

CROP MODELLING IN THE ERA OF SMART FARMING: TRENDS, CHALLENGES AND OPPORTUNITIES

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ABSTRACT

Modern smart farming leverages artificial intelligence, Internet of Things (IoT), and digital twin technologies to transform crop modelling from static, parameter-heavy systems into adaptive, real-time predictive frameworks. The paper illustrates how the integration of process-based models with machine learning, IoT-enabled sensing platforms, and digital twin technologies contributes to a new paradigm in predictive agriculture. The reviews investigate the design principles, comparative strengths, and applications of traditional tools such as DSSAT and APSIM alongside emerging approaches that include IoT–ML hybrids, generative models, and explainable AI frameworks. Furthermore, research highlights the novel role of digital twin systems as dynamic virtual counterparts of crops, emphasizing their ability to synchronize field data with computational simulations for enhanced monitoring and optimization. The study also identifies critical challenges including heterogeneous datasets, limited model generalization across agro-ecological contexts, cybersecurity vulnerabilities, and the heavy computational demands of AI-intensive infrastructures. The review further discusses hybrid frameworks that integrate explainable AI with mechanistic crop models, explicitly linking genotype × environment × management interactions to yield outcomes and strengthening interpretability. The work demonstrates a conceptual and comparative novelty by framing future research needs in multi-scale modelling, multi-modal data fusion, and edge–cloud deployments, thereby providing an integrative roadmap for sustainable, resilient, and transparent agricultural systems.

KEYWORDS: Crop Modelling, Smart Farming, Digital Twin, Internet of Things (IoT), Explainable Artificial Intelligence (EAI), Precision Agriculture.

1. INTRODUCTION

Crop modelling has been a staple of agricultural research since then, supplying computational models to gain insights into the behaviour of growth, yield potential, and resource demand. The traditional process-based models, (DSSAT and APSIM), were designed to model physiological and biophysical processes, but might require substantial amount of calibration and long-term parameterization and therefore could not flexibly represent a wide range of environmental conditions (Kim and Kisekka., 2021; Jing., 2023). That paradigm shift has become easier to make in the era of smart farming in the presence of data-rich environments since models, in fact, are becoming connected to the IoT-enabled sensing geography, the machine learning algorithms and real-world weather predictions (Miller et al., 2025; Saha et al., 2025; Sharafat et al., 2025).

The broad application of IoT sensors, remote sensing satellites, etc. enable constant data acquisition and the consumer of adaptive models can be updated with even near-real-time predictions (Garg et al., 2021; Albanese et al., 2021). The developments reduce manual calibration dependence and have the potential of growing to field to regional scales. Further, as the digital-twin-grounded technologies transform the context of crop modelling, dynamic virtual concepts of crops and farming systems incorporating both real-world and simulated data streams are being generated (Melesse., 2025; Escriba-Gelonch et al., 2024; Gund et al., 2025).

The interpretability has also appeared as a crucial requirement along with predictive accurateness. The new attempts at making the models more open using explainable AI (XAI) involved not only making the models predictive, but also explaining in what factors crop yield depends (Paudel et al., 2023; Yenikar et al., 2025; Mohan et al., 2025). This is especially so when it comes to decision support situations, when predictions are clouded, but farmers and policy makers need actionable information.

Despite these advances however, there is a challenge. Such plant modelling systems will need to deal with heterogeneous data, the variety of the agro-ecological environment, the complexity of the genotype x-environment x-management (G x E x M) interactions (Mamassi et al., 2023; Dlamini et al., 2023). Furthermore, decision-making pipelines are also compromised since IoT-enabling structures are vulnerable to cyberattacks (Al Asif et al., 2021). To overcome these issues, the field of agronomy, computer science and systems engineering is the field of interdisciplinary solutions to these problems.

This review discusses the radically new aspect of radiation in crop modelling in smart farming, and combines process and IoT-ML models, generative and digital twin models. One of its concerns is cybersecurity,

computational demands, and cross-zone generalization and provides a route to finding smart, multi-scale, interpretable, and resilient systems in farming.

2. Theoretical Background for Crop Modelling

Crop modelling is a critical tool in as far as modern agriculture is regarded since it enables the simulation of the growth, development and the yield of crops under varying environmental and managerial conditions. It is an integration of physiological, climatic and soil-specific variables to forecast and predict outcomes, optimize the use of resources and make swift choices. The traits of smart farming include the addition of more exact data to crop models where sensor, satellite imagery and IoT make the data, and through it, the prospect of modifying and examining scenarios up to date. The models are employed in the analysis of impacts of climate change, irrigation techniques, management of nutrients and containment of pests thus facilitating sustainable agriculture, increase in yields and wastage of resource.

2.1 Overview of Crop Modelling

Crop modelling gives a model to simulate the growth of plants, their yield and the reaction to the environment and management. Precursors of models, including DSSAT and APSIM, were intended to model physiological processes based on mechanistic equations, which make them useful in resource management and policy analysis (Kim and Kisekka., 2021; Jing., 2023). These models have limited adaptability, as they are high-parameter models which are difficult to calibration and which cannot capture dynamic real-time conditions, even though they are effective in controlled settings. The new methods are not limited to deterministic simulations, but they also use real-time sensing, probability models, reconfigurable algorithms to react to environmental changes (Mamassi et al., 2023; Dlamini et al., 2023).

2.2 Data-Driven and IoT-Enabled Models

Smart farming has brought about IoT sensors, drones and satellite imaging as essential sources of data used in crop modelling. The IoT-based systems are capable of constant monitoring of soil moisture, nutrient processes, and climatic parameters that are directly associated with predicting crop growth (Miller et al., 2025; Saha et al., 2025). Predictive accuracy is improved with machine learning models trained on such high-frequency datasets by identifying patterns that are not covered by the process-based models. Prototype IoT - ML devices are further going to be developed as mild next generation IoT devices for predictive the real time yield of the crops which up to now show the hardware dimension of precision agriculture innovations (Siam et al. 2023). As an example, the systems that combine multimodal based on the IoT and ML may allow precision agriculture by fusing heterogeneous streams of data to predict yields and stress (Garg et al., 2021; Albanese et al., 2021). Additionally, it can be connected to AI-based decision support systems and thus, offer real-time suggestions on irrigation timetables, fertilizer applications, and pesticide treatments (Niranjan et al., 2025; Sharafat et al., 2025). Moreover, IoT-AI integration has been advanced to localized weather prediction system such as climate aware intelligence leading to great improvement in the crop prediction pipeline (Das and Nayak, 2024).

2.3 Digital Twin-Based Crop Modelling

Digital twin (DT) systems are a disruptive technology in the sense that they imply the construction of virtual replicas of crops that grow alongside actual systems and continuously process the data. It can be tested in the field and can be optimized to grow, and can also detect the stress at an early stage due to the alignment of the field conditions with the models through these platforms (Melesse., 2025; Escriba-Gelonch et al., 2024; Gund et al., 2025). Edge cloud systems also begin to feature support of structures of DT, as they can also simulate at a scale and with reduced latency (Du et al., 2025). In more recent work, DT has also been combined with more sophisticated inference models such as large language models to further predictively solve vegetable crop growth simulations (Chunjiang et al., 2024). Multi-scale crop representation (genotype, environmental and management interaction) is another area of expansion of DT applications, through the use of new modelling approaches (Archambault et al., 2024; Singh and Saini., 2023). In addition, a detailed overview of digital twin technologies for agriculture emphasizes their orchestration potential and wide use cases across farming systems (Zhang et al., 2025), and re-frames digital twins as transformative tools for optimizing farming systems.

2.4 Explainable and Hybrid AI Approaches

AI black-box models exhibit a very high degree of predictive accuracy, but generally are not interpretable, which is desirable in real-world farming. Explainable artificial intelligence (XAI) models being used in crop models are becoming an emerging trend that ensures transparency and trust in decision-making. Using interpretable structures as an example, hybrid methods of employing deep learning will focus on the factors contributing substantially to the change in yield and response to the environment (Paudel et al., 2023; Yenikar et al., 2025). It is also discovered that XAI-based systems are more interpretable and control and adoption pathways regarding agricultural technology (Shawon et al., 2025; Mohan et al., 2025). Additionally, hybrid systems weaknesses that incorporated the AI and the traditional crop models have been proposed to achieve the mechanistic knowledge and the information-driven knowledge to bring a trade-off to the resilient modelling (Banerjee et al., 2025; Awais et al., 2025; Nawaz and Babar., 2025).

3. Comparative Study Models

The development of crop modelling can be considered through the comparison of the conventional process-based schemes and the new trends of AI-inspired and hybrid-based methodologies. All paradigms have distinct advantages and disadvantages in regard to scalability, interpretability, and applicability to smart farming environments.

Table 1. Comparative overview of crop modelling approaches in smart farming

Model Approach	Architecture / Basis	Applications	Strengths	Limitations	References
Process-Based Models (e.g., DSSAT, APSIM)	Mechanistic equations representing crop physiology and environment	Yield prediction, water and nutrient management	Strong physiological basis; widely validated	Require extensive calibration; static parameters limit adaptability	Kim & Kisekka., (2021); Jing (2023)
IoT-Enabled ML Models	Integration of IoT sensor data with ML (ANN, SVM, DL)	Real-time yield prediction, irrigation scheduling, pest detection	Real-time adaptability; scalable across farms; data-rich	Vulnerable to data heterogeneity, sensor failures, and cybersecurity risks	Miller et al., (2025); Saha et al., (2025); Garg et al., (2021); Albanese et al., (2021)
Digital Twin Platforms	Virtual replicas linked to field data via edge-cloud integration	Growth monitoring, scenario testing, optimization	High fidelity, dynamic synchronization, multi-scale representation	High computational cost; requires dense data streams	Melesse., (2025); Escribà-Gelonch et al., (2024); Gund et al., (2025); Du et al., (2025); Chunjiang et al., (2024)
GAN-Based Crop Simulation	Multi-conditional Generative Adversarial Networks (MC-GANs) for image and time-series	Simulation of crop growth and stress responses	Can generate synthetic data for model training; captures variability	Lack of interpretability; high computational demand	Drees et al., (2024)
Explainable AI (XAI) Hybrids	Combination of ML/DL with interpretable frameworks (e.g., SHAP, LIME, symbolic AI)	Yield forecasting, climate-aware decision support	Improves transparency; supports farmer trust; balances accuracy & interpretability	Still developing; may trade off some accuracy	Paudel et al., (2023); Yenikar et al., (2025); Mohan et al., (2025); Banerjee et al., (2025); Awais et al., (2025)

This comparison shows that even though the process-based models continue to play a significant role in the foundational knowledge, the IoT-ML and digital twins can transform the nature of crop modelling by allowing it to be flexible and more precise. Meanwhile, as a solution to challenges of trust and adoption between black-box forecasts and advisable agricultural suggestions, explainable, and hybrid AI options can be deployed.

Specifically, alternatives can be generated models, like multi-conditional GANs, to create the possibility of the simulation of the crop developmental path, the reaction to various circumstances and produce artificial data that can be used to further train the model (Drees et al., 2024). To the same end, explainable artificial intelligence hybrids, models that combine deep learning with interpretable models (such as SHAP and LIME) have an ability to improve transparency by revealing what the cause and driver of the variability in yields, reactions to environment in-fact actually is (Paudel et al., 2023; Yenikar et al., 2025; Mohan et al., 2025). These complementary approaches further evolve the modelling paradigm making them more flexible, readable and robust in the smart farming scenarios.

4. Challenges and Limitations

Even though great progress has been made, crop modelling in the smart farming age is still encountering challenging issues that limit its scalability, robustness and adoption. These restrictions are brought about by environment, socio-economic and technical.

4.1 Data Heterogeneity and Quality Issues

Cutting-edge farming landscape captures huge amount of data across all variety of sources like IoT sensors, drones and satellite platforms. But the data of this heterogeneity (between the high-resolution image data and the time-series soil moisture measurement data) poses a challenge in integrating this data. Models may introduce error propagation because of data gaps, noise, inconsistency within the superimposed calibration (Miller et al., 2025; Saha et al., 2025). This challenge is reinforced by a recent systematic review of review which underlines how inconsistencies between machine learning, remote sensing and IoT-driven yield prediction pipelines typically limit reproducibility and scalability (Bassine et al., 2023).

4.2 Generalization Across Agro-Ecological Zones

The majority of the models have been trained and tested under the particular conditions in the environment and management, and therefore, they cannot be utilized to predict new agro-ecological systems. To give an example, interactions of genotype $\times$ environment $\times$ management ($G \times E \times M$) are hard to reflect in dynamic and scalable ways (Mamassi et al., 2023; Dlamini et al., 2023). This limits generalization of models to the wide geographical area and crops.

4.3 Cybersecurity and Privacy Risks

Combining both IoT and cloud-based computing structures presents security gaps in the transfer and storage of the data. IoT-enabled systems are susceptible to cyberattacks that can interfere with the integrity of data, as well as cause disruption to predictive pipelines and potentially endanger the farm operation (Al Asif et al., 2021). The creation of safe, encrypted and durable information structures remains one of the most pressing and unanswered issues of intelligent agriculture. They will pose even greater risks in AI-intensive pipes, where the corrupted information or manipulated data may spread through deep learning and digital twin systems and cause incorrect yield forecasts and inefficient decision support. The solution to this does not just involve encryption but also constant observation, oddity policies, and resiliency policies based on an agricultural IoT ecosystem.

4.4 Computational and Infrastructure Demands

The platforms built on digital twins, those models simulated with the use of GANs, and the ensemble AI machines consume large amounts of the computational power and bandwidth data streams. Agricultural environments Limited poverty levels of these systems due to insufficient infrastructure in many places to implement such complex systems present inequalities in adoption (Du et al., 2025; Drees et al., 2024; Nawaz and Babar., 2025). We also have the dependency on scale of use of generative models, an explainable AI layer, and edge cloud synchronization that is even more overhead-rampant. Unless architectures are optimized to allow scales of resource management, these strategies will have to stay within technologically agile regions leaving the smallholder farmers out of the benefits of smart farming.

4.5 Interpretability and Trust

Although deep learning and hybrid AI models are more accurate, they are not transparent because they are black-box models. Policymakers, stakeholders and farmers usually require interpretable outputs that can help them in making decisions and gain trust. Explainable methods on the one hand, explainable AI methods have already been presented, but they are used in large-scale systems only in a limited fashion (Paudel et al., 2023; Yenikar et al., 2025; Mohan et al., 2025).

5. Future Directions

Inspired by the synthetic conceptualization discussed in this review, future crop modelling systems are projected to become fluid, open, and resourceful based on the progressive clearance in artificial intelligence, digital twins, and IoT-permitted systems. It seems that emerging platforms will combine the approaches of digital twins with multi-scale modelling to express crop dynamics in genetic, field, and regional scale in a single framework to facilitate virtual experimentation, scenario exploration, and management strategy optimisation prior to field implementation (Melesse., 2025; Escribà-Gelonch et al., 2024; Xu et al., 2025). Moreover, the combination of multi-source America will lead to better predictive capabilities and the further development of techniques of integrating group data streams, which are deep ensemble learning and vision transformer, will streamline the process of integrating various streams of data (Yewle et al., 2025; Kamangir et al., 2024). Interpretability and transparency will also be prioritized in the next generation of crop models and introduce explainable AI to the modelling pipelines to install trust in farmers, acceptance from regulators, and actionable information about the variability of yield and resource use (Paudel et al., 2023; Yenikar et al., 2025; Mohan et al., 2025).

Besides, edge computing in tandem with a cloud integration will open up real-time forecasts in the less connected settings, and enhance the availability of sophisticated crop modelling to smallholder and resource-constrained settings (Du et al., 2025; Nawaz and Babar., 2025). GANs and large language model inference as examples of generative and adaptive modelling have more opportunities to simulate stages of crop and plant growth and reaction to different types of stresses and yield, and even create synthetic datasets in order to mitigate low data amounts and expand the VE power envelope (Chunjiang et al., 2024; Drees et al., 2024; Banerjee et al., 2025). Taken together, these guidelines are all aimed at more robust, interpretable, and sustainable crop modelling systems that reflect on the developing principles of smart farming.

6. Revealing Structural–Function Relationships

One of the primary goals of crop modelling in the smart farming phenomenon is to clarify the nature of structural variables, including genetic parameters of plants or environmental communication to functional outcomes such as yields, resource effectiveness, and resistance to stress. The emerging modelling frameworks represent the

increasing representation of these interactions with capturing mechanistic knowledge, sensor-driven data and explainable AI algorithms.

6.1 Genotype × Environment × Management (G×E×M) Interactions

The application of G×E×M interactions in which genetic characteristics and environmental variability interact with management decisions, provides the structural basis of crop performance. These interactions are introduced into different advanced models in order to model crop adaptation and yield potential across different agro-ecological zones (Mamassi et al., 2023; Jing., 2023). Assimilation supported by remote sensing builds on this even stronger because observed growth patterns are provided dynamically in the models (Dlamini et al., 2023).

6.2 Data-Driven Insights into Growth Dynamics

Crop models based on AI understand how to grow through learning on time-series and multi-modal involvements with the help of information gathered gradually over time. To give an example, IoT and ML-based frameworks are already used to consider how microclimatic variations can affect the physiology of crops, and the ensemble systems unify the data of soil, weather, and imagery towards improved growth prediction (Miller et al., 2025; Sharafat et al., 2025; Saha et al., 2025). The GAN-based simulations can give potential growth trajectories, which can specify further insights on a structure in the case of low observation (Drees et al., 2024). Likewise, remote sensing and AI approaches have been reported providing effective solutions for automated crop yield estimation by validating the role of multi-modal data in predictive agriculture (Ilyas et al., 2023)

6.3 Digital Twin Platforms as Structural Mirrors

Digital twin systems are dynamic reflections of crop structures; the interactive models of crops are constantly synchronized with real-time purchase data. The systems give a chance to the researchers to realize how the change in environment or management intervention reorganizes structural characteristics and functional performances including the yield or the water-use efficiency (Melesse., 2025; Gund et al., 2025; Xu et al., 2025). The ability to infer small structural differences on crop development is also augmented by adding the concept of inference by using large language models within DTs (Chunjiang et al., 2024).

6.4 Explainable AI for Structure–Function Transparency

One of the key difficulties of data-driven modelling occurs on how to correlate abstract predictions of models to real structural determinants. Explainable AI (XAI) methods deal with this by making the features important, sensitive and causal factors in crop yield prediction. Recent work has demonstrated that the models that incorporate interpretable layers or other visualization devices brings clarity to how the nutrients (including specific key macro or micronutrients) in soil, climatic variables or canopy features affect functional outcomes (Paudel et al., 2023; Yenikar et al., 2025; Mohan et al., 2025). This type of transparency would not only increase the trust of the farmers but also help scientific research to improve the understanding of the relationship between crop structure and functioning.

7. CONCLUSION

Crop modelling is in the midst of a transformation in the age of smart farming as static, process-based systems cede ground to adaptive, data and smart, and digital twin-enabled systems. This review described the ongoing value of process-based models such as DSSAT and APSIM that offer robust physiological foundation and IoT-ML hybrids or Digital Twin systems that function as dynamic virtual relatives of the crops and Hybrid explainable AI approaches that boost the model's interpretability and trust in its predictions. A novel aspect of this review is the synthesis of these different paradigms process-based, IoT-ML, generative, digital twin, and explainable AI into a single comparison framework alongside a perspective roadmap forward-looking and explicit genotype x environment x management interactions with multi-toehold digital twins, multi-modal data fusion, and interpretable AI to gaining structural-functional transparency in crop modelling. Despite this progress, the field is still confronted with significant challenges such as heterogeneous data set, the generalization challenge within diverse agro-ecological setups, heavy computational loads associated with advanced infrastructures, and the liabilities found in IoT-enabled networks. The urgent need is present for interdisciplinary solutions that include agronomy, computer science, and systems engineering to counter these challenges. Looking ahead, the path ahead of crop modelling is to combine mechanistic models with data-driven and generative approaches, introducing concepts of explainability in data pipelines and extending multi-modal and multi-scale digital twin offerings for transparent, resilient and sustainable smart farming systems.

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