



An Overview of Artificial Intelligence-Driven Intelligent Agronomy for Sustainable Productivity and Agri-Finance Transformation

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Abstract

This review investigates how Artificial intelligence (AI) can improve agriculture's sustainability, production and finances. It uses AI-powered forecasting models to improve farm management, resource allocation and decision-making. Using time-series analysis, machine learning, deep learning, and hybrid models, agricultural data like weather, soil moisture, satellite imagery and market patterns is turned into information. Resource efficiency and inefficiency are improved via irrigation, pest control, production projections and market demand estimates. This review highlights how AI models help open-field, hydroponic and vertical farms. Depending on conditions and crop type, irrigation water use can be reduced by 25%, crop yields increased by 8-18%, and energy use reduced by 20%. In agricultural finance, AI forecasts financial risks, yield variability and loan approval. Although these benefits exist, fragmented data, model transferability between domains, and visible AI interpretations impede widespread adoption. To further intelligent agronomy, this review suggests boosting data quality, model flexibility and AI interpretability. With research and collaboration, AI can make agriculture more sustainable, efficient, financially inclusive and ecologically friendly. The review links AI-enabled agronomic advancements to Sustainable Development Goals, highlighting their significance in resilient, resource-efficient and climate-responsive agriculture.

Keywords: Intelligent agronomy; Forecasting; Food chain supply; Agri-finance; Agricultural innovation; Artificial intelligence.

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1. Introduction

Agriculture feeds people, supports rural livelihoods, and anchors national economies. However, agriculture now operates under tight constraints: climate variability makes rainfall less predictable; heat waves and floods occur more often; soils degrade under intensive use; inputs such as water, fertiliser, energy, and labour are costly; and supply chains face shocks from disease outbreaks, conflict, and market volatility.^[1] Many countries must raise production while using fewer resources and meeting stricter environmental standards. At the same time, food must be safe, affordable, and accessible to consumers in cities and remote areas. These pressures have

increased the value of timely and reliable information. When farmers, processors, logistics managers, and lenders can anticipate future conditions, even a few days ahead, they can adjust plans, reduce losses, and allocate scarce resources more effectively.^[2] Forecasting supported by artificial intelligence (AI) offers practical tools to address this need. Forecasts convert streams of data, including weather, soil moisture, satellite imagery, plant physiology, market prices, and transportation patterns, into expected outcomes, such as water demand for crops next week, the likelihood of a pest outbreak, the shelf life remaining for a perishable product, or the price range in each market.^[3] Recently, methodological progress has been rapid. Classical time-series models are useful for short, regular patterns and add flexibility to capture nonlinear effects. Deep-learning methods can learn from images and sequences, while hybrid approaches blend agronomic knowledge with data-driven patterns to enhance robustness in situations with limited data.^[4-5] However, the practical impact of these models depends on whether they lead to decisions such as opening or closing a valve, changing the planting date,

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prioritising a harvest lot, rerouting a truck, or adjusting a credit limit. This study adopts a decision-centric view of forecasting: the value of a prediction lies in the action it enables and the measurable change in outcomes that follows.^[6]

We use four widely recognised dimensions of food security as an organising lens: availability (is there enough food?), access (can people obtain it physically and economically?), utilisation (is food safe and nutritionally adequate?), and stability (are these three sustained over time?).^[7] Forecasting contributes to each dimension. Yield and evapotranspiration forecasts guide irrigation and fertiliser plans that sustain availability. Price and demand forecasts inform the planting choices, distribution, and support access. Shelf life and quality forecasts guide the processing and inventory practices that protect utilisation. Early warning systems for pests, diseases, and extreme weather enhance stability by allowing preventive action rather than reactive crisis management.^[8–9] The practical question is not which algorithm is the most sophisticated, but which prediction changes a decision under real constraints. A grower managing a water budget needs the next week's water demand by block, expressed in millimetres, and linked to the valve settings. A packhouse manager requires the likely remaining shelf life of each lot to set the dispatch sequence. A distributor needs a sense of demand and travel time to place inventory and avoid stockouts. A lender needs a stable, auditable measure of field-level yield volatility to judge repayment risk. For this reason, throughout the manuscript every prediction is tied to an explicit decision hook—a simple rule that maps “what we expect” to “what we do”, such as “if seven-day reference ET exceeds threshold and soil moisture is below set-point, apply 12 mm tonight”; “if predicted shelf life for Lot A is under 48 h, ship A before B”; “if forecast demand exceeds pack-house capacity, trigger contract packing per schedule.” The goal is to make the pathway from data to actions visible and testable in daily work.^[10–14]

Different model families contribute to different points. Time-series methods (e.g., ARIMA/SARIMA, exponential smoothing, and state-space) are reliable baselines for short-horizon patterns in demand or ET.^[15–17] Tree-based ensembles and gradient boosting capture nonlinearities and interactions in tabular and remote sensing features for irrigated-area mapping, yield classification, and price risk.^[14–17] Sequence and vision networks (LSTM, CNN, Transformers) learn from multivariate time series and imagery for yield, pest pressure, and quality prediction.^[11–13,18–19] Physics-informed hybrids weave agronomic structure-crop water balance, heat-mass transfer, and phenology-into learning, so models remain stable

when labelled data are limited or when conditions shift.^[20–21] Model choice should follow the decision and data: what horizon matters, which constraints bind (water, labour, energy, storage, capital), and which metric shows improvement (yield per hectare, litres per kilogram, service level, shrink, margin). Using predictions to set points and schedules results in tangible gains. Studies in both open-field and controlled-environment systems describe 10–25% reductions in irrigation water use with ET-informed scheduling, 8–18% increases in output when lighting and climate are tuned to growth signals, 10–20% energy savings in vertical farms under forecast-aware regimes, and 20–30% reductions in processing or retail waste when shelf-life and demand forecasts guide dispatch and stocking. Remote-sensing-aided yield and irrigated-area mapping improve regional water allocation, early warnings for pest and disease risk protect stability, and demand and travel-time forecasts reduce stock-outs and shrink in distribution. These effects align with broader goals set by international agencies regarding resilience and resource efficiency.^[20–22]

The three obstacles occur during deployment and must be addressed directly. First, there were data gaps and inconsistencies. Smallholders often lack continuous, standardised measurements; weather station records may be incomplete; satellite images may be obscured by clouds; and operational logs may mix units. Missing or misaligned data degrades predictions and can mislead actions if untreated. Practical responses include imputation (e.g., MissForest), ensembling to reduce variance, transfer learning to adapt models to new regions with few labels, and multimodal data fusion to combine satellite, sensor, and agronomic records into a coherent picture.^[23] Adopting FAIR data principles and geospatial/IoT standards, such as OGC SensorThings and ISO 19115, reduces friction by ensuring that sources are findable, accessible, interoperable, and reusable across various projects and regions. The second is portability across regions and systems. A model trained in one climate, soil, cultivation, or management regime may underperform elsewhere, and open-field models do not transfer directly to hydroponics, aquaponics, or vertical farms, where water chemistry, nutrient cycling, light spectra, and energy costs dominate. Portability improves when physics-aware features (growing-degree days, reference ET) are used when learners are regularised and domain-adapted and when validation is reported by agro-ecological zones and system types.^[24] Third, they are understandable and skilled. Even accurate models falter without clear outputs or basic monitoring practices. Here explainable AI (XAI) is essential: SHAP and LIME can attribute predictions to inputs; counterfactuals show the minimal change that would alter a recommendation; surrogate rule lists can summarise complex models into simple, auditable policies; and calibration aligns predicted probabilities with observed frequencies, so a “20% risk” occurs about one in five times over the season.^[25] With XAI, a field manager can see that an increase in irrigation is driven by high expected ET, wind, and low soil moisture, and a risk

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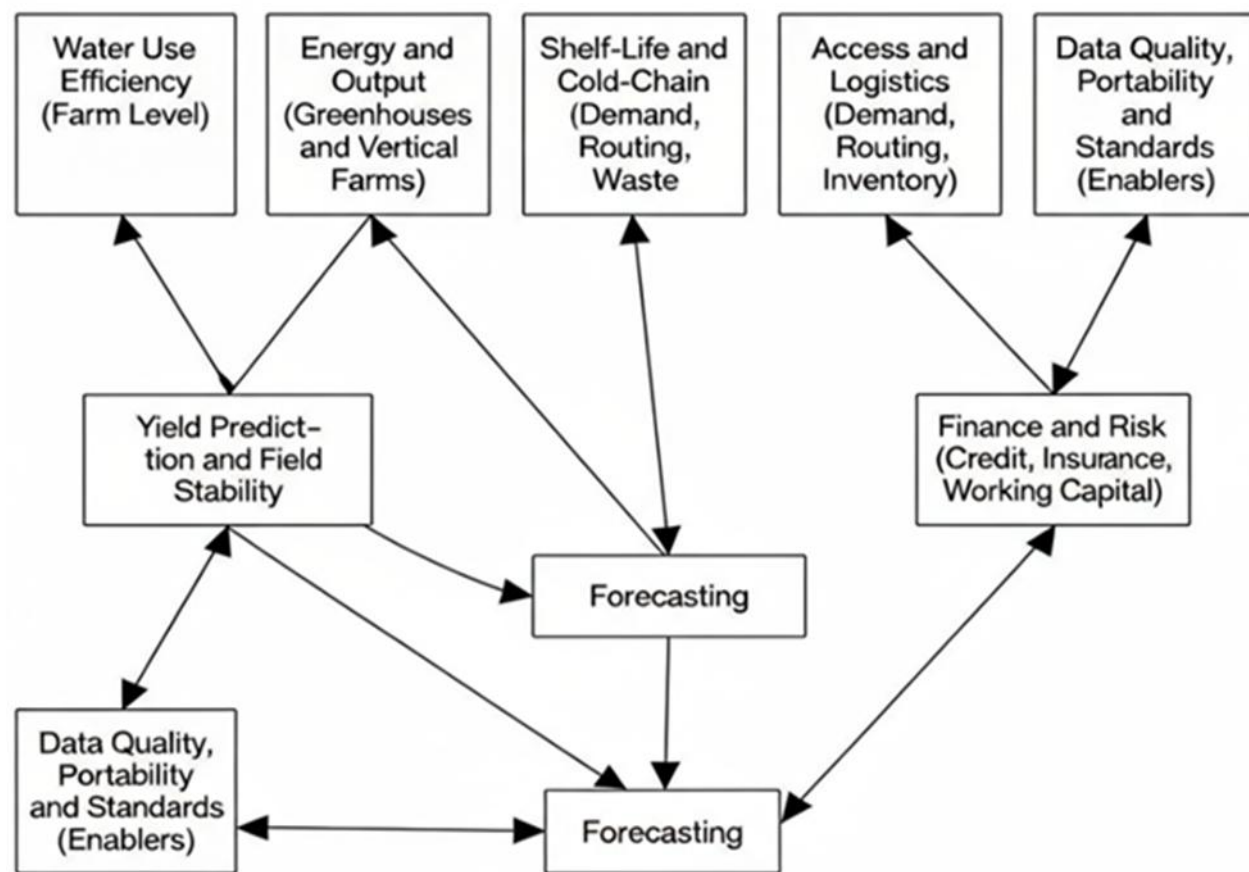


Fig. 1: Flowchart of key agricultural productivity verticals linked to forecasting and improved decision-making for sustainability.

officer can rely on a volatility feature when its data lineage, calibration, and confidence intervals are documented.^[26]

Therefore, the evaluation should look beyond the error scores. RMSE and MAPE remain useful for comparing models on a task, but decision-makers need decision-level outcomes: litres of water per kilogram, yield stability, energy per kilogram, service level, shrinkage, margin, variance reduction, default rate, and claim cycle time.^[27-28] For rare events, such as pest outbreaks, precision, recall, and F1 are more informative than accuracy because class imbalance can lead to misleading accuracy. Where possible, value-of-information analysis estimates the uplift from using forecasts compared to current heuristics, clarifying whether better predictions translate into profit and resilience. When forecasts inform credit and insurance, features must be audit-ready, grounded in agronomic and operational signals, and accompanied by calibration checks and documentation so that decisions remain explainable and fair over time.^[29] The scope of Intelligent Agronomy spans farms, processing and freight. On farms, forecast-guided irrigation and fertigation improve

yield per litre, stabilise growth, and reduce nutrient leaching, whereas planting density, pest scouting, and harvest timing benefit from near-term climate and growth signals. In controlled environments, lighting and climate schedules are tuned to physiological conditions and demand, which lift output and reduce energy per kilogram, with attention paid to peak tariffs and equipment limits. In processing, predictive sequencing with temperature-humidity control and lot prioritisation based on remaining shelf life reduces spoilage and improves service levels, whereas demand and travel time forecasts reduce stock-outs and shrinkage while balancing storage and transport costs. Across these stages, the pattern is the same: clearer foresight and explicit rules yield more stable operations and healthier cash flows, reinforcing availability, access, utilisation, and stability.^[26-34] AI, machine learning, and decision support systems fundamentally transform agricultural productivity and sustainability across diverse verticals, from resource management and processing efficiency to real-time supply chain optimization and risk finance, as shown in Fig. 1.

To provide practitioners and researchers with a focused synthesis, Table 1 maps representative studies across the major productivity themes in agricultural innovation. Each study was analyzed for its technical approach, problem addressed, key gains reported, strengths and weaknesses, and recommended path for future research.

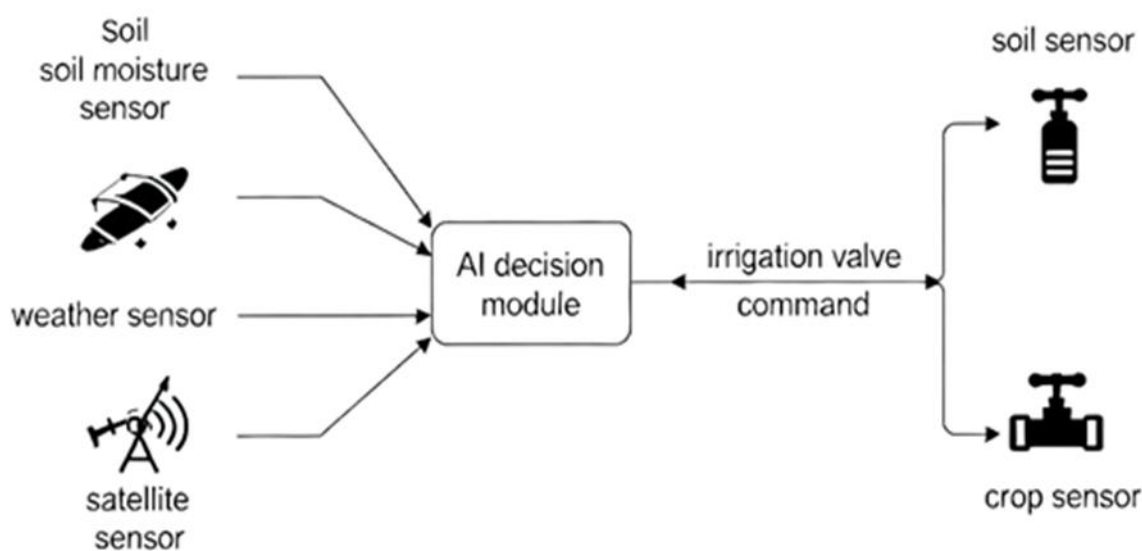
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Table 1: Summary of key studies demonstrating AI-driven forecasting and decision-support innovations across major agricultural productivity verticals.

References	Application Area	Technique Used	Dataset / Region	Problem Solved	Weakness	Accuracy
Bazzi <i>et al.</i> , 2021 ^[35]	Water-use efficiency (farms)	Satellite Imaging + RF	Morocco – farm-level satellite data	Precise irrigation mapping	Data and sensor cost	$R^2 = 0.82$; RMSE = 0.19
Dhal <i>et al.</i> , 2024 ^[36]	Yield prediction & stability	LSTM + CNN + RF	India – Rice & maize seasonal datasets	In-season crop and canopy forecasts	Large labelled data needed	Error reduction = 5–20%; RMSE = 0.24
Ghosal <i>et al.</i> , 2018 ^[37]	Plant disease and pollution detection	CNN + DL	USA – open leaf disease dataset	Early pest/disease detection	Requires labelled data	Accuracy = 93–96%

**Fig. 2:** AI-driven irrigation system integrating sensor data with automated water control.

2. Methodology

This review covers literature published between 2013 and 2025. We searched Scopus, Web of Science, IEEE Xplore and Google Scholar using keywords including “artificial intelligence”, “machine learning”, “yield prediction”, “crop forecasting”, “precision agriculture”, “remote sensing”, and “agri-finance”. We included peer-reviewed studies that described datasets, model methods, or measurable outcomes. Non-technical commentaries were excluded. This study systematically explored the applications of artificial intelligence and machine learning across key agricultural productivity verticals. It starts by establishing a comprehensive context for each vertical, defining the prevalent challenges, such as resource inefficiency, environmental variability, and supply chain complexity. The methodology includes an examination of AI techniques applied to each vertical, ranging from classical machine learning algorithms such as random forests and support vector machines to advanced deep learning models, including convolutional neural networks and long short-term memory networks. These models are analyzed as both standalone predictive tools and hybrid combinations with domain-

specific agronomic or physical models. For each productivity domain, the review breaks down typical input data sources, such as IoT sensors, satellite and UAV imagery, time-series weather data, and financial records, and explains how these data are integrated and processed through AI frameworks to generate actionable insights and support decisions. The aim is to provide a holistic understanding of the state-of-the-art AI applications that drive sustainable productivity gains in agriculture. This review directly contributes to the United Nations Sustainable Development Goals (SDGs) by aligning with SDG 2 (Zero Hunger) through improved food security, SDG 6 (Clean Water and Sanitation) via optimized irrigation, SDG 7 (Affordable and Clean Energy) by improving energy efficiency, and SDG 13 (Climate Action) by promoting data-driven adaptation and resilience strategies. It also advances SDG 9 (Industry, Innovation, and Infrastructure) through the adoption of intelligent agritech ecosystems that foster sustainable growth and financial inclusion.

2.1 Water use efficiency (Farm level)

Water use efficiency is critical for sustainable agriculture, particularly under conditions of climate variability and

resource scarcity. The challenge lies in applying just enough water to meet crop needs while minimising waste and environmental damage. AI approaches integrate IoT soil moisture sensors, weather data, and remote sensing (e.g., NDVI from satellites), as shown in Fig. 2, with machine learning models, such as Random Forests and Support Vector Machines, to predict crop water demand and optimize irrigation schedules.

Fuzzy logic and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) add robustness by handling uncertainties and nonlinearities in soil-water-plant interactions. A fundamental agronomic equation, the Penman–Monteith model, estimates the reference evapotranspiration (ET_0), where each term relates to climatic and physical parameters influencing water loss. AI models use ET_0 along with local measurements to recommend irrigation volumes.

Penman–Monteith evapotranspiration in Eq. (1).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where

ET_0 = Reference evapotranspiration (mm/d)

Δ = Slope of vapor pressure curve (kPa/°C)

R_n = Net radiation at the crop surface (MJ/m²/day)

G = Soil heat flux density (MJ/m²/day)

u_2 = wind speed at 2m height (m/s)

e_s = Saturation vapor pressure (kPa)

e_a = Actual vapor pressure (kPa)

γ = Psychrometric constant (kPa/°C)

T = Mean air temperature at 2m height (°C)

Required infrastructure, such as sensors and connectivity, can be costly. Models require sufficient historical data for training and can be region-specific, requiring calibration. The initial setup with sensors and AI systems involves capital, but operational savings from water reduction can offset this.

2.2 Energy and output optimization in controlled environments (Greenhouses, Vertical farms)

Controlled environmental agriculture requires precise regulation of light, temperature, humidity, and CO₂ to maximise crop yield and quality while reducing energy consumption. AI techniques include sensor arrays for continuous monitoring and reinforcement learning to optimize dynamic control strategies, as shown in Fig. 3.

Deep-learning models, such as LSTM, predict plant growth stages and environmental responses. The photosynthetic response is often modelled using saturation kinetics, as shown in Eq. (2):

$$P = P_{max} \times \frac{I}{I + K_s} \quad (2)$$

where P is the photosynthesis rate, I is the light intensity, P_{max} is the Maximum photosynthetic capacity, and K_s is the Half-saturation constant (the light intensity at which the photosynthesis rate is half (P_{max})). Reinforcement learning algorithms iteratively adjust lighting and climate schedules to maximize photosynthesis per unit of energy. The limitations are the high equipment and data-processing costs. However, sophisticated algorithms require expert tuning.

The energy savings achieved can reach 20%; however, the upfront costs for sensors, controllers, and AI infrastructure can be substantial.

2.3 Yield prediction and field stability

Yield forecasting must integrate diverse data types including multispectral images, historical yields, and weather sequences. Convolutional Neural Networks (CNNs) extract spatial patterns from UAV or satellite imagery, whereas Long Short-Term Memory networks (LSTMs) process temporal weather and crop growth data, as shown in Fig. 4.

Hybrid models combine physiological crop growth models

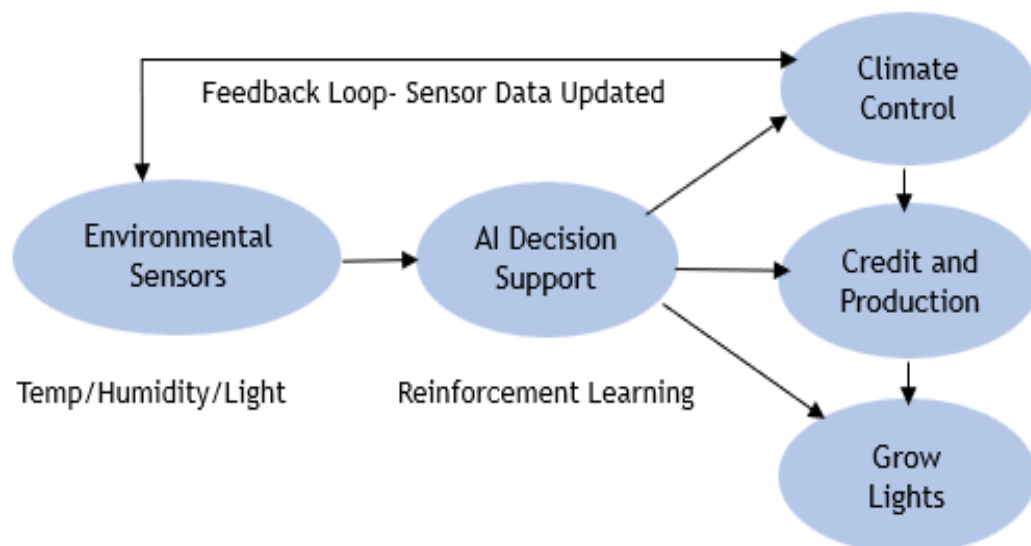


Fig. 3: Feedback-control loop for AI-driven climate and lighting management in controlled agriculture.

with artificial intelligence (AI) components to enhance stability and interpretability. A typical LSTM update is represented by Eq. (3):

$$h_t = \sigma(W \cdot x_t + U \cdot h_{t-1} + b) \quad (3)$$

where

h_t = Hidden state at time t

σ = activation function (typically sigmoid or tanh).

W = Weight matrix for input x_t

x_t = Input vector at time t (e.g., weather observations).

U = Weight matrix for the previous hidden state

h_{t-1} = Hidden state at time $t - 1$

b = Bias term

Deep learning models require large annotated datasets to perform effectively, which can be a major hurdle in fields where such data are scarce. Also, the computational power required to train these models can be substantial, often necessitating specialized hardware such as GPUs. The complexity of the architectures used in deep learning further reduces interpretability, making it difficult to understand how the model arrives at specific decisions, which can be a concern for domains that require transparency and trust. The need for a high-performance computing infrastructure to train these models is expensive, especially when dealing with massive datasets. Furthermore, acquiring and labeling data for training can be both time-consuming and labor-intensive, thereby adding another layer of complexity to the process.

2.4 Shelf-life, processing, and cold-chain waste

Maintaining food quality postharvest is essential to reduce waste and ensure safety. AI-driven predictive analytics uses IoT temperature and humidity sensors combined with spoilage models, as shown in Fig. 5 such as time-temperature integrals, as shown in Eq. (4):

$$D = \int_0^t k(T(t))dt \quad (4)$$

where

D = Damage or spoilage accumulated over time.

$k(T)$ = temperature-dependent spoilage rate constant

t = Time elapsed

$T(t)$ = temperature as a function of time

Dependence on a continuous sensing infrastructure can be a major challenge, as these systems require ongoing maintenance and monitoring to ensure accuracy and reliability. The initial investment can also be high, which may be particularly difficult for small-scale supply chains. Despite these challenges, investment in IoT can lead to significant long-term benefits. One of the main advantages is the reduction in spoilage, with some supply chains seeing decreases of up to 30%, which can offset upfront costs by improving efficiency and reducing waste.

2.5 Access and logistics (Demand forecasting, routing, inventory)

Supply chain resilience depends on accurate demand forecasts and optimized routing, as shown in Fig. 6. AI uses time-series models Autoregressive Integrated Moving Average and Long Short-Term Memory (neural network) (ARIMA and LSTM) to forecast demand using ensemble approaches to capture seasonality and trends. Route logistics uses metaheuristics (genetic algorithms and ant colony optimization) to minimize transport costs and delays. The system is complex and data-intensive, and requires real-time inputs to function effectively. This complexity is further amplified by the need for seamless integration across stakeholders, which can create coordination challenges. However, investment in specialized software and connectivity is often necessary to streamline operations and ensure smooth communication across all parties. Despite the initial costs, operational savings through optimized routing can be substantial, offering significant long-term financial benefits by increasing efficiency and reducing overall transportation costs.

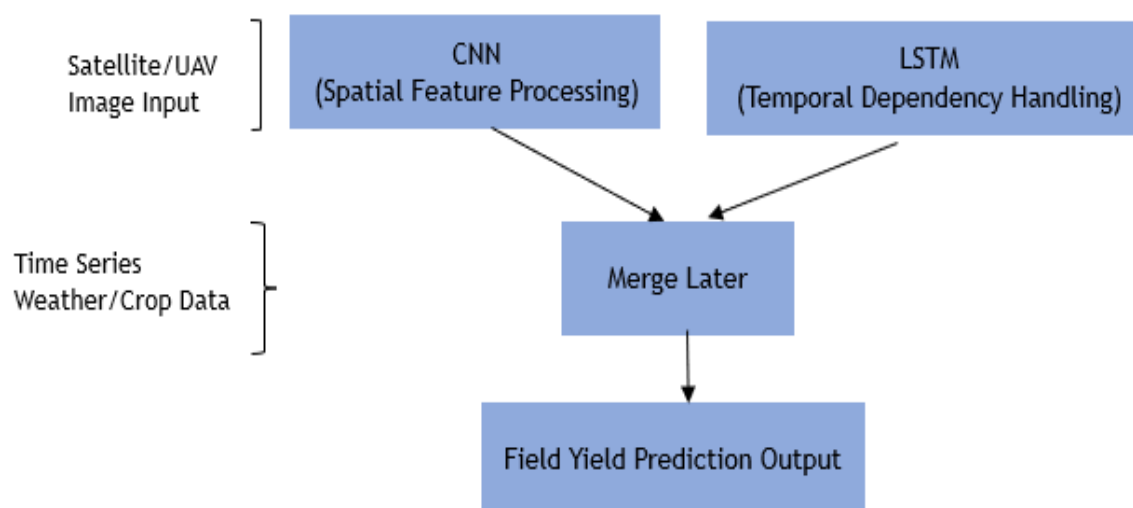


Fig. 4: Layered architecture diagram illustrating CNN and LSTM fusion for yield prediction from image and time-series data.

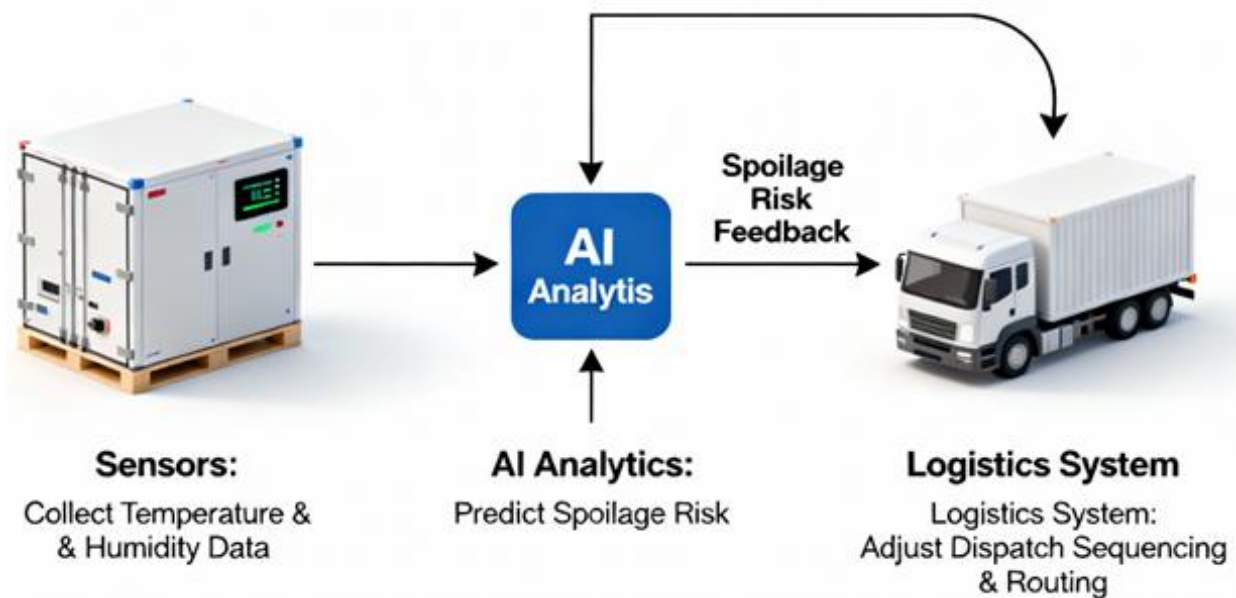


Fig. 5: Flowchart depicting sensor-based shipment monitoring feeding AI spoilage prediction and logistics dispatch adjustment to optimize cold-chain management.

2.6 Finance and Risk (Credit, Insurance, Working Capital)

AI supports rural finance by predicting the loan default risk and insurance claims based on integrated field-level yield data, climate variables, and historical payments. Classification models such as Random Forests and SVMs assign risk scores, whereas deep learning further enhances prediction using temporal sequences, as shown in Fig. 7. Decision support systems (DSS) make these accessible to lenders through clear explanations.

The system requires adequate data digitization to ensure that information is accurate and accessible for analysis. Without proper digitization, the effectiveness of the model may be compromised. In addition, there is a risk of model bias if the training data are limited or unrepresentative, which could lead to skewed results and unfair outcomes. While the development of decision support system (DSS) platforms can be resource-intensive, they can significantly improve access to finance for underserved farmers by providing data-driven insights and improving decision-making, thus fostering financial inclusion.

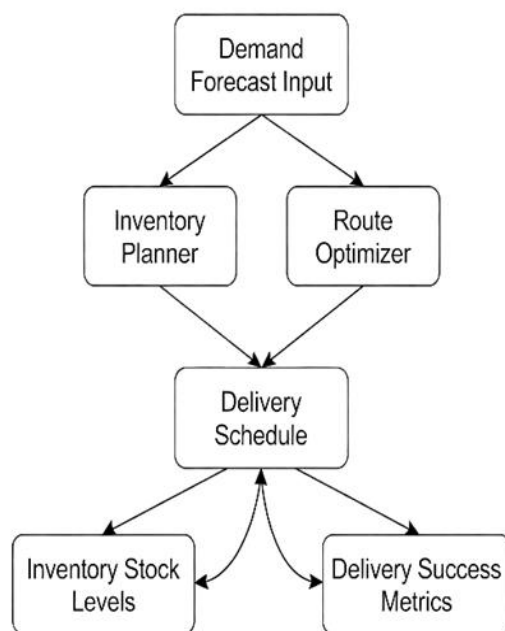


Fig. 6: Flowchart illustrating integrated demand forecasting and vehicle routing optimization, connecting forecast input to inventory planning, route optimization, and real-time feedback from inventory and delivery metrics.

2.7 Data quality, portability, and standards (Enablers)

Data inconsistency limits the model accuracy and transferability. AI-driven imputation methods, such as MissForest, handle missing values. Transfer learning adapts the models to new regions with minimal retraining. The adoption of FAIR principles and standards, such as OGC SensorThings and ISO 19115, promotes interoperability and reusability.

Synthetic data methods, although useful for augmenting datasets, may introduce bias if not carefully managed, leading to skewed results or inaccurate predictions. Additionally, the uptake of standardization across industries or organizations can be uneven, making it difficult to ensure consistency and interoperability. However, investments in data governance can simplify the scaling process by providing clear guidelines and structures for data management, reducing redundancy and inefficiencies across systems, and ensuring better quality and consistency in data usage, as shown in Fig. 8.

3. Overview of the forecasting models used in agricultural productivity

This Section discusses the results of the literature study, which

focuses on four main aspects of food security: availability, access, utilization, and stability, as well as issues such as climate change, data quality, and how to improve the supply chain. It examines how forecasting models can help with these aspects in both traditional and alternative farming systems, as well as in modern food processing and supply lines. The review looks at different types of prediction models, such as time-series models, ML, DL, and hybrid models, which help farmers get the most out of their resources, predict changes in the market, and ensure that the supply chain works smoothly.

3.1 Key forecasting models for food security

These four elements of food security-availability, access, usage, and stability-are essential for sustaining global food security. Forecasting models offer critical predictive insights into these variables, assisting decision-makers in risk mitigation and the optimal management of food systems.

Machine learning models

Machine Learning (ML) models, such as Random Forest (RF) and Gradient Boosting (XGBoost, LightGBM), are widely used in food security forecasting because of their robustness with heterogeneous household, socioeconomic, and climate datasets collected from surveys, remote sensing, and market sources, as shown in Table 2. RF models achieved accuracy of approximately 98.6% and F1 scores of approximately 0.986 by aggregating multiple decision trees to capture the nonlinear interactions between variables related to malnutrition and food insecurity. These models are strong in handling missing data and noise, but can overfit small, imbalanced datasets. These are applied to household-level vulnerability predictions, geographic food insecurity trends, and early crisis warnings.

Support Vector Machines (SVMs) are mostly used for binary classification tasks, such as distinguishing between secure and insecure households. They rely on finding optimal hyperplanes to separate classes in the feature space and perform well on well-labeled, preprocessed datasets. The accuracy ranged from 96.5% to 98.1% in reported studies. Advantages include their use in moderate-sized datasets, but they become computationally expensive for large-scale or highly nonlinear data common in food security, limiting interpretability.^[38]

Gradient Boosting Machines (GBM), including XGBoost and LightGBM, leverage sequential tree boosting to incrementally improve model predictions by focusing on errors. They scaled well with large, complex agricultural and demographic datasets, achieving high accuracy (up to 98.5%) and F1 scores beyond 0.97. GBMs are effective for crisis forecasting with multi-source inputs, although they require careful tuning to prevent overfitting and to handle noisy inputs. Logistic Regression (LR), a classical linear model, is used for straightforward binary outcomes with interpretable coefficients, typically delivering slightly lower accuracy (~94.7–97.1%) than advanced ML models.^[24] Its strength lies in its simplicity and clarity; however, it lacks the capacity to model complex nonlinear interactions in food security datasets.^[39]

Artificial Neural Networks (ANNs) have gained traction when large-scale multi-modal data becomes available. Their ability to model complex nonlinearities and interactions makes them suitable for intricate food security tasks such as integrating spatial satellite data with temporal climate records. ANNs often surpass classical ML models in terms of accuracy but may require larger datasets and careful tuning.

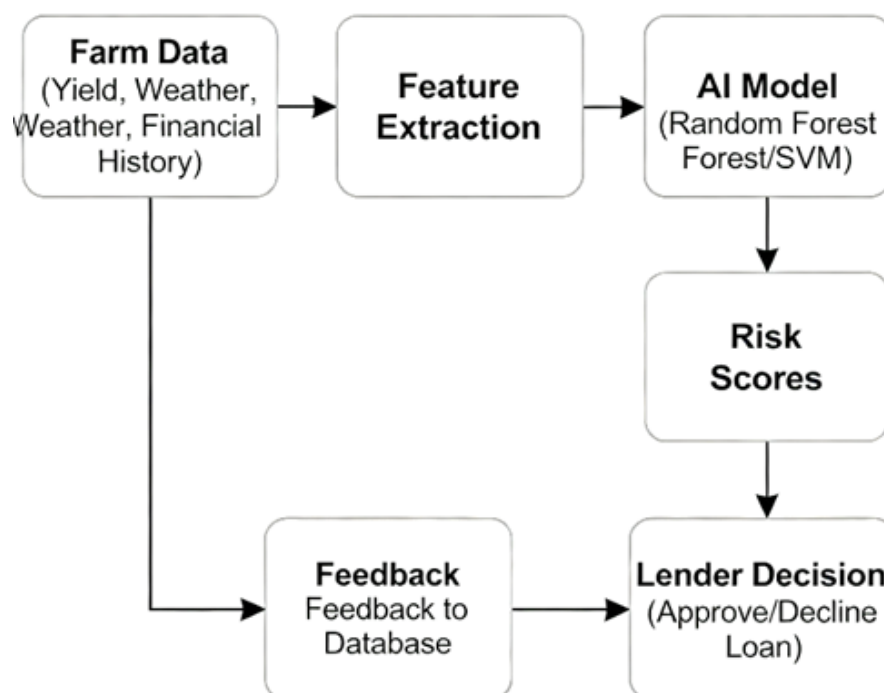


Fig. 7: AI agricultural credit risk modeling system.

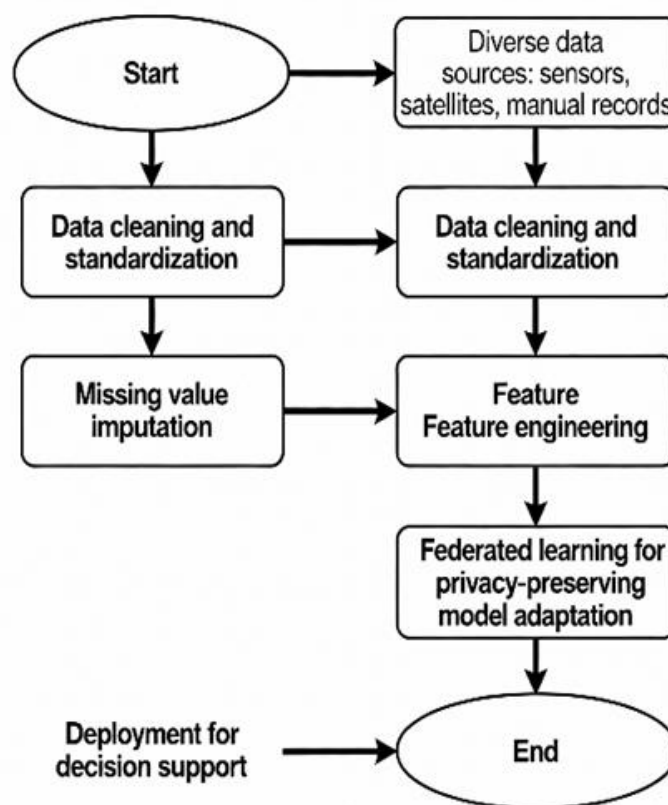


Fig. 8: Data lifecycle for robust AI in agriculture: acquisition, standardization, imputation, and transfer learning.

Table 2: Machine Learning and Deep Learning Forecasting Models for Food Security.

Reference (Authors, Year)	Model		Application		Description	Limitations	Accuracy / Metrics
Gholami <i>et al.</i> , 2022 ^[24]	Logistic (LR)	Regression	Binary classification	outcome	Statistical linear model predicting probabilities; baseline model	Limited for nonlinear, complex feature interactions	Accuracy around 94.7%- 97.1%
Ghoshal <i>et al.</i> , 2024 ^[37]	Artificial Networks (ANN)	Neural	Household vulnerability forecasting		Deep learning captures nonlinear patterns in multi-modal data	Requires large datasets and computational resources; interpretability challenges	Accuracy up to 99.15%, R ² = 0.94 for yield prediction
Herteux <i>et al.</i> , 2024 ^[40]	Reservoir Computing		Food monitoring	consumption	Recurrent neural network optimized for sequential data and real-time applications	Less mainstream; limited libraries/tools	Outperforms LSTM and XGBoost in some 60-day forecasts
Yoon <i>et al.</i> , 2023 ^[41]	Semi-Supervised Learning		Forecasting in data- poor regions		Combines labeled and unlabeled data to improve prediction robustness	Relies on quality of unlabeled data; model complexity	Enables model transfer with better generalization

Table 3: Time Series Forecasting models for Food Security.

Reference (Authors, Year)	Model	Application	Accuracy/Metric	Strengths	Weaknesses
Herteux <i>et al.</i> , 2024 ^[40]	Reservoir Computing	60-day food consumption forecasting	Outperforms LSTM/XGBoost	Robust, efficient, high-performance for real-time	Not mainstream, limited tools
Westerveld <i>et al.</i> , 2021 ^[26]	Extreme Gradient Boosting	Monthly transitions in food security	High classification accuracy	Handles transitions, multi-source, scalable	Sensitive to parameter tuning
Kerdprasop <i>et al.</i> , 2022 ^[42]	ARIMA, ANN, AdaBoost	Food production forecasting	Compared RMSE, MAPE	Ensemble/hybrid approaches, multiple methodologies	Performance varies by region
Deleglise <i>et al.</i> , 2022 ^[17]	Deep Learning Time-Series	Sub-national food insecurity	Performance rises with long series	Improves with more data/coverage	Needs large training datasets
Mahaluca <i>et al.</i> , 2025 ^[43]	ARIMA + Monte Carlo Sim.	Food price forecasting	Lower RMSE vs legacy	Prediction intervals, uncertainty quantification	Assumes stationarity, limited exogenous variables

Table 4: Forecasting models for Climate.

Reference (Author, Year)	Model Type	Application	Core Data Sources	Accuracy/Metric	Strengths	Weaknesses
Hansen <i>et al.</i> , 2005 ^[44]	Integrated Climate-Crop Sim.	Seasonal yield & risk forecasting	Seasonal climate, crop models, weather	Robust for anomalies	Actionable advice	Scale mismatch, complexity
Dewitte <i>et al.</i> , 2021 ^[20]	Short-Term AI Weather	Daily to 7-day farm weather	Satellite, IoT sensors, local climate	85–92% short-term	High accuracy, coverage	Limited forecast horizon
Limpo <i>et al.</i> , 2022 ^[4]	Seasonal Prediction/Planting	Rice sowing, precipitation	Seasonal climate, historic rainfall	Good for sowing	Economic evaluation, planning support	Moderate for extremes

Time series models

Time series forecasting in food security employs Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), to capture sequential dependencies in consumption and vulnerability data over days to months. An innovative approach is Reservoir Computing, a computationally efficient recurrent network that outperforms classical LSTM and machine learning baselines, such as XGBoost, in 60-day food consumption forecasting, as shown in Table 3. These models enable actionable early warning signals and robust forecasting in data-scarce environments, owing to their efficiency and generalizability. Semi-supervised learning strategies often augment time-series analysis by leveraging unlabeled data to improve forecast resilience, particularly in under-monitored regions.

3.2 Climate forecasting models

3.2.1 Data-driven climate prediction

Climate prediction benefits from ML models, including Random Forest, Support Vector Regression, and various deep learning models (CNNs, ConvLSTM) that learn patterns in spatiotemporal datasets, such as rainfall and temperature sequences. These models augment or correct physical climate simulations, improve localized accuracy, and enable impact forecasting on agricultural productivity. The ensemble ML approaches integrate diverse climate variables for robust outcomes and scenario generation, as shown in Table 4.

3.2.2 Hybrid ML-physical models

ML models are often paired with physical climate simulations, and ML algorithms focus on bias correction, residual analysis, or scenario expansion. This hybridization increases reliability, especially under data scarcity or extreme event predictions.

3.3 Yield forecasting models

Yield prediction leverages ML models, such as Linear Regression, Random Forest, Gradient Boosting, KNN, and deep learning methods (CNNs for image data; LSTM for time series), as shown in Table 5 which improve yield estimates by capturing complex interactions in weather, soil, and management data, and often outperform classical process-based models. Image-based neural networks extract crop conditions from satellite or drone imagery, whereas fusion models combine these features with time-series weather or management data for higher accuracy.

CNNs and transformer networks applied to satellite or UAV imagery enable fine-grained yield monitoring, particularly when fused with sensor and weather data in composite models. Stacked or ensemble models aggregate multiple prediction streams for enhanced robustness across the field and time horizons.

3.4 Finance and risk forecasting models

Random Forest, XGBoost, and logistic regression models were used for agricultural credit scoring, evaluating farmer

and enterprise risk factors, and loan eligibility. Explainable AI tools, such as SHAP and LIME, are increasingly being adopted to improve transparency and regulatory confidence. Ensemble ML methods forecast catastrophe risks and insurance losses, integrating weather, yield, and financial data to predict claim frequency and severity and support risk-pooling strategies. Market prices and output trends are forecasted using time-series ML models (LSTM and Prophet) and classification algorithms (SVM and RF), enabling better planning and market segmentation for producers and investors.^[45,46]

3.5 Shelf-life prediction and post-harvest models

Shelf-life prediction and post-harvest modeling have rapidly advanced with AI techniques, integrating machine learning (ML), deep learning (DL), and hybrid models to accurately estimate food freshness and optimize supply chains. Traditional shelf-life estimation methods such as chemical/microbial analysis and sensory evaluation are often slow, labor-intensive, and challenging for large-scale applications. AI-driven approaches offer rapid, real-time shelf-life predictions for diverse food products and storage settings.

Recent research has implemented ML and DL models for fruits, vegetables, meat, grains, and seafood. Techniques such as Random Forests, Artificial Neural Networks, Decision Trees, Support Vector Regression, and hybrid systems have shown high predictive accuracy for shelf life under variable conditions. A multi-objective ML model predicted the shelf life of five marine fish species at different temperatures, utilizing 14 input features and achieving reliable multioutput results.^[47,48] In tomato post-harvest logistics, sensor and IoT-based image analysis systems paired with regression and ensemble ML models provide reliable humidity, gas composition, and shelf-life estimates, even with small datasets.^[49-50] Deep learning models, such as CNNs, LSTMs, and transfer learning, are becoming increasingly popular for shelf-life forecasting. Novel hybrid models, such as CNN-LSTM, can capture both spatial (e.g., microbial activity and quality in image data) and temporal patterns (storage temperature fluctuations), outperforming classical models, especially under dynamic environments. Nondestructive methods, including hyperspectral imaging and Raman spectroscopy, further enhance real-time shelf-life estimation by monitoring changes in freshness and spoilage biochemistry.^[51]

Table 5: Yield forecasting models.

Reference (Authors, Year)	Model/Algorithm	Data Source/Features	Accuracy/Metric	Strengths	Weaknesses
Jabed <i>et al.</i> , 2024 ^[11]	Random Forest (RF)	Soil, weather, crops, historical	93–98% (several crops)	Fast, robust to outliers, interpretable	Prone to overfit with small data
Shawon <i>et al.</i> , 2024 ^[7]	Deep Neural Net (DNN)	Remote sensing, climate, RGB	93.7% (Deep Recurrent Q-Network)	Learns complex nonlinear features	Needs large computation/resources
Goel <i>et al.</i> , 2024 ^[38]	Gaussian Process Regression	Multisource, maize, time series	nRMSE 13.3% (maize)	Uncertainty quantification, interpretable	Complex setup, slow with big data

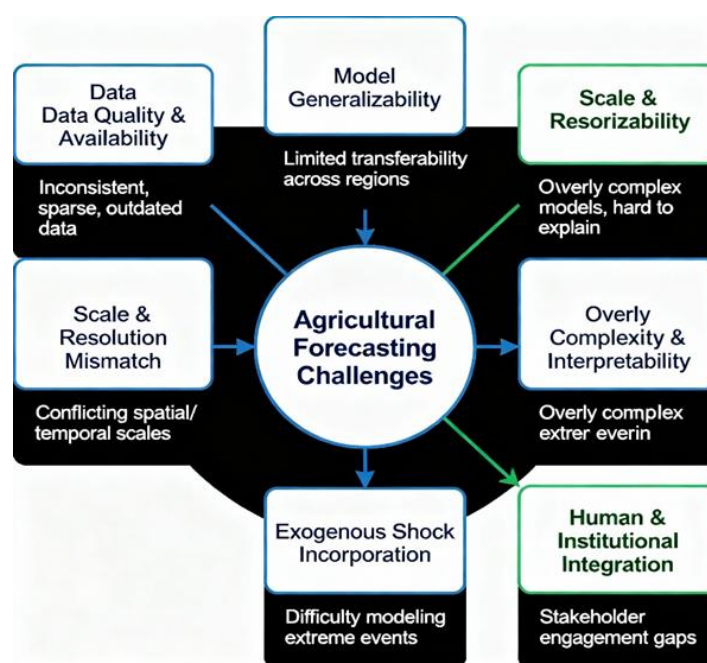


Fig. 9: Challenges in agricultural forecasting models: key limitations and barriers.

Table 6: Main limitations of agricultural forecasting models with supporting references.

Reference (Authors, Year)	Model(s)	Limitation	Description and Impact
Machefer <i>et al.</i> , 2025 ^[51]	ML, Feature-Based Models	Data Complexity, Factor Interactions	Complex interactions between climatic, socioeconomic, and crop factors challenge prediction accuracy and feature selection.
Kusunose <i>et al.</i> , 2016 ^[52]	Climate Forecast, Statistical	Forecast Skill and Utilization	Forecasts can be imprecise or insufficiently accurate for on-farm decisions, leading to underuse by farmers.
Paul <i>et al.</i> , 2022 ^[53]	GRNN, ARIMA, ML	Data Stationarity and Model Assumptions	ML models may outperform traditional ARIMA, but all are affected by non-stationary price data and unrealistic model assumptions.
Attri <i>et al.</i> , 2023 ^[54]	Deep Learning	Limited Data, Domain Adaptation, Transparency	DL models in agriculture face issues with labeled data, domain transfer, and interpretability/trust for farmers.
Paudel <i>et al.</i> , 2023 ^[15]	Deep Learning, LSTM, GBDT	Interpretability and Explainability	DL models (LSTM, CNN) learn features well but can be difficult to interpret or explain to agronomists and decision-makers.
Zarbakhsh <i>et al.</i> , 2025 ^[55]	Supervised/Ensemble ML	Feature Engineering and Pest Data Integration	Models require extensive manual feature engineering and may miss pest/disease events without good integration.

In garlic post-harvest management, ML models have been combined with physicochemical and packaging optimization techniques to maximize product quality and reduce waste, highlighting the necessity of factors in storage temperature and packaging material in predictive models. PCA and ML-driven environmental correlations explain most of the variance in shelf-life and quality parameters, supporting integrated supply chain optimization.^[52] Despite these advancements, challenges remain in terms of model generalizability across regions, variety differences, and unforeseen logistical disruptions. Small datasets, limited real-world calibration, and variable sensor data quality are the frequently cited issues. Ongoing research seeks to expand the training sets, integrate more biological and logistical factors, and validate models under broad real-world conditions.

4. Limitations of forecasting models

Forecasting models in agriculture and food systems offer vital insights for planning and risk mitigation; however, they face several key limitations, as shown in Table 6 and Fig. 9.

- **Data quality and availability:** Many models depend on historical, sensor, and survey data that may be incomplete, low-frequency, or inconsistently formatted across regions. Data scarcity, especially in the Global South, undermines the reliability and transferability of predictions.

- **Model generalizability and transferability:** Most high-performing models are calibrated on site-specific or crop-specific datasets, and their performance often deteriorates when applied across new geographies, crop types, or social contexts owing to ecological and management variability.

- **Scale and resolution mismatch:** Forecasts produced at coarse spatial or temporal scales (*e.g.*, regional averages or seasonal summaries) may lack actionable relevance for individual farmers, farm plots, or very short-term management decisions. The needs of end users often differ from those of granularity models.

- **Complexity and interpretability:** Advanced ML and DL models (*e.g.*, deep nets and hybrid stacks) may achieve high accuracy but function as "black boxes" with limited interpretability, creating challenges for trust, adoption, and troubleshooting by non-expert users.

- **Incorporation of exogenous shocks:** Many models struggle to capture rapid, non-linear disruptions due to climate extremes, pests, market volatility, or sociopolitical events. Consequently, they may lag in detecting crises or overfitting past stable patterns.

- **Integration with human and institutional systems:** Forecasts must mesh with local decisions, extension services, and policy responses; however, mismatches in timing, uncertainty communication, or institutional capacity often undermine the impact on ground-level outcomes.

- **Computational and resource demands:** High-fidelity models, especially those incorporating remote sensing, weather ensembles, and multi-modal data, can require substantial computing power, making real-time or resource-constrained deployment difficult.

- **Lack of feedback and iterative improvement:** Many operational models lack robust mechanisms for incorporating observed outcomes, farmer actions, or ground-truth feedback, limiting continuous model refinement and learning from the deployment experience.

5. Case studies

Forecasting models have increased agricultural productivity in real-world contexts. These models provide farmers and policymakers meaningful insights from satellite imagery, weather stations, soil sensors, and market patterns. They anticipate crop yields, optimize input utilization, forecast insect outbreaks, stabilize food prices, and improve resource efficiency, harvesting, and livelihoods. AI and machine-learning solutions for smallholder farms have made precision agriculture more accessible and scalable worldwide. We

present a thorough case study of the practical effects of the forecasting models.

5.1 AI-driven precision farming in india

India, characterized by its extensive smallholder farming population, has achieved significant advancements through the implementation of AI-driven technologies for precision agriculture. These platforms utilize real-time satellite data and soil sensor inputs to assess crop health and soil moisture levels. Machine learning models forecast insect infestations and propose better schedules for fertilizer and water applications. The outcomes have been remarkable: farmers have decreased input expenses by 15-20%, reduced chemical pesticide application by 25%, and attained yield improvements despite adverse climatic conditions. This case illustrates how data-driven advice custom-made for unique farm conditions can promote sustainable and economically viable agriculture.^[56]

5.2 COMPASS satellite-based crop forecast in latin america

To provide weekly updates on the state of crops in Mexico and Argentina, COMPASS uses satellite imagery in conjunction with crop models. Mobile alerts were sent to farmers regarding potential yield gaps, irrigation timing, and pest monitoring at their locations. It is possible to implement timely interventions owing to the early detection capabilities of the system, which in turn reduces losses and improves harvest predictability. The efficacy of remote sensing and artificial intelligence in assisting smallholder production in Latin America was demonstrated by the fact that this scalable strategy reached over 20,000 users during the test phases.^[57]

5.3 Mobile crop selection tool for indian farmers

In the Indian states of Maharashtra and Uttar Pradesh, a smartphone application powered by machine learning assists farmers in selecting the most suitable crops for the soil and climatic conditions of their respective regions. Personalized crop suggestions that maximize profitability and minimize risks are provided by the application, which incorporates soil tests, weather forecasts, and market pricing to deliver customized recommendations. The use of this technology assists farmers in making decisions, particularly in areas prone to drought or marginal, which ultimately results in increased yield stability and revenue diversification. Through the use of this technology, farmers were provided with access to scientific data that were previously unavailable in rural areas.^[58]

5.4 Hazelnut yield prediction in turkey's black sea region

Machine learning and crop growth simulations are combined in HADES, which allows the prediction of hazelnut yields several months before harvest. It combines satellite data with local weather and field observations, which allows it to provide cooperatives with estimates of harvest time and quantity. Through the utilization of these insights, farmers

can manage labor and marketing with better precision, thus avoiding waste and expanding earnings. Policymakers also utilize these forecasts to stabilize exports and plan food security situations. Hybrid physical-machine learning crop models have been shown to be beneficial to both producers and regulators.^[59]

6. Future directions

AI has great potential in farming, but some important areas need more research and development before we can fully realize its potential. The following are the most important future directions that will help AI applications in agriculture grow and change, as shown on Fig. 10.



Fig. 10: Key future directions for AI in agriculture.

• **Improving the quality and availability of data:** AI algorithms require trustworthy, high-quality data to make accurate predictions. Farmers in many areas, especially in underdeveloped countries, do not always have access to real-time high-quality data. Future initiatives should focus on making data collection easier by adding more IoT networks, satellite images, and local sensors. This will also mean fixing problems with the data, such as missing values, and ensuring that the data is standardized and easy to access on all platforms so that AI systems can work better.

• **Model adaptability and transferability:** One problem with the present AI models is that they do not work well in different parts of the world, farming methods, or weather conditions. Models trained in one place typically have trouble adjusting to a new one. Future research should concentrate on developing more versatile AI models that can function in many agricultural settings. One way to do this is through transfer learning, where models are trained in one area and then improved for use in another area with very little new data. Combining local knowledge with global data in hybrid models can also make them more adaptable.

• **Making AI models easier to grasp and trust:** People often

call AI systems, especially deep learning models, "black boxes" because it is difficult to grasp how they make decisions. To gain the trust of farmers and other stakeholders, AI systems must be easier to understand. Explainable AI (XAI) methods like SHAP (Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), could make decision hooks that translate AI predictions into irrigation decisions, pest alerts, fertilizer timing clearer. Several methods have been used in earlier studies to measure the impact of decisions. These include: (i) before–after field comparisons, (ii) model-versus-farmer performance comparisons, and (iii) controlled pilot plot trials. These give measurable values such as water saved, yield gained, or reduction in chemical use. Farmers will be more willing to trust and use AI technology if it is easier to understand.

• **Integration with traditional agricultural practices:** AI can be very useful for farming, but it needs to work well with the way things are done for it to be useful. AI solutions should not replace the present farming systems; instead, they should work with them and make them better. Future efforts should concentrate on developing user-friendly interfaces and decision-support systems that enable farmers to make data-driven choices while still relying on established knowledge and habits. This "human-in-the-loop" method, in which AI tools help but don't completely automate decision-making, might make it easier for farmers to make the switch.

• **Data privacy and security:** AI in farming depends on a large amount of data, so it is very important to keep this data private and safe. Unauthorized access to, or use of, personal and farm-related information must be stopped. Future work should focus on creating strong data governance structures to ensure that farmers maintain control of their data. In addition, to develop confidence among farmers, agribusinesses, and technology providers, data-sharing processes should be safe and open.

• **Reducing the environmental impact of AI:** Training AI models, especially deep learning models, can consume a lot of computing power, which makes people worry about the environmental effects of using AI on a large scale. Future research should concentrate on enhancing the energy efficiency of AI models and formulating "green AI" methodologies that mitigate the carbon footprint of AI systems. Making AI algorithms more energy efficient could help lessen the environmental effects of using AI on a large scale in farming.

• **AI-driven climate resilience:** Climate change is a major problem for farming because it makes the weather less predictable and more likely to cause droughts and floods. AI can help farmers deal with these changes by giving them better weather forecasts, finding crops that can survive, and suggesting ways to farm that are more flexible. To help farmers to better prepare for and deal with climate threats, future AI models should focus on making crops more resistant to climate change by combining local meteorological data, climate models, and crop-specific information.

• **Creating AI solutions that smallholder farmers can afford:** The expense of technology is a major reason why smallholder farmers in underdeveloped nations do not use AI. Future research should concentrate on enhancing the affordability and accessibility of AI tools to smallholder farmers. To do this, we need to develop cheap sensors, mobile apps, and cloud-based AI solutions that do not require much hardware or infrastructure. Additionally, working with local governments, NGOs, and agribusinesses can assist smallholders in paying for AI technology.

• **Collaboration across sectors:** For AI to work in farming, people from different fields, such as farming, technology, finance, and policy, must work together. Future efforts should concentrate on establishing interdisciplinary teams capable of addressing the technological, economic, and social dimensions of AI adoption. To ensure that everyone benefits from AI in agriculture, governments, commercial firms, and academic institutes must work together to create policies and rules that encourage its appropriate usage.

• **Long-term sustainability and scaling:** As AI models show their worth in farming, attention should be paid to finding ways to make these solutions bigger in a way that lasts. This means dealing with problems in infrastructure, training, and capacity building to ensure that AI solutions can be used in many areas and types of agriculture. It is also important to keep an eye on how AI affects agricultural ecosystems in the long term and ensure that these technologies are employed in ways that are good for the environment and fair to everyone.

6. Conclusion

Artificial intelligence (AI) has emerged as a transformative force in modern agriculture, offering data-driven solutions to enhance productivity, sustainability, and decision-making accuracy. AI-driven models support precise irrigation scheduling, pest control, and energy optimization by integrating data from weather stations, soil sensors, satellite imagery, and market dynamics. Advanced forecasting techniques, such as ARIMA and SARIMA, effectively model seasonal trends, whereas machine learning approaches, such as Random Forest and XGBoost, uncover nonlinear interactions influencing crop health and yield. Deep learning models, particularly long short-term memory (LSTM) networks, excel in time-series forecasting, enabling accurate predictions of crop yields and disease outbreaks. The integration of hybrid AI agronomic models has further improved the cost-effectiveness and reliability, even in data-scarce regions. Empirical studies have reported significant performance gains, including a 10–25% reduction in irrigation water usage, an 8–18% increase in crop yields, and 10–20% energy savings in controlled farming environments. AI's role of AI also extends to agricultural finance, enhancing credit access and risk management for farmers. However, challenges such as data inconsistency, limited transferability of models, and opacity of AI algorithms hinder their wider adoption. To ensure a practical impact, AI models must be transparent,

interpretable, and adaptable across diverse agricultural contexts. Future research should focus on improving the data quality, model scalability, and trustworthiness to promote inclusive and sustainable adoption. When effectively aligned with traditional knowledge and local practices, AI-powered systems can potentially create resilient, resource-efficient, and intelligent agricultural ecosystems worldwide.

7. Research gap and future scope

Despite significant advancements in AI-driven agronomy, numerous critical gaps continue to constrain its practical effectiveness. Numerous studies rely on limited or region-specific variables, rendering the models challenging to generalize across diverse climates, soil types, and agricultural practices. Limited studies document field-level experiments or quantify the impact of AI-driven decisions on yield, water consumption, or production efficiency, highlighting a distinct disparity between the precision of research and the practical results. Model explainability continues to pose a significant barrier, as most systems function as black boxes, thereby complicating trust and adoption among farmers, extension workers, and policymakers. Moreover, contemporary AI technologies are seldom integrated with agri-finance systems, like crop insurance, credit scoring, or risk assessment, even though these financial connections are essential for enhancing adoption and enabling small farmers to capitalize on the technology. There is a necessity for comprehensive, multi-season datasets that integrate weather, soil, remote sensing, agricultural inputs, and market trends in a cohesive format to facilitate more rigorous analysis. Subsequent research should concentrate on generating diverse, high-quality datasets, enhancing model transferability across regions, devising explainable and user-friendly AI systems for farmers, validating outcomes through actual field tests, and constructing integrated platforms that connect agronomic predictions with financial and policy decisions. Enhancing these domains would facilitate the transition of AI in agriculture from experimental achievements to dependable, scalable, and egalitarian solutions for farmers and institutions.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

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CRedit Statement

Kaiss Redouane: Conceptualization, Methodology; Supervision, Writing – Original draft. **Yahya Fikri:** Data curation, Formal analysis, Visualization, Writing – Original

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