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Integration of Field Observation Data and Computational Methods for Crop Management Optimization

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Abstract The integration of field observation data and computational methods provides a powerful approach for optimizing crop management under increasingly complex agricultural environments. This review summarizes recent advances in the acquisition, processing, and application of multi-source field data, including soil properties, climatic conditions, remote sensing information, and crop growth indicators. Statistical models, machine learning algorithms, deep learning approaches, and crop process-based models have been widely applied to reveal crop-environment interactions, predict yield performance, and support precision management decisions. Data assimilation and hybrid modeling strategies further enhance the accuracy and reliability of agricultural prediction systems by combining empirical observations with mechanistic knowledge. Case studies demonstrate the effectiveness of data-driven approaches in yield forecasting, precision water and fertilizer management, and crop stress identification. Despite significant progress, challenges remain in data quality control, model transferability, and the integration of artificial intelligence with agricultural knowledge. Future research should focus on developing intelligent, explainable, and scalable agricultural management systems to improve resource-use efficiency, crop productivity, and sustainable agricultural development.

Keywords Field observation data; Computational methods; Precision agriculture; Machine learning; Crop management optimization

1 Introduction

Modern agriculture is under growing pressure to increase productivity, improve resource-use efficiency, and reduce environmental burdens under conditions of climate variability, land constraints, and rising food demand. Data-driven management has therefore become a central paradigm in precision agriculture because it replaces coarse, experience-based interventions with decisions informed by measurable variability in crops, soils, and microenvironments. In this transition, digital agriculture platforms increasingly combine sensor observations, weather information, remote sensing, and farm records to support critical operational decisions such as irrigation, fertilization, pest control, and harvest planning (Fuentes-Peñailillo et al., 2024). The core promise of this approach is not simply more data, but better timing and targeting of interventions, allowing growers to reduce waste, improve profitability, and limit environmental externalities associated with over-application of inputs. At the same time, the shift toward data-driven management remains incomplete because agricultural systems are highly heterogeneous across fields, seasons, and regions, making reliable data acquisition and scalable decision support difficult (Elbasi et al., 2023; Mansoor et al., 2025). Current implementations also face practical barriers related to data quality, data volume, interoperability, infrastructure, connectivity, and the technical expertise needed to convert raw measurements into useful recommendations. These constraints are especially important for small and medium-sized farms, where the cost of sensing, storage, analytics, and system maintenance can outweigh immediate returns and slow technology adoption. Even where precision agriculture tools are available, predictive systems are often limited by incomplete feature collection, insufficient local calibration, and weak integration into daily farm workflows. As a result, the central challenge in modern crop management is no longer whether agricultural data matter, but how to integrate diverse observations into robust, adaptive, and operationally feasible decision systems that can function under real farm conditions.

Field observation data occupy a foundational role in this problem because they provide the direct empirical description of crop state on which timely management actions depend. Traditional field management has long relied on visual inspection and farmer experience, but this approach produces sparse, subjective, and often delayed information relative to the spatial and temporal variability of crop development. Recent sensing and IoT systems have expanded field observation from occasional manual scouting to continuous, high-resolution monitoring of the soil–plant–atmosphere continuum, enabling quantitative assessment of soil moisture, nutrient status, water availability, crop stress, pest pressure, and local environmental conditions (Fuentes-Peñailillo et al., 2024). These observations can be gathered through in situ sensors, weather stations, UAV surveys, spectral imaging, GPS-enabled devices, and mobile platforms, producing a richer representation of field conditions than any single source alone. Their practical importance lies in supporting management decisions at each cultivation stage, from crop selection and seeding through irrigation, fertilization, disease surveillance, growth monitoring, and harvest timing (Senapaty et al., 2023). High-throughput phenotyping and remote sensing have further strengthened this role by allowing plant traits and stress signals to be monitored at larger scales while still informing field-level actions such as nutrient management, irrigation scheduling, and pest intervention. However, observation itself is not cost-free. In-field measurement remains labor-intensive, time-consuming, and expensive in many contexts, and temporally complete observations are often unrealistic before every decision point. This creates a fundamental tradeoff between information value and collection burden, particularly in regions with limited infrastructure or low data availability. It also means that field observation data must be treated not only as inputs to optimization, but as resources that themselves require strategic design, filtering, validation, and prioritization. For crop management optimization, the key issue is therefore not merely collecting more observations, but ensuring that field data are accurate, timely, representative, and sufficiently integrated to support decisions under uncertainty.

Against this background, computational methods have emerged as the main mechanism for transforming heterogeneous field observations into agricultural intelligence. Machine learning and deep learning methods are increasingly used because they can analyze large, multimodal datasets and detect nonlinear patterns linking soil, weather, crop status, topography, and management history to agronomic outcomes. In practice, these methods support prediction, classification, anomaly detection, recommendation, and automation tasks across yield estimation, disease recognition, nutrient diagnosis, water management, and growth assessment. Commonly used approaches include random forests, support vector machines, artificial neural networks, convolutional neural networks, and recurrent models such as LSTM, with model choice depending on data structure, target task, and the need to represent spatial or temporal dependencies. Evidence from comparative studies shows that high-capacity computational models can achieve strong predictive performance in agricultural applications, for example with random forest outperforming several alternatives in subfield yield prediction and other crop-yield studies. Recent work also highlights the value of multimodal data fusion, where remote sensing, IoT devices, weather data, and historical farm records are jointly analyzed to improve accuracy and provide more comprehensive support for farm management. At the frontier, adaptive systems are beginning to integrate decision-making with measurement strategy itself, as shown by reinforcement-learning approaches that recommend both when to collect crop-state observations and when to apply management actions under explicit cost constraints. Nevertheless, computational progress has not eliminated several persistent research gaps, including scarce labeled data, poor model generalizability across environments, limited interpretability, slow deployment in operational farm systems, and the need for interfaces that farmers can trust and use effectively. These limitations indicate that agricultural intelligence development depends not only on more sophisticated algorithms, but also on tighter coupling between domain knowledge, field observation design, and scalable digital infrastructure. Therefore, integrating field observation data with computational methods is a necessary step toward crop management optimization, because it links the reality of field conditions with predictive and prescriptive models capable of supporting timely, site-specific, and economically viable decisions across the production cycle.

2 Acquisition of Field Observation Data and Multi-Source Information Integration Technologies

2.1 Construction of long-term crop growth environment monitoring systems

Long-term crop growth environment monitoring systems are the foundation of data-driven crop management because they convert discontinuous manual observation into continuous measurement of the soil-plant-atmosphere continuum. Recent Ag-IoT architectures increasingly support a full pipeline of sensing, transmission, storage, visualization, analysis, and decision-making, which makes them suitable not only for observation but also for operational management. In practice, these systems monitor variables such as soil moisture, temperature, humidity, electrical conductivity, pH, and light, while newer deployments also include gaseous indicators and nutrient-related parameters to broaden environmental situational awareness. Low-cost and edge-enabled platforms have improved feasibility by wirelessly transmitting real-time data to cloud dashboards and generating threshold-based alerts, which is especially relevant for small and medium-sized farms (Kalaivani et al., 2025).

The design of long-term monitoring systems depends on network reliability, energy efficiency, and the ability to adapt sensor combinations to local agronomic conditions. Wireless sensor networks and IoT platforms are valuable because they allow farm managers to track weather, water use, soil status, and plant morpho-physiological indicators without substantially increasing field workload (Alexopoulos et al., 2023). Field studies also show that real-time soil and weather sensing can directly support irrigation scheduling, water conservation, and crop productivity, while AI-linked mobile or web interfaces can translate sensor streams into management recommendations. However, large-scale adoption still faces persistent constraints related to implementation cost, connectivity, data security, and farmers' digital literacy, so robust long-term systems must be technically resilient as well as economically and operationally accessible.

2.2 Applications of remote sensing and proximal sensing technologies in field monitoring

Remote sensing and proximal sensing have become central field monitoring technologies because they reveal spatial and temporal crop variability that cannot be captured by sparse point measurements alone. Satellite imagery provides broad and repeated coverage, and its multispectral products have been used to assess agronomic traits such as nitrogen status and chlorophyll-related variation across crop fields. UAV-based sensing extends this capability by delivering higher spatial and temporal resolution for localized observations, which makes it especially useful for crop health assessment, yield-oriented mapping, and rapid in-season diagnosis (Bazrafkan et al., 2025). Proximal sensing complements aerial and orbital observations by collecting close-range, high-resolution measurements of crop and soil conditions in real time, with flexibility in sensor choice for disease detection, crop monitoring, and resource optimization (Figure 1).

The main strength of combining these sensing modes is complementarity across scale, precision, and continuity (Alexopoulos et al., 2023). Ground-based sensing often provides the most trustworthy direct measurements for variables such as soil moisture and plant water status, and these observations are frequently used to train or validate remote-sensing and machine-learning models. At the same time, UAV and handheld proximal sensors can show very strong agreement for vegetation indices, supporting multi-scale crop assessment and more robust monitoring of growth stages and field heterogeneity. Even so, each modality has constraints: satellites can overgeneralize within-field variability, UAVs require skilled operators and substantial data processing, and proximal sensing has limited coverage area, so effective field monitoring increasingly depends on coordinated multi-platform observation rather than reliance on any single sensor source.

2.3 Multi-source agricultural data integration and standardization methods

Multi-source agricultural data integration is necessary because intelligent crop management depends on combining heterogeneous observations rather than analyzing isolated data streams. Unimodal approaches are often incomplete and vulnerable to environmental disturbance, whereas coordinated sensing across aerial, ground, and subsurface platforms provides a more comprehensive basis for perception and decision-making. In applied crop management, integrated datasets may include remote-sensing imagery, weather series, soil properties, topographic information, crop records, pest data, and vegetation indices collected at different spatial and temporal

resolutions. This heterogeneity makes preprocessing and harmonization essential, because practical systems must handle missing values, outliers, inconsistent formats, and mismatched resolutions before the data can support analytics or decision support (Martínez-Ruedas et al., 2026).

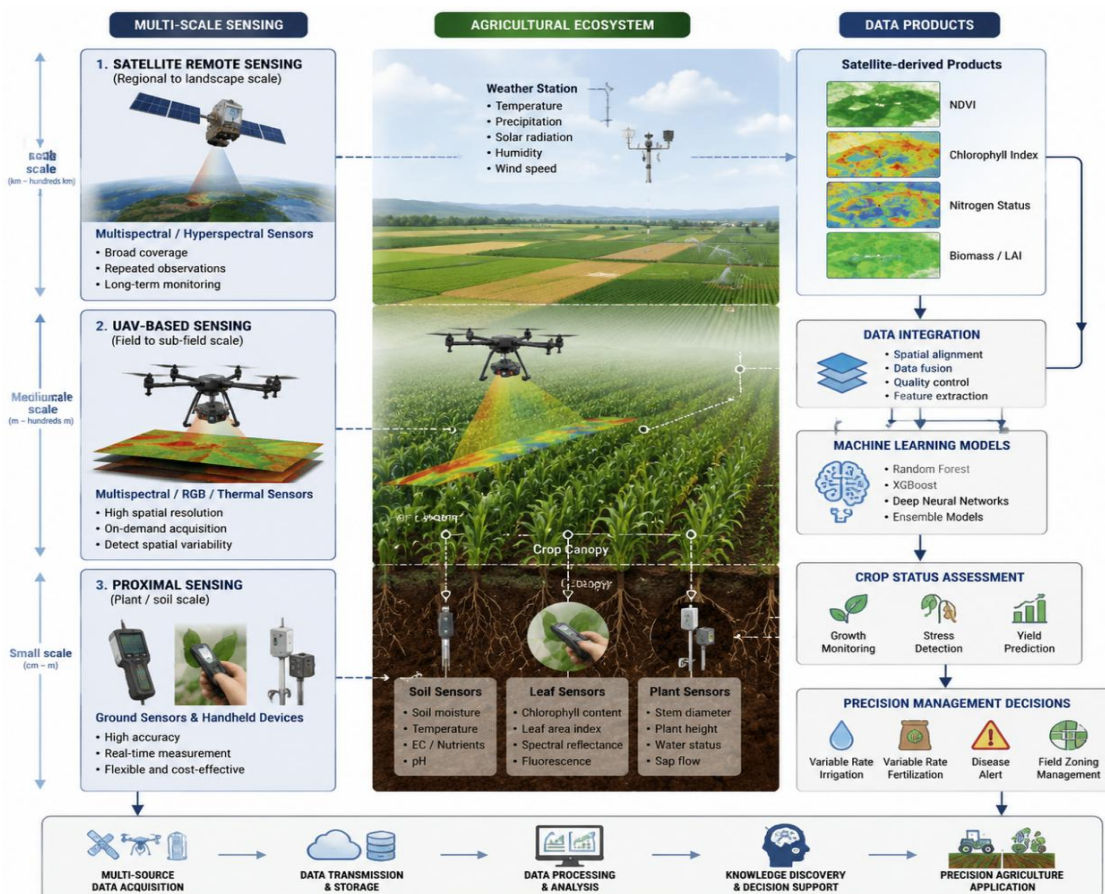


Figure 1 Multi-scale integration framework of remote sensing and proximal sensing technologies for crop field monitoring

Standardization methods therefore focus on creating interoperable platforms, unified data models, and fusion pipelines that turn diverse measurements into operational knowledge. Open interfaces and protocols are especially important because they allow heterogeneous information sources to be integrated into a common structure while preserving exchangeability with third-party systems. Recent studies also show that fusion improves agronomic usefulness: combining soil conductivity, chemical properties, and Sentinel-2 indices yields stable management zones over multiple years, while adaptive multi-view models that integrate imagery, weather, soil, and topography outperform conventional yield-prediction approaches (Jovanović et al., 2025). More advanced multimodal frameworks further indicate that integrating nutrient, moisture, image, and geographic data can improve both recommendation accuracy and response efficiency, but these gains depend on solving persistent challenges in interoperability, synchronization, and model generalization. In summary, field observation data acquisition and multi-source integration technologies are becoming the technical core of crop management optimization. Long-term IoT monitoring provides continuous environmental context, remote and proximal sensing supply spatially explicit crop information, and standardized fusion frameworks connect these streams into actionable decision support for precision agriculture.

3 Statistical Approaches for Analyzing Crop Growth Patterns

3.1 Applications of traditional statistical models in agricultural data analysis

Traditional statistical models remain central to crop growth analysis because they provide transparent ways to quantify relationships between agronomic outcomes and explanatory variables. In plant and crop research, ANOVA, regression, and correlation analysis have long served as core tools for experimental design, treatment comparison, and response interpretation. Regression models are especially valuable in agriculture because they

link production, cultivated area, temperature, humidity, and other management-related variables to measurable outcomes, thereby supporting resource optimization and risk-aware decision-making.

Within field experiments, these methods are commonly used to distinguish treatment effects and estimate response functions for management variables such as fertilizer and irrigation. ANOVA remains important because it partitions variation and tests mean differences among multiple treatments in a single framework. At the same time, empirical response modeling has expanded beyond simple linear forms, and comparative on-farm studies show that sigmoid, additive, Bayesian, and linear regression structures can all be used to forecast crop responses, although their performance depends strongly on field and year context.

3.2 Time-series analysis and dynamic simulation of crop growth processes

Time-series analysis extends conventional statistical modeling by representing crop growth as a dynamic process rather than a single end-of-season outcome. Functional data analysis is particularly useful because it transforms repeated environmental observations into continuous curves, allowing crop yield to be modeled as a function of evolving temperature, radiation, and other time-dependent drivers (Matsui and Mochida, 2024). This perspective fits crop systems well because growth and development unfold over time, and dynamic statistical models can reveal seasonal shifts in the effects of environmental factors on yield formation.

Dynamic simulation approaches go further by describing growth trajectories, phenological stages, and limiting factors during the season. Minimal-complexity crop growth models based on differential equations can capture genotype–environment–management interactions over time, even when designed for parsimonious interpretation rather than full mechanistic detail (Van Voorn et al., 2023). Time-series satellite imagery and sequential phenotyping data also strengthen this approach, because normalized vegetation curves, sigmoid growth functions, and multimodal temporal observations can characterize stage-specific development and improve practical forecasting of biomass, canopy establishment, and yield-related traits.

3.3 Limitations of statistical models in precision agricultural decision-making

Despite their utility, statistical models have important limitations in precision agriculture because field conditions are heterogeneous, nonlinear, and often outside the range represented in training data. Statistical yield models can describe responses to observed combinations of weather, nutrients, and irrigation, but they generally do not extrapolate well to threshold behavior or nonlinear responses beyond the conditions used to build them. This problem becomes more serious in precision farming datasets, where heterogeneity, multicollinearity, and outliers can bias inference and reduce the reliability of conventional homogeneous-model assumptions.

These weaknesses also appear in model specification, evaluation, and operational deployment. In horticultural trials, repeated-measures ANOVA can violate assumptions such as homogeneity and independence of residuals, whereas nonlinear growth models sometimes provide more biologically meaningful and statistically valid fits. More broadly, predictive performance in precision agriculture is easily overstated when cross-validation is poorly designed, test data are reused during model selection, or seasonal block effects are ignored, which means that trustworthy decision support requires not only better models but also stronger validation protocols and adaptation to data-poor or uncertain environments (Chen et al., 2025). In summary, statistical approaches remain indispensable for analyzing crop growth patterns, especially where interpretability and experimental comparison are priorities. However, crop management optimization increasingly requires statistical methods to be combined with temporal modeling, dynamic simulation, and more robust validation strategies so that decisions remain reliable under spatial heterogeneity, environmental uncertainty, and changing field conditions.

4 Applications of Machine Learning and Artificial Intelligence in Crop Management Optimization

4.1 Applications of machine learning algorithms in crop yield prediction

Machine learning has become a practical tool for crop yield prediction because it supports decisions both before planting and during the growing season. Across the yield-prediction literature, commonly used input variables include temperature, rainfall, soil type, humidity, and vegetation indices, showing that predictive performance

depends on combining environmental and agronomic signals rather than relying on a single factor. Algorithm choice strongly affects prediction performance, and comparative studies repeatedly show that tree-based and neural approaches are among the most effective options. In one recent XAI-oriented yield study, LightGBM and Random Forest outperformed a decision tree regressor (Mohan et al., 2025). At larger operational scales, reusable machine-learning workflows built from weather, soil, remote sensing, and crop-model-derived features have already produced sub-national yield forecasts that are comparable to established forecasting systems in several crop-country cases.

Recent research also shows that yield prediction improves when machine learning is coupled with agronomic knowledge rather than used as a purely generic prediction engine. A systematic review found that artificial neural networks were the most frequently applied machine-learning models in crop-yield studies, while CNN, LSTM, and DNN dominated deep-learning applications. This pattern reflects the need to represent both nonlinear feature interactions and temporal or spatial variability in agricultural systems. Hybrid approaches are especially important for optimization because they add process-level information that weather-only models often miss. In the US Corn Belt, adding APSIM simulation variables to machine-learning models reduced yield-prediction RMSE by 7%-20%, and soil-moisture-related variables were among the most influential predictors (Shahhosseini et al., 2020). More broadly, machine-learning baselines become more useful when they are designed around explainable agronomic features, modular workflows, and strict avoidance of information leakage, since these properties improve transferability and operational reuse.

4.2 Deep learning approaches for understanding complex agroecosystem processes

Deep learning is increasingly used in agriculture because it can learn nonlinear relationships from image, geospatial, and time-series data without requiring strong a priori assumptions about how drivers and responses are linked (Aderale et al., 2025). This matters in agroecosystems, where crop growth, hydrology, nutrient cycling, and stress responses are shaped by interacting processes across multiple spatial and temporal scales. Different deep-learning architectures support different forms of agroecosystem understanding. CNNs have been widely applied to satellite and drone imagery for crop-health assessment and yield estimation, where their main strength is extracting spatial patterns from multispectral and hyperspectral observations. Recurrent and hybrid recurrent models are valuable when prediction depends on within-season dynamics, and reviews report that RNN-LSTM structures often achieve higher accuracy than simpler network designs for agricultural forecasting.

Deep learning is also useful beyond end-of-season yield prediction because it can represent broader environmental and biophysical processes. Recent syntheses describe applications to precipitation forecasting, soil moisture, evapotranspiration, groundwater behavior, plant phenotyping, irrigation management, and disease detection, showing that AI can support management by modeling interacting components of the field environment. In Earth-system-oriented analyses, deep learning is particularly valuable when behavior is dominated by spatial and temporal context, because it can extract these cues automatically and thereby improve process understanding as well as prediction (Figure 2). The main frontier is no longer standalone deep learning, but hybrid modeling that combines domain knowledge with flexible data-driven learning. Reviews of agroecosystem modeling classify these integrations into three forms: replacing process-based models with data-driven models, using both approaches simultaneously, or training machine learning to emulate process-based models (Aderale et al., 2025). Evidence from hybrid studies further suggests that models informed by physical or biological knowledge can outperform both conventional process-based models and unconstrained black-box deep learning, while also generalizing better to noisy data and unseen locations.

4.3 Explainable artificial intelligence for improving the reliability of agricultural decision-making

As AI models become more accurate, their practical value increasingly depends on whether users can understand and trust the basis of their predictions. This is a major issue in agriculture because many high-performing methods are black-box models, and lack of transparency can limit confidence in decisions that affect yield, input use, and climate-risk adaptation (Rajbongshi et al., 2026). Explainable AI addresses this problem by making model behavior more transparent to the intended audience, which is now widely recognized as a requirement for

responsible deployment. In agricultural applications, the most commonly discussed XAI tools are SHAP, LIME, and Grad-CAM. These methods help identify the variables driving predictions and express their contributions in forms that are easier for agronomists and farmers to interpret. In yield-prediction settings, this means AI outputs can be translated into interpretable importance patterns for temperature, precipitation, soil moisture, and nutrient-related variables, making predictions more actionable for crop management.

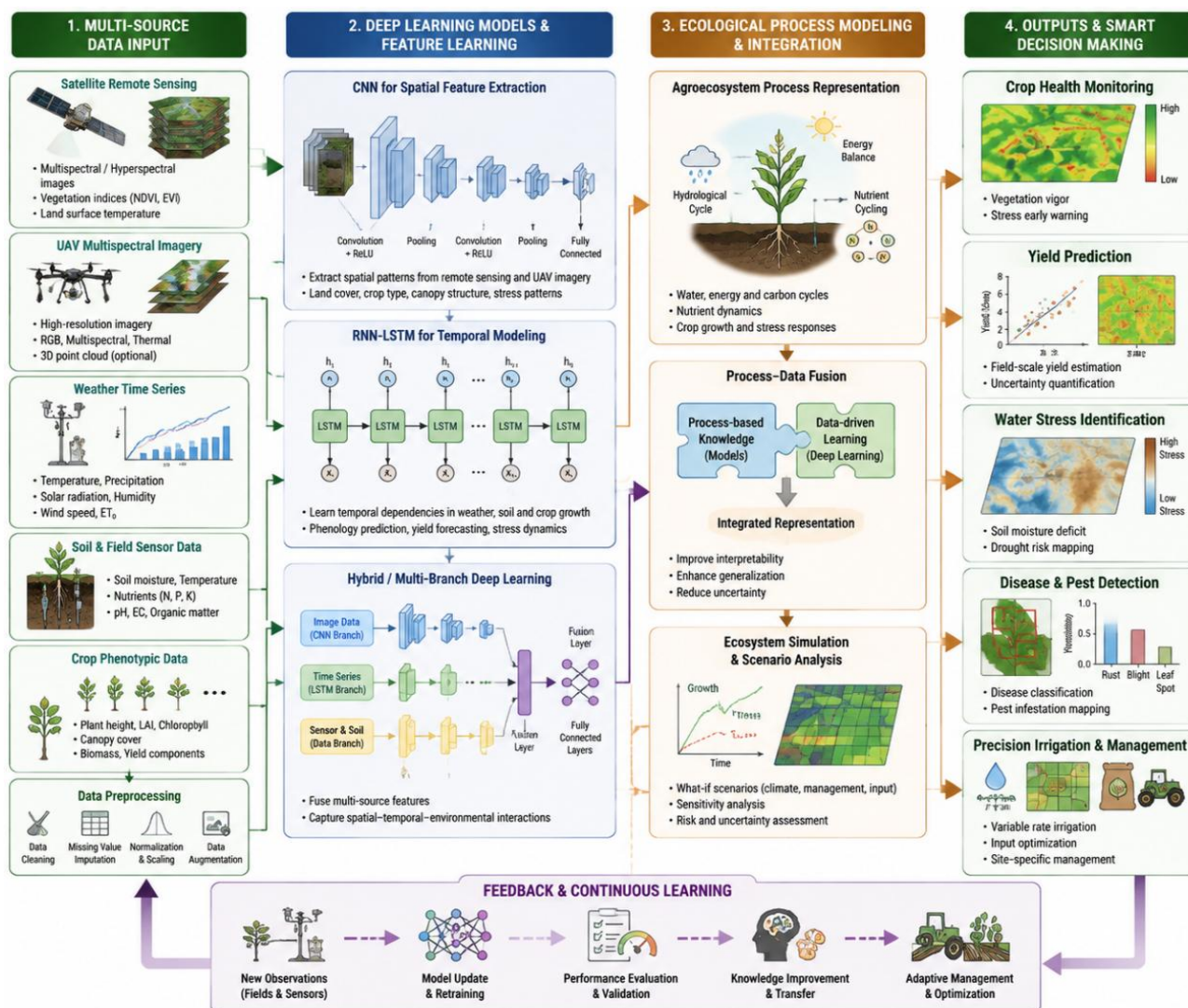


Figure 2 Deep learning framework for agroecosystem analysis integrating multi-source agricultural data and crop management applications

XAI also improves reliability by answering questions that raw performance metrics cannot. Interpretable machine-learning frameworks can reveal which variables matter most, which interactions are influential, how predictors are associated with the response, and why a specific instance received a particular prediction. This is important because agricultural decision support is weakened when models only produce accurate outputs but do not clarify whether those outputs are biologically plausible or management-relevant. Current research therefore treats explainability as part of model design rather than a cosmetic add-on after prediction. Reviews of agricultural XAI conclude that explainability is necessary not only for machine-learning and deep-learning models, but also for real-time monitoring and operational field systems. At the same time, broader XAI scholarship emphasizes that practical deployment must balance predictive power with fairness, accountability, and audience-centered explanation, which is especially relevant for high-stakes agricultural decisions under uncertainty. Taken together, machine learning and AI are becoming core tools for crop management optimization because they improve prediction, capture complex agroecosystem dynamics, and strengthen decision support when combined with

explainability. The most promising direction is the integration of agronomic knowledge, multi-source field data, hybrid modeling, and XAI so that predictive systems become not only more accurate, but also more robust and usable in real farming contexts.

5 Integration Strategies of Crop Growth Process Models and Data-Driven Models

5.1 Applications of process-based models in agricultural management simulation

Process-based crop models are widely used in agricultural management simulation because they represent crop growth as the interaction of weather, soil, genotype, and management variables, allowing agronomic decisions to be evaluated before they are implemented in the field. In practical decision support, models such as APSIM and DSSAT are used to test planting dates, irrigation, fertilization, and other management options while reducing the time and cost required for long field experiments. Their value is especially strong when management must be optimized under climate variability, because they can simulate crop productivity responses under different environmental and resource conditions. Reviews across multiple crops also show that APSIM and DSSAT are among the fastest and most reliable broad-output models, while model ensembles often produce smaller errors than single-model applications (Gavasso-Rita et al., 2023).

These models are not only conceptual tools but operational simulation systems that have shown useful accuracy after local calibration and validation. In West African sorghum, APSIM, DSSAT, and Samara reproduced phenology and leaf development reasonably well across varieties with different photoperiod sensitivities, although grain filling and yield partitioning were harder to predict accurately. In Ethiopian maize environments, APSIM-maize, DSSAT CERES-maize, and AquaCrop all simulated flowering, maturity, and yield with acceptable skill, and the ensemble mean reduced normalized RMSE and improved agreement relative to individual models. Soil-focused bibliometric evidence also shows that process-based crop models are now routinely applied to water balance, nutrient dynamics, greenhouse gas emissions, and nitrogen leaching, extending their relevance beyond yield alone (Wimalasiri et al., 2023). This breadth makes them suitable as core engines for management simulation, but their uncertainty remains sensitive to parameterization, local data quality, and model structure.

5.2 Data assimilation technologies for improving model prediction accuracy

Data assimilation improves crop model prediction accuracy by repeatedly updating model states or parameters with observations collected during the growing season. This approach is increasingly used to address the weak field transferability and limited yield accuracy of standalone crop models, especially in precision agriculture and early warning applications. Remote sensing is the dominant observation source in this literature because it provides canopy and soil information over large areas, and assimilation frameworks commonly incorporate variables such as LAI, vegetation indices, and soil moisture into process-based crop models. Recent reviews show that sequential assimilation is the most commonly used strategy, with the ensemble Kalman filter remaining the most widely adopted algorithm, while hierarchical Bayesian methods are emerging as promising alternatives. At the same time, successful assimilation depends strongly on calibration quality and on the temporal, spatial, and radiometric suitability of the observation data being injected into the model (Dlamini et al., 2023).

Empirical studies show that assimilation can produce substantial gains, but the magnitude depends on the variable assimilated and the background uncertainty structure. In a classic maize case, assimilating remotely sensed soil moisture and LAI together improved yield correlation from 0.47 to 0.65 and reduced error more than assimilating either variable alone, indicating that joint state updating can better capture coupled water-canopy dynamics. In sugar beet, assimilating four to six remote-sensing observations into the SUCROS model reduced relative field-scale yield RMSE from about 20% to 10%, while the timing and number of images determined which parameters could be reliably re-estimated. More recent multi-model work in winter wheat found that particle-filter assimilation of LAI improved LAI simulation across all models and reduced yield prediction bias in the ensemble from 19% to 7%, whereas gains for individual models depended on their internal error structure (Zare et al., 2024). Even so, uncertainty in remote-sensing products, limited robustness under drought, and weaker constraints on downstream variables such as drainage and nitrate leaching remain important bottlenecks.

5.3 Hybrid modeling approaches for advancing precision agriculture

Hybrid modeling combines process-based crop models with machine learning or deep learning so that mechanistic understanding and statistical flexibility can be used together. This strategy has emerged because process-based models are interpretable but often struggle with parameter uncertainty and heterogeneous environments, whereas data-driven models capture nonlinear patterns well but are usually less transparent and more dependent on large datasets (Aderale et al., 2025). The main hybrid logic is therefore complementary: process models contribute physically meaningful structure, and machine learning contributes pattern extraction, bias correction, or surrogate prediction under complex genotype–environment–management interactions. Current architectures generally fall into two broad classes, namely DL-informed PBMs, in which neural models refine or drive process-model components, and PBM-informed DL, in which physical rules or simulated states constrain the data-driven model.

Evidence across recent studies indicates that hybrid methods often outperform either component alone in prediction tasks relevant to precision agriculture. In the US Corn Belt, adding APSIM-derived variables to machine-learning models reduced yield prediction RMSE by 7%-20%, and soil-moisture-related simulation outputs were the most influential added features, showing that weather data alone were insufficient for best performance. Broader hybrid reviews report that these models are more robust to noisy data and generalize better across unseen locations than standalone process-based or deep-learning models. Hybrid deep-learning studies on soybean also show that combining representation learning with structured predictors can achieve strong accuracy, with a CNN-DNN model reaching an R^2 of 0.87 in one benchmark dataset (Oikonomidis et al., 2022). However, the next challenge is operational integration: future systems must improve interpretability, data efficiency, and scalability so that hybrid models can support real-time crop monitoring, stress diagnosis, and management recommendations across diverse farming systems. Overall, Section 5 shows that crop management optimization increasingly depends on linking mechanistic simulation with observational updating and machine-learning enhancement. Process-based models provide the agronomic backbone, data assimilation improves in-season state estimation, and hybrid modeling offers a practical path toward more accurate and scalable precision agriculture systems.

6 Case Studies: Optimization of Crop Management through Field Observation Data and Computational Methods

6.1 Crop yield prediction based on environmental monitoring and machine learning

Crop yield prediction has become one of the clearest examples of how field observation data and computational methods can be integrated for management optimization. Yield depends strongly on environmental and soil conditions, including rainfall, temperature, humidity, irrigation, and soil properties, so prediction models become more useful when they are built from monitoring systems that capture these variables over time. Case studies across broadacre and commercial systems show that combining field-level yield monitor data with soil conductivity, soil tests, rainfall records, and satellite products creates multi-layered datasets that support practical machine-learning forecasts at management-relevant time points. The predictive value of these systems generally improves as more within-season information becomes available. In Western Australia, random-forest models built from multi-farm and multi-year data predicted wheat, barley, and canola yield with cross-validated RMSE of 0.36-0.42 t ha⁻¹, and performance improved from pre-sowing to late season because rainfall and other in-season observations were added progressively. Similar case evidence appears in crop-specific studies: random forest performed best for Irish potato and maize yield prediction from rainfall and temperature in Rwanda, while field-level sweet corn prediction identified precipitation and minimum temperature during anthesis as among the most influential weather variables (Kuradusenge et al., 2023).

High-resolution sensing further strengthens yield forecasting when models are trained on spatially explicit crop and soil measurements rather than coarse regional averages. In Atlantic Canada, proximal sensing of soil electrical conductivity, soil moisture, slope, NDVI, and soil chemistry supported machine-learning prediction of potato tuber yield, with support vector regression outperforming linear regression, elastic net, and k-nearest neighbors across four provincial-year datasets. Deep-learning and remote-sensing reviews also show that vegetation indices are among the most widely used predictive features, and that CNN and LSTM architectures are especially

prominent when yield estimation depends on image sequences or other temporally structured inputs (Muruganantham et al., 2022). These case studies indicate that the main advantage of environmental monitoring is not only higher accuracy, but earlier and more actionable forecasting. When weather data, field observations, and remote-sensing indicators are merged through machine learning, prediction can inform fertilization timing, harvest planning, and risk management before yield losses are fully realized. At the same time, model quality remains sensitive to feature selection, data history length, and generalization across places and years, so robust deployment depends on longer time series and carefully structured training datasets rather than algorithm choice alone (Figure 3).

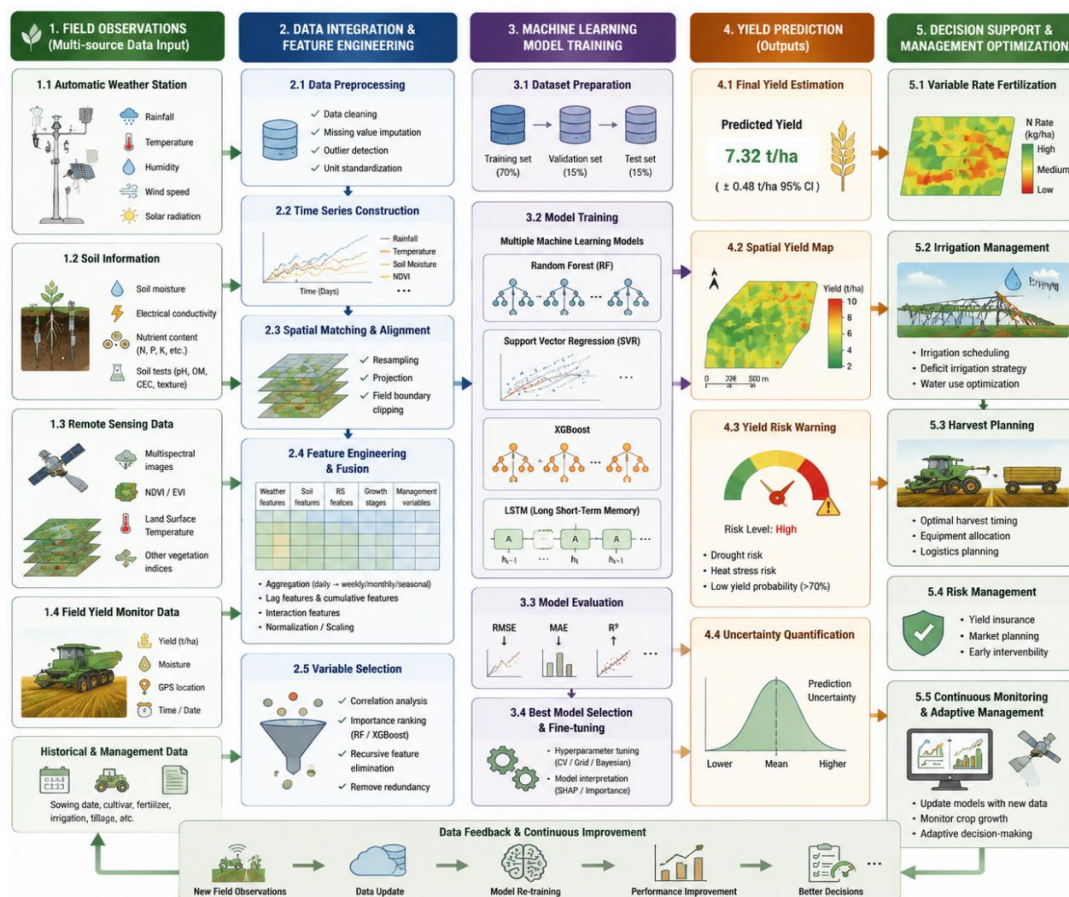


Figure 3 Framework of crop yield prediction integrating field observations, environmental monitoring, and machine-learning models

6.2 Precision water and fertilizer management based on sensor data integration

Precision water and fertilizer management is a second major case area in which field observation data are converted directly into operational control decisions. IoT-enabled soil and water sensors now monitor moisture, pH, temperature, salinity, electrical conductivity, and nutrient content in real time, creating the data basis for site-specific irrigation and fertilization rather than uniform application across a field. These sensor streams become management tools when linked to AI or cloud platforms that analyze trends and recommend actions, including irrigation scheduling, nutrient dosing, and anomaly detection. The irrigation case is especially well developed because water demand varies quickly with both soil condition and weather. Recent smart-agriculture reviews describe AI-enabled precision irrigation systems that combine soil-moisture sensing with weather forecasts to optimize water distribution, while automated drip and variable-rate irrigation can deliver water according to real-time crop need rather than fixed schedules. Field-oriented integrated systems also report substantial resource savings: one IoT-driven framework using fuzzy control reduced water use by about 70% while simultaneously supporting soil monitoring and crop recommendation functions.

Nutrient management shows a similar pattern, but with stronger dependence on multi-parameter sensing. Real-time systems that monitor soil moisture, nutrients, pH, and temperature can guide fertilizer application decisions and reduce excessive input use, which directly supports both yield stability and environmental

protection. More advanced AIoT frameworks extend this logic by integrating soil sensors, UAVs, and predictive analytics to assess nutrient availability and support optimized fertilization strategies, with the explicit goal of improving nutrient-use efficiency while reducing runoff and other forms of degradation (Bayar et al., 2025). These cases show that sensor integration matters more than any single device. Precision management becomes effective when electromagnetic soil mapping, in situ nutrient sensing, weather data, and decision-support interfaces are combined into one system that can translate variability into action. However, large-scale adoption still depends on solving practical barriers such as connectivity, interoperability, sensor reliability, and cost, especially for smallholder and medium-scale operations.

6.3 Crop stress identification using remote sensing and artificial intelligence

Crop stress identification is one of the strongest case-study domains for integrating observation data with AI because stress often emerges first as subtle physiological change rather than visible damage. Traditional field surveys and expert judgment are too sparse to track early-stage stress development across large areas, especially under fast-changing drought, heat, salinity, or nutrient conditions. Remote sensing addresses this gap by providing continuous, high-resolution observations from satellites, UAVs, and ground sensor networks, which enables non-destructive monitoring of plant health across extensive agricultural landscapes. The most effective stress-detection systems rely on multiple sensing modalities because different stresses appear through different plant signals. Reviews of multiscale agricultural sensing emphasize that RGB, multispectral, hyperspectral, thermal, and SAR imagery now provide rich information for abiotic and biotic stress monitoring, while deep learning helps extract useful features from these high-dimensional image streams. Multi-dimensional optical sensing studies further show that drought, nutrient deficiency, and temperature stress alter spectral signatures through mechanisms such as chlorophyll degradation and water-content change, making stress inference possible across proximal, UAV, and satellite scales.

Artificial intelligence improves these systems by automating classification, localization, and early warning. Machine-learning models trained on spectral, thermal, and image-based features can identify drought stress, nutrient deficiencies, and disease-related symptoms, and in some cases can detect stress development before visible symptoms appear in the field. Recent deep-learning reviews report that CNN, RNN, vision transformers, and related architectures are increasingly applied to stress phenotyping using IoT sensor data together with field, UAV, and satellite imagery, particularly for water, nutrient, salinity, temperature, and heavy-metal stress assessment (Subeesh and Chauhan, 2025). The main lesson from these case studies is that stress monitoring is moving from reactive diagnosis to predictive intervention. AI plus remote sensing can support continuous, reliable, and scalable monitoring by fusing optical, thermal, hyperspectral, and radar data across space-air-ground platforms, which is especially valuable for early warning and disaster mitigation. Even so, operational deployment remains limited by fragmented data infrastructure, weak model generalization, limited labeled datasets, and the need for more interpretable systems that connect predictions to agronomic mechanisms. Overall, these case studies show that crop management optimization is most effective when field observation systems and computational methods are tightly coupled. Yield forecasting, precision input management, and stress identification all improve when multi-source measurements are converted into timely, site-specific recommendations that farmers can act on under real production conditions.

7 Development Directions and Application Prospects of Data-Driven Agricultural Management Systems

7.1 Development of agricultural internet of things and intelligent decision platforms

The next stage of agricultural Internet of Things development is moving from isolated sensing devices to integrated intelligent decision platforms that connect field monitoring, analytics, and automated control. Recent reviews describe IoT, AI, remote sensing, and variable-rate technologies as a convergent technical stack for smart farming, with real-time sensing increasingly used to guide irrigation, fertilization, and pest management decisions. This shift matters because IoT sensor networks now provide continuous measurements of soil, crop, and environmental conditions, while AI-enabled platforms transform these observations into predictive and adaptive recommendations rather than simple dashboards. As a result, future platforms are likely to function as operational

farm intelligence systems in which data collection, diagnosis, forecasting, and intervention are tightly linked across the growing season (Sharma and Shivandu, 2024).

A major development direction is improving the scalability and responsiveness of these platforms under real farm conditions. Better rural connectivity through 5G and LPWAN networks is expected to expand real-time monitoring and control, while edge computing can reduce cloud burden and support faster local inference in the field (Mansoor et al., 2025). At the same time, wider adoption will depend less on algorithmic novelty than on affordability, usability, training, and trusted governance, since high infrastructure cost, interoperability gaps, and data ownership concerns remain persistent barriers to deployment.

7.2 Development of multi-scale agricultural digital twin systems

Multi-scale agricultural digital twin systems are emerging as the next integrative layer above sensing platforms because they create virtual representations of crops, soils, weather, machinery, and whole farms for monitoring, simulation, and intervention planning. Current evidence shows that digital twins are evolving from basic cloud-based representations toward predictive and prescriptive systems that can simulate weather, test treatments, and optimize resource use across the production cycle (Verdouw et al., 2021). Their future value lies in coupling real-time field data with simulation and AI so that farmers can evaluate alternative decisions in a virtual environment before acting in the physical field.

The main research direction is scaling digital twins from single entities to interoperable, farm- and network-level systems. Reviews of agricultural digital twins emphasize that future systems must integrate heterogeneous data streams from sensors, meteorological archives, satellite imagery, and third-party services through secure and interoperable access mechanisms. They also stress that current adoption remains early because standardization, computational efficiency, model accuracy, and cross-platform interoperability are still unresolved, especially for large-scale and smallholder applications (Awais et al., 2025).

7.3 Sustainable agricultural strategies based on intelligent management

The application prospect of intelligent management systems is strongest where sustainability goals and production goals must be optimized simultaneously. Data-driven agriculture appears well suited to this task because sustainability is inherently knowledge intensive, and sensor data combined with AI can reveal interactions among water, soil, climate, and management that are difficult to capture through manual observation alone (Rozenstein et al., 2023). Across recent reviews, intelligent management is associated with more precise use of water, fertilizer, and pesticides, which improves resource efficiency while reducing waste, greenhouse gas emissions, and other environmental burdens.

Future sustainable strategies will likely depend on holistic decision systems rather than single-task tools. Proposed directions include low-cost environmental sensing, integration of remote sensing with crop and pasture models, data-sharing frameworks that reinforce trust, and management systems that support climate adaptation and resilience across entire farming networks. At the same time, sustainable intelligent agriculture will require policy support, equitable access, and safeguards around cybersecurity and data governance, because the benefits of AI-, IoT-, and digital-twin-based systems will remain uneven unless legal, economic, and social constraints are addressed alongside technical innovation (Purcell et al., 2023). Overall, the development direction of data-driven agricultural management systems is toward integrated sensing, multi-scale digital twins, and sustainability-oriented intelligence. Their long-term impact will depend not only on better prediction and automation, but on interoperability, trusted data governance, and practical accessibility across diverse farming systems.

8 Current Challenges and Future Research Priorities

8.1 Issues regarding agricultural data quality and data-sharing mechanisms

Agricultural data quality remains a foundational constraint on data-driven crop management because digital farming systems depend on accurate, consistent, and contextually relevant observations for model training and decision support. Recent reviews show that data problems are not limited to technical noise, but include

heterogeneity, weak interoperability, validation difficulty across space and time, and socio-technical barriers such as low data literacy and organizational resistance (Da Silva et al., 2025). These problems are intensified in smart agriculture when unstable data sources, algorithmic bias, and fragmented system integration generate “data noise,” “data fog,” and “data islands,” which reduce the usability of information for management decisions. For this reason, future research needs to treat data quality as a full-system issue spanning collection, preprocessing, annotation, validation, and downstream use rather than as a narrow database-cleaning problem.

Data-sharing mechanisms face equally serious obstacles because farm data are sensitive, commercially valuable, and often distributed across incompatible platforms. Precision agriculture studies consistently identify privacy, ownership, and secure sharing as major barriers to collaborative intelligence, especially when raw data must move across farms, institutions, or devices. At the infrastructure level, the lack of standardization and interoperability among heterogeneous IoT systems still limits seamless information exchange and context-aware decision-making. Emerging solutions therefore emphasize privacy-preserving collaboration, including federated learning, which enables distributed model training without exposing raw farm data. Complementary work on secure irrigation data sharing also suggests that blockchain-based access control and data-probe layers can support controlled, traceable exchange across heterogeneous databases without altering the original data structures.

8.2 Model generalization capability and limitations in practical applications

Model generalization remains one of the main reasons why agricultural AI systems perform well in experiments yet weaken under real production conditions. Agricultural environments vary strongly across regions, seasons, cultivars, and management systems, so models trained in one setting often fail when transferred to another. This limitation is especially visible in remote sensing and image analysis, where representative labeled datasets are costly to acquire and often too narrow to capture the environmental and biological diversity that real deployment requires (Barbedo, 2025). Reviews therefore identify adaptable models as a major research frontier and recommend transfer learning and related strategies to make systems more versatile across agricultural scenarios.

Recent case studies show that generalization can improve, but only when transferability is addressed explicitly. In crop classification, interannual training over multiple seasons improved generalization to unseen years, while performance still differed substantially across regions and classifiers, showing that no single algorithm is uniformly robust (Rusňák et al., 2023). In nutrient retrieval, transfer learning reduced normalized error across potato growth stages, confirming that stage-related domain shift can be mitigated but not ignored. Comparable results appear in yield prediction and crop mapping: feature-based domain adaptation can make maize models more reliable across spatial and temporal domains, yet transfer success depends on the divergence between source and target conditions. Likewise, inter-continental transfer of a rice mapping model was feasible with few samples, but phenological differences, especially transplanting timing, still reduced generalization capability.

8.3 Future directions for integrating artificial intelligence with agricultural knowledge

The most important future direction is integrating AI with agricultural knowledge rather than treating prediction as a purely data-driven task. Multiple reviews now argue that robust agricultural AI will require combining multimodal sensing with expert knowledge, because explainability and robustness are essential in high-stakes domains such as crop and soil management (Holzinger et al., 2022). Human-centered AI is therefore becoming a preferred framework, in which farmers and domain experts remain part of the loop and contribute experience, conceptual understanding, and verification that statistical learning alone cannot provide. This perspective aligns with broader agricultural reviews that call for blending predictive analytics with local expertise to improve both trust and practical adoption.

A second priority is the deeper fusion of AI with physical, biological, and organizational knowledge structures. Recent wheat-focused synthesis highlights hybrid AI-physical models as a promising way to retain pattern-recognition flexibility while improving generalization under diverse and changing environments. At the same time, future systems are expected to rely more on multimodal data fusion across satellite, UAV, ground-sensor, and meteorological streams, supported by shared research platforms, open benchmarks, and coordinated field trials. Progress will also depend on expanding AI into underdeveloped areas such as nutrient

management and broader sensor integration, while sustaining interdisciplinary collaboration among agronomists, remote-sensing specialists, engineers, and computer scientists. Overall, the main challenge for Section 8 is not simply improving algorithms, but building trustworthy, transferable, and knowledge-aware agricultural intelligence systems. Future progress depends on better data ecosystems, stronger cross-domain generalization, and tighter integration between AI methods and agronomic expertise.

9 Conclusions

The integration of field observation data with computational methods has clear scientific significance because it shifts crop management from static, experience-based adjustment toward dynamic, evidence-based optimization. Field sensors, UAVs, satellite imagery, and proximal observations now provide continuous measurements of crop, soil, and environmental states, while computational tools convert these observations into predictive assessments of irrigation, fertilization, growth, and stress responses. This integration is scientifically important because it improves the timeliness and precision of management decisions, allowing agricultural systems to respond to variability in weather, soil, and crop condition rather than relying on uniform recommendations. Its significance also lies in the way it connects empirical observation with mechanistic and statistical reasoning. Remote sensing-integrated crop modeling has been shown to improve simulation performance while simplifying input requirements, making field-scale growth prediction more accurate and more transferable across regions. At the same time, data assimilation and multi-model fusion can convert high-resolution observations into spatially explicit early yield or water-productivity estimates, demonstrating that observational data are not merely descriptive but can directly strengthen predictive agricultural science.

The most practical pathway for establishing intelligent crop management systems is to build them as layered architectures linking data collection, processing, analysis, and information use. Farm information frameworks for smart agriculture increasingly emphasize this full chain, because effective management depends not only on sensing but on transforming raw observations into actionable prescriptions for irrigation, fertilization, and crop protection. In operational terms, this means combining IoT sensor networks, remote sensing, cloud or edge computing, and decision algorithms into a unified platform that supports continuous monitoring and timely intervention. A second pathway is the development of digital-twin-centered management systems that connect physical fields with virtual models able to simulate interventions before implementation. Digital twins enable near-real-time monitoring, predictive analytics, and automated decision-making, and they allow farmers to compare alternative irrigation, fertilization, and pest-control strategies using current field data rather than retrospective summaries. Recent interoperable designs also show that integrating digital twins with reinforcement learning and field-data assimilation can support adaptive recommendations for fertilizer and pesticide management, suggesting a path from monitoring platforms toward genuinely autonomous yet context-aware crop management systems.

Future agricultural production systems are likely to become more integrated, predictive, and sustainability-oriented. Reviews of smart farming consistently indicate that AI, IoT, remote sensing, and automated control are converging into systems capable of real-time monitoring and management of crops, resources, and environmental conditions. This convergence is expected to strengthen precision input use, improve climate resilience, and support more efficient production under rising pressure from food demand, water scarcity, and environmental regulation. Another clear trend is the movement toward human-centered and interoperable agricultural intelligence rather than purely automated black-box systems. Human-centered AI frameworks argue that agricultural expertise must remain in the loop because effective farm management depends on contextual judgment, experiential knowledge, and oversight that current AI systems cannot fully replace. At the same time, future smart agriculture will depend on open, compatible, and scalable infrastructures-including edge intelligence, cross-platform standards, and secure connectivity-so that advanced tools become usable beyond isolated pilot systems and across diverse farm sizes and regions. Overall, the integration of field observation data and computational methods has become a central scientific route for crop management optimization. Its long-term value will depend on turning increasingly rich observations into interoperable, adaptive, and trustworthy management systems that improve productivity while sustaining water, nutrient, and ecological resources.

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