selection promises to accelerate cultivar development, though this convergence demands unprecedented collaboration between data scientists and breeding programmes^[45]. Foundation models large-scale networks pre-trained on diverse agricultural data and fine-tuned for specific tasks offer a pathway to overcome data scarcity through transfer learning^[22]. The imperative to serve smallholder farming systems necessitates low-cost AI solutions operating on affordable hardware; edge AI compression techniques and open-source ecosystems will be critical enablers of equitable access^[6]. AI-powered sustainable intensification the strategic application of algorithmic optimization to achieve yield gains through improved input use efficiency aligns technical capabilities with the goals of agricultural sustainability^[19].

Conclusion

Artificial intelligence has transformed the methodological landscape of agronomic research, generating capabilities for crop monitoring, prediction, and management that were inconceivable a decade ago. The evidence reviewed demonstrates that AI systems can achieve high accuracy in yield prediction, disease diagnosis, weed identification, and nutrient management under controlled conditions, with increasingly robust methodologies for handling spatial and temporal complexity. However, the translation of these capabilities into widespread agronomic practice remains incomplete, impeded by technical limitations in data quality and model generalization, economic barriers to technology access, and social factors including trust deficits and digital literacy gaps.

A critical assessment suggests that AI will not replace agronomic expertise but augment it providing decision-support tools that enhance the capacity of farmers and advisors to manage complexity, anticipate risk, and optimize resource use. The most promising directions emphasize explainability, edge deployment, and farmer-centric design, recognizing that the success of AI in agronomy depends on earning practitioner trust and delivering value within the constraints of real farming operations. The research community must prioritise interdisciplinary collaboration, open data initiatives, and ethical governance to ensure that the benefits of AI-enabled agronomy are distributed equitably across the diverse global agricultural landscape.

References

1. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: a review. *Sensors*. 2018;18(8):2674. doi:10.3390/s18082674.
2. Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: a comprehensive updated review. *Sensors*. 2021;21(11):3758. doi:10.3390/s21113758.
3. Sharma A, Jain A, Gupta P, Chowdary V. Machine learning applications for precision agriculture: a comprehensive review. *IEEE Access*. 2021;9:4843-4873. doi:10.1109/ACCESS.2020.3048415.
4. Saleem MH, Potgieter J, Arif KM. Automation in agriculture by machine and deep learning techniques: a review of recent developments. *Precision Agriculture*. 2021;22:2053-2091. doi:10.1007/s11119-021-09806-x.
5. Talaviya T, Shah D, Patel N, Yagnik H, Shah M. Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*. 2020;4:58-73. doi:10.1016/j.aiia.2020.04.002.
6. Oliveira R, Silva RDS. Artificial intelligence in agriculture: benefits, challenges, and trends. *Applied Sciences*. 2023;13(13):7407. doi:10.3390/app13137407.
7. Araújo S, Peres RS, Ramalho JC, Lidon F, Barata J. Machine learning applications in agriculture: current trends, challenges, and future perspectives. *Agronomy*. 2023;13(12):2976. doi:10.3390/agronomy13122976.
8. Taneja A, Nair G, Joshi M, Sharma S, Sharma S, Jambrak AR, *et al.* Artificial intelligence: implications for the agri-food sector. *Agronomy*. 2023;13(5):1397. doi:10.3390/agronomy13051397.
9. Shaikh TA, Mir W, Rasool T, Sofi S. Machine learning for smart agriculture and precision farming: towards making the fields talk. *Archives of Computational Methods in Engineering*. 2022;29:2571-2595. doi:10.1007/s11831-021-09601-2.
10. Attri I, Awasthi L, Sharma TP. Machine learning in agriculture: a review of crop management applications. *Multimedia Tools and Applications*. 2023;82:56021-56060. doi:10.1007/s11042-022-13697-8.
11. Elbasi E, Mostafa N, AlArnaout Z, Zreikat A, Cina E, Varghese G, *et al.* Artificial intelligence technology in the agricultural sector: a systematic literature review. *IEEE Access*. 2024;12:17380-17415. doi:10.1109/ACCESS.2024.3354571.
12. Javaid M, Haleem A, Khan IH, Suman R. Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*. 2022;1(1):15-30. doi:10.1016/j.aac.2022.10.001.
13. Ryan M, Isakhanyan G, Tekinerdogan B. An interdisciplinary approach to artificial intelligence in agriculture. *NJAS: Impact in Agricultural and Life Sciences*. 2023;95(1):2164830. doi:10.1080/27685241.2023.2164830.
14. Holzinger A, Fister I Jr, Fister I, Kaul HP, Asseng S. Human-centered AI in smart farming: toward agriculture 5.0. *IEEE Access*. 2023;11:69161-69185. doi:10.1109/ACCESS.2023.3292847.
15. Mana AA, Allouhi A, Hamrani A, Rahman S, El Jamaoui I, Jayachandran K. Sustainable AI-based production agriculture: exploring AI applications and implications in agricultural practices. *Smart Agricultural Technology*. 2024;7:100445. doi:10.1016/j.atech.2024.100445.
16. Sharma K, Shivandu SK. Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture. *Sensors International*. 2024;5:100417. doi:10.1016/j.sintl.2024.100417.
17. Marinello F, Zou X, Liu Z, Zhu X, Zhang W, Qian Y, *et al.* The path to smart farming: innovations and opportunities in precision agriculture. *Agriculture*. 2023;13(8):1593. doi:10.3390/agriculture13081593.
18. Daraojimba DO, Adewusi AO, Asuzu OF, Olorunsogo T, Iwuanyanwu C, Adaga E. AI in precision agriculture: a review of technologies for sustainable farming practices. *World Journal of Advanced Research and Reviews*.

- 2024;21(1):2276-2285. doi:10.30574/wjarr.2024.21.1.0314.
19. Gamage A, Gangahagedara R, Subasinghe S, Gamage JTKH, Guruge C, Senaratne S, *et al.* Advancing sustainability: the impact of emerging technologies in agriculture. *Current Plant Biology*. 2024;40:100356. doi:10.1016/j.cpb.2024.100356.
 20. Condran S, Bewong M, Islam MM, Maphosa L, Zheng L. Machine learning in precision agriculture: a survey on trends, applications and evaluations over two decades. *IEEE Access*. 2022;10:73786-73803. doi:10.1109/ACCESS.2022.3188649.
 21. Waqas M, Naseem A, Humphries U, Hlaing PT, Dechpichai P, Wangwongchai A. Applications of machine learning and deep learning in agriculture: a comprehensive review. *Green Technologies and Sustainability*. 2025;3:100159. doi:10.1016/j.grets.2025.100159.
 22. Ge C, Zhang G, Wang Y, Shao D, Song X, Wang Z. Research status and development trends of artificial intelligence in smart agriculture. *Agriculture*. 2025;15(21):2247. doi:10.3390/agriculture15212247.
 23. Zhu Y, Zhang S, Tang S, Gao Q. Research progress and applications of artificial intelligence in agricultural equipment. *Agriculture*. 2025;15(15):1703. doi:10.3390/agriculture15151703.
 24. Paudel D, Boogaard H, de Wit A, Janssen S, Osinga S, Pylaniadis C, Athanasiadis IN. Machine learning for large-scale crop yield forecasting. *Agricultural Systems*. 2021;187:103016. doi:10.1016/j.agry.2020.103016.
 25. Shawon SM, Ema FB, Mahi AK, Niha FL, Zubair H. Crop yield prediction using machine learning: an extensive and systematic literature review. *Smart Agricultural Technology*. 2024;9:100612. doi:10.1016/j.atech.2024.100612.
 26. Wang Y, Zhang Q, Yu F, Zhang N, Zhang X, Li Y, *et al.* Progress in research on deep learning-based crop yield prediction. *Agronomy*. 2024;14(10):2190. doi:10.3390/agronomy14102190.
 27. Muruganantham P, Wibowo S, Grandhi S, Samrat NH, Islam N. A systematic literature review on crop yield prediction with deep learning and remote sensing. *Remote Sensing*. 2022;14(9):1990. doi:10.3390/rs14091990.
 28. Joshi A, Pradhan B, Gite S, Chakraborty S. Remote-sensing data and deep-learning techniques in crop mapping and yield prediction: a systematic review. *Remote Sensing*. 2023;15(8):2018. doi:10.3390/rs15082018.
 29. Iniyar S, Varma VA, Naidu C. Crop yield prediction using machine learning techniques. *Advances in Engineering Software*. 2023;180:103429. doi:10.1016/j.advengsoft.2023.103429.
 30. Lu J, Li J, Fu H, Tang X, Liu Z, Chen H, *et al.* Deep learning for multi-source data-driven crop yield prediction in Northeast China. *Agriculture*. 2024;14(6):857. doi:10.3390/agriculture14060857.
 31. Mohan R, Rayanothala P, Sree RP. Next-gen agriculture: integrating AI and XAI for precision crop yield predictions. *Frontiers in Plant Science*. 2025;15:1508905. doi:10.3389/fpls.2025.1508905.
 32. Meghraoui K, Sebari I, Pilz J, Ait El Kadi K, Bensiali S. Applied deep learning-based crop yield prediction: a systematic analysis of current developments and potential challenges. *Technologies*. 2024;12(4):57. doi:10.3390/technologies12040057.
 33. Morales A, Villalobos FJ. Using machine learning for crop yield prediction in the past or the future. *Frontiers in Plant Science*. 2023;14:1128378. doi:10.3389/fpls.2023.1128378.
 34. Javed M, Murad MAA. Crop yield prediction in agriculture: a comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. *Heliyon*. 2024;10(21):e39710. doi:10.1016/j.heliyon.2024.e39710.
 35. Elavarasan D, Durairaj PM. Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. *IEEE Access*. 2020;8:86886-86901. doi:10.1109/ACCESS.2020.2992480.
 36. Jhajharia K, Mathur P, Jain S, Nijhawan S. Crop yield prediction using machine learning and deep learning techniques. *Procedia Computer Science*. 2023;218:406-415. doi:10.1016/j.procs.2022.12.436.
 37. Elbasi E, Zaki C, Topcu A, Abdelbaki W, Zreikat A, Cina E, *et al.* Crop prediction model using machine learning algorithms. *Applied Sciences*. 2023;13(16):9288. doi:10.3390/app13169288.
 38. Virnodkar SS, Pachghare VK, Patil VC, Jha SK. Remote sensing and machine learning for crop water stress determination in various crops: a critical review. *Precision Agriculture*. 2020;21:1121-1155. doi:10.1007/s11119-020-09711-5.
 39. Pokhariyal S, Patel NR, Govind A. Machine learning-driven remote sensing applications for agriculture in India: a systematic review. *Agronomy*. 2023;13(9):2230. doi:10.3390/agronomy13092230.
 40. Demissie W, Sebastiani L, Rossetto R. Integration of artificial intelligence and remote sensing for crop yield prediction and crop growth parameter estimation in Mediterranean agroecosystems: methodologies, emerging technologies, research gaps, and future directions. *European Journal of Agronomy*. 2026;154:127582. doi:10.1016/j.eja.2025.127582.
 41. Ghazal S, Munir A, Qureshi WS. Computer vision in smart agriculture and precision farming: techniques and applications. *Artificial Intelligence in Agriculture*. 2024;10:100219. doi:10.1016/j.aiaa.2024.100219.
 42. Miller T, Mikiciuk G, Durlik I, Mikiciuk M, Łobodzińska A, Śnieg M. The IoT and AI in agriculture: the time is now – a systematic review of smart sensing technologies. *Sensors*. 2025;25(11):3456. doi:10.3390/s25113456.
 43. Jafar A, Bibi N, Naqvi RA, Sadeghi-Niaraki A, Jeong D. Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. *Frontiers in Plant Science*. 2024;15:1364740. doi:10.3389/fpls.2024.1364740.
 44. Saini AK, Yadav A, Dhiraj. A comprehensive review on technological breakthroughs in precision agriculture: IoT and emerging data analytics. *European Journal of Agronomy*. 2025;150:127314. doi:10.1016/j.eja.2024.127314.
 45. Nath P, Mishra AK, Sharma R, Bhunia B, Mishra B, Tiwari A, *et al.* Recent advances in artificial intelligence towards the sustainable future of agri-food industry. *Food Chemistry*. 2024;443:138529. doi:10.1016/j.foodchem.2024.138529.
 46. Chandra SSV, Albaaji GF. Precision farming for sustainability: an agricultural intelligence model. *Computers and Electronics in Agriculture*. 2024;226:109174. doi:10.1016/j.compag.2024.109174.
 47. Ruiz-Real JL, Uribe-Toril J, Torres Arriaza JA, de Pablo Valenciano J. A look at the past, present and future research trends of artificial intelligence in agriculture. *Agronomy*.

- 2020;10(11):1839. doi:10.3390/agronomy10111839.
48. Smith MJ. Getting value from artificial intelligence in agriculture. *Animal Production Science*. 2020;60(1):46-54. doi:10.1071/AN18522.
 49. Sparrow R, Howard M, Degeling C. Managing the risks of artificial intelligence in agriculture. *NJAS: Impact in Agricultural and Life Sciences*. 2021;93(1):1917540. doi:10.1080/27685241.2021.1917540.
 50. Ryan M, van der Burg S, Bogaardt MJ. Identifying key ethical debates for autonomous robots in agri-food: a research agenda. *AI and Ethics*. 2021;2:453-466. doi:10.1007/s43681-021-00086-w.
 51. Rose DC, Chilvers J. Agriculture 4.0: broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*. 2018;2:87. doi:10.3389/fsufs.2018.00087.
 52. Schimmelpfennig D, Ebel R. Sequential adoption and cost savings from precision agriculture. *Journal of Agricultural and Resource Economics*. 2016;41(1):97-115. doi:10.22004/ag.econ.229399.
 53. Silva S, Alcáda-Almeida L, Dias LC. Development of a web-based multicriteria spatial decision support system for the assessment of environmental sustainability of dairy farms. *Computers and Electronics in Agriculture*. 2014;108:154-164. doi:10.1016/j.compag.2014.06.009.
 54. Sood A, Sharma RK, Bhardwaj AK. Artificial intelligence research in agriculture: a review. *Online Information Review*. 2022;46(6):1231-1257. doi:10.1108/OIR-06-2021-0301.
 55. Sparrow R, Howard M. Robots in agriculture: prospects, impacts, ethics, and policy. *Precision Agriculture*. 2022;23:818-833. doi:10.1007/s11119-021-09841-8.
 56. Shepherd M, Turner JA, Small B, Wheeler D. Priorities for science to overcome hurdles thwarting the full promise of the digital agriculture revolution. *Journal of the Science of Food and Agriculture*. 2020;100(14):5083-5092. doi:10.1002/jsfa.9346.
 57. Lu B, Dao PD, Liu J, He Y, Shang J. Recent advances of hyperspectral imaging technology and applications in agriculture. *Remote Sensing*. 2020;12(16):2599. doi:10.3390/rs12162599.
 58. Maresma Á, Martínez E, Lloveras J, Martínez-Casasnovas JA. Analysis of vegetation indices to determine nitrogen application and yield prediction in maize from a standard UAV service. *Remote Sensing*. 2016;8(12):973. doi:10.3390/rs8120973.
 59. Maheswari P, Raja P, Hoang V. Intelligent yield estimation for tomato crop using SegNet with VGG19 architecture. *Scientific Reports*. 2022;12:17840. doi:10.1038/s41598-022-17840-6.
 60. Liu Y, He M, Wang Y, Sun Y, Gao X. Farmland aerial image fast-stitching method and application based on improved SIFT algorithm. *IEEE Access*. 2022;10. doi:10.1109/ACCESS.2022.3204657.
 61. Liu J, Jiang W, Han H, He M, Gu W. Satellite Internet of Things for smart agriculture applications: a case study of computer vision. In: *Proceedings of IEEE SECON*. 2023. doi:10.1109/SECON58729.2023.10287508.