Simulation-Driven Neuro-Symbolic Explainable AI for Trustworthy Precision Agriculture: A Review

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Abstract: Precision agriculture uses artificial intelligence to support farming decisions, but many existing AI models work like black boxes and do not clearly explain their outputs. Farmers and decision-makers are less inclined to apply it in real life because of this lack of transparency and evidence. This paper discusses simulation-driven techniques to increase the trustworthiness and dependability of precision agricultural systems using explainable AI, neuro-symbolic AI, and blockchain-based verification. The article discusses explainable AI techniques that make it simpler to comprehend how models generate judgments, neuro-symbolic approaches that integrate data-driven learning with farming expert knowledge, and digital twins and modeling settings for experimenting with farming choices. It also examines how data sources, model modifications, and decision records may be verified using blockchain technology. The primary findings demonstrate that modeling-based neuro-symbolic models simplify, solidify, aid in decision validation, and reduce the need for costly field testing. These techniques aid in improving the testing of agricultural strategies prior to implementation. The techniques examined may be used to yield forecasting, disease detection, field tracking, irrigation planning, and sustainable resource management. These techniques contribute to the development of more transparent and reliable AI systems for contemporary farming.

Keywords: Precision agriculture; Explainable artificial intelligence; Neuro-symbolic AI; Simulation-driven modeling; Digital twins; Trustworthy AI; Blockchain validation; Decision support systems

Introduction

Precision agriculture has evolved into a data-driven paradigm that leverages artificial intelligence (AI), Internet of Things (IoT), and advanced sensing technologies to improve productivity, efficiency, and sustainability in farming systems. Early interdisciplinary research demonstrated how computational modeling and optimization of crop-based systems can support informed decision-making even in constrained and high-risk environments, establishing foundations transferable to terrestrial agriculture [1]. With the rapid expansion of IoT infrastructures, large-scale data acquisition and automation have become integral to precision agriculture, enabling continuous monitoring and control of farm operations [5].

Despite these advances, many AI-based agricultural decision-support systems continue to operate as *black-box* models, offering predictions without transparent reasoning. This lack of interpretability and formal validation reduces trust among farmers, agronomists, and policymakers and has been identified as a major barrier to real-world adoption [24]. To overcome these limitations, researchers have increasingly adopted simulation-based paradigms—most notably digital twins—which enable virtual replication of physical systems for safe experimentation and performance evaluation. The digital twin concept, initially introduced as a convergence of sensing, modeling, and multimedia technologies, enables continuous synchronization between physical entities and their virtual counterparts [2]. A formalized definition and conceptual grounding of digital twins was later provided by industry consortia, emphasizing real-time data integration and bidirectional interaction [3].

Subsequent engineering research expanded digital twin architectures to cyber-physical systems, highlighting their role in system monitoring, optimization, and decision support [14]. Comprehensive reviews have further analyzed the challenges and enablers of digital twin deployment, including scalability, interoperability, and data fidelity, which are particularly critical in dynamic environments such as agriculture [4]. In the agricultural domain, early implementations demonstrated how digital twins could support farm management by integrating sensing, modeling, and decision logic within unified platforms [17]. Building on this foundation, researchers proposed digital twin–based frameworks aimed at advancing the next generation of agricultural digitalization, emphasizing predictive capability and system-level reasoning [19].

More recent studies have shown that digital twins can effectively support crop monitoring by simulating plant growth dynamics and environmental interactions, enabling evaluation of management strategies prior to field deployment [22]. A comprehensive review focusing on smart agriculture further demonstrated how digital twins enhance operational efficiency and sustainability by enabling adaptive and data-driven decision-making [20]. Advancing this line of work, orchestration-centric approaches have highlighted the importance of coordinating multiple digital twins across agricultural processes to support complex, system-wide decision workflows [21]. The most recent large-scale reviews consolidate these findings and identify digital twins as a core enabling technology for future precision agriculture systems, while also outlining remaining research gaps in validation and integration [23].

However, simulation environments alone are insufficient to establish trust unless the AI models embedded within them are interpretable and knowledge-aware. Neuro-symbolic artificial intelligence addresses this gap by combining the pattern-recognition capabilities of neural networks with symbolic reasoning and expert-defined domain knowledge. Foundational work on neuromorphic and spiking neuron models laid the theoretical basis for biologically inspired computation and structured learning [9], [10]. When extended into neuro-symbolic frameworks, these principles enable AI systems to incorporate agronomic rules, constraints, and causal relationships, resulting in more robust and explainable decision-making.

Explainable artificial intelligence (XAI) techniques further enhance transparency by revealing how models arrive at specific predictions. Model-agnostic explanation methods were first introduced to justify classifier decisions across diverse applications [25], followed by unified frameworks for feature attribution in complex models [26]. Gradient-based visualization techniques later enabled spatial interpretation of deep neural network decisions, making them especially useful for image-based agricultural tasks such as disease detection and crop assessment [27]. In agricultural contexts, XAI has been systematically reviewed as a key enabler of trust in AI-driven quality assessment and decision support [24].

In addition to interpretability, trustworthy precision agriculture systems require verifiable data integrity and accountable decision records. Blockchain technology has been widely studied as a solution for ensuring traceability and immutability in agricultural product lifecycles [28]. Recent systematic reviews further emphasize that blockchain characteristics such as decentralization and tamper resistance are essential for validating data sources, model updates, and AI-driven decisions in agri-food systems [29].

In summary, this review examines simulation-driven precision agriculture frameworks that integrate digital twins, neuro-symbolic AI, explainable AI, and blockchain-based validation. The surveyed literature demonstrates that such hybrid approaches significantly improve interpretability, robustness, and trust while reducing dependence on expensive and time-consuming field experiments. These methods are applicable across key agricultural domains, including irrigation planning, crop monitoring, disease detection, yield prediction, and sustainable resource management, thereby supporting the development of transparent and reliable AI systems for modern agriculture.

Related Works

A. Digital Twins: Core Concepts, Architectures, and Engineering Foundations

Digital twins (DTs) originated as a convergence of sensing, modeling, and interactive multimedia that enables a "living" virtual representation of a physical system, continuously updated through data streams and analytics. El Saddik formalized this convergence view by emphasizing the role of real-time data, simulation, and visualization in maintaining fidelity between physical and virtual entities [2]. To standardize DT definitions and make them operational, the Digital Twin Consortium (DTC) provided a widely adopted reference definition that frames DTs as integrated capabilities for monitoring, reasoning, and controlled interaction with physical assets [3].

Engineering research has shaped DTs into actionable tools for design and production workflows. Schleich et al. highlighted DTs as enablers for design-production alignment, where feedback loops from production refine design constraints and performance targets [13]. Complementing this, Alam and El Saddik proposed the C2PS reference model for cloud-based cyber-physical systems, positioning DTs as architectural mediators between sensors/actuators, data services, and analytics pipelines [14]. Rasheed et al. synthesized DT "value propositions" (optimization, prediction, decision support), while also outlining barriers such as model calibration, uncertainty, and interoperability—issues that become more complex in open environments like agriculture [16]. Botín-Sanabria et al. expanded this view with a comprehensive review focusing on DT challenges and applications across domains, emphasizing that DT success depends on data quality, model fidelity, integration, and governance mechanisms [4].

Relevance to precision agriculture: agriculture inherits all DT engineering challenges, but amplifies them through (i) non-stationary environments (weather/soil variability), (ii) sparse ground truth, and (iii) deployment constraints (connectivity, cost).

B. Enabling Stack: IoT/IIoT, Edge Computing, and Industrial Interoperability

Precision agriculture DTs depend on scalable IoT infrastructure for real-time sensing and actuation. Hou et al. reviewed trends and challenges across IoT/IIoT/AIoT implementation, showing that large-scale deployments face issues of heterogeneous devices, security, data governance, latency, and system integration—constraints directly impacting DT synchronization and decision latency [5]. Market-level perspectives also indicate rapid global IoT adoption and expansion, reinforcing the practicality of DT-enabled agriculture as connected infrastructure matures [6].

From a computing standpoint, edge computing is critical for reducing latency, bandwidth costs, and dependence on cloud connectivity—especially relevant for remote farms. Yu et al. surveyed edge computing for IoT and highlighted core motivations: near-device analytics, distributed intelligence, and responsiveness for real-time applications [7]. In industrial-grade systems, interoperability and determinism matter; Ferrari et al. evaluated communication delay in OPC UA-based IoT applications, providing evidence that protocol and network design directly influence end-to-end responsiveness—an important design parameter for DT control loops and timely farm interventions [8].

Relevance to precision agriculture: DT performance is bounded by sensing quality + communication latency + compute placement (edge/cloud). A DT that cannot update reliably becomes a static model, undermining trust and utility.

C. Digital Twins in Agriculture: Evolution from Farm Management to Orchestrated Decision Systems

Early agriculture DT work emphasized farm management integration and decision-support platforms. Verdouw and Kruize provided illustrative DT implementations in farm management contexts, showing how platforms can combine sensors, contextual information, and decision logic to support operational planning [17]. As the field matured, Nasirahmadi and Hensel argued for DTs as a cornerstone of next-generation agricultural digitalization, highlighting predictive monitoring, adaptive control, and system-wide optimization [19].

At the survey level, Mihai et al. reviewed DT enabling technologies, trends, and future prospects, reinforcing that DT growth depends on standards, scalable architectures, and trustworthy data pipelines—conditions still uneven in agriculture deployments [18]. Peladarinos et al. provided an agriculture-focused DT review, emphasizing that DTs can enhance smart farming through planning, monitoring, and sustainability optimization, but also noting integration and validation challenges [20]. Escribà-Gelonch et al. advanced the discussion by focusing on orchestration and applications, highlighting the need to coordinate multiple twins (crop, soil, irrigation, logistics) into an integrated decision workflow rather than isolated models [21].

Recent works increasingly focus on crop monitoring and comprehensive agriculture DT ecosystems. Melesse et al. reviewed DT-based crop monitoring applications, indicating practical pathways for DT integration into observation, forecasting, and management pipelines under variable field conditions [22]. Zhang et al. provided a comprehensive 2025 review of DT technology in agriculture, consolidating architectures, use cases, and limitations such as insufficient benchmarking, weak validation protocols, and limited cross-farm generalization [23]. These gaps directly motivate simulation-driven validation and robust interpretability mechanisms discussed in your abstract.

Key gap: Many agriculture DT studies show feasibility but not *trustworthy decision validation*; systems often lack transparent reasoning and auditable decision trails.

D. Explainable AI: From Generic Explainability to Agriculture-Specific Trust

Precision agriculture increasingly uses ML/DL for tasks like quality assessment, disease detection, and yield prediction, but black-box behavior reduces adoption. Ahmed et al. systematically reviewed explainable AI for spectroscopic agricultural quality assessment and emphasized the importance of interpretability, stakeholder trust, and traceability of decisions—especially where model outputs inform economic and safety-critical actions [24].

Foundational XAI methods supply the toolkit. Ribeiro et al. introduced LIME as a model-agnostic framework for locally explaining predictions, making it useful when different crop/soil models are deployed across farms [25]. Lundberg and Lee proposed SHAP, enabling consistent feature-attribution explanations across models—valuable for understanding the influence of soil moisture, nutrient levels, weather, and management actions [26]. Selvaraju et al. introduced Grad-CAM for visual explanations in deep networks, particularly relevant for plant disease recognition and remote sensing imagery interpretation (e.g., highlighting leaf regions or canopy zones driving predictions) [27].

E. Blockchain for Validation: Data Provenance, Tamper Resistance, and Decision Traceability

Blockchain is increasingly used in agri-food systems to ensure traceability, provenance, and accountability—properties that directly support "trust and validation" requirements. Lv et al. systematically reviewed blockchain-based traceability for agricultural products and showed how immutable ledgers can support end-to-end tracking of product flows and records [28]. Pakseresht et al. further analyzed blockchain characteristics essential to agri-food systems (e.g., immutability, decentralization, transparency, auditability), reinforcing suitability for verifying data sources and lifecycle events [29].

F. Decision Optimization and Application Domains: Irrigation as a High-Impact Use Case

Among precision agriculture tasks, irrigation scheduling is a prominent target due to water scarcity and operational importance. Saikai et al. applied deep reinforcement learning for irrigation scheduling, demonstrating that learning-based control can optimize irrigation decisions under dynamic conditions [30]. However, such controllers require careful validation and interpretability; integrating them within DT simulation environments and explaining actions via XAI aligns directly with your proposed simulation-driven trust pipeline.

G. Sensing and Connectivity: RFID and LPWA as Practical Enablers

Farm environments demand rugged, low-power sensing and reliable connectivity. Rayhana et al. reviewed RFID sensing technologies for smart agriculture, showing the role of identification and sensing in tracking assets, environmental conditions, and supply chain integration [31]. Sinha et al. surveyed LPWA technologies such as LoRa and NB-IoT, which are critical to maintain connectivity in wide-area rural deployments—directly impacting DT synchronization and real-time monitoring feasibility [32].

H. Visualization and Human Interaction: Building Stakeholder Trust through Digital Interfaces

DT value is amplified when outputs are understandable and actionable. Harrington et al. presented AR/VR plant models as "virtual nature" DT constructs, highlighting how faithful 3D representations can support training, inspection, and communication of system states [33]. Eilola et al. reviewed 3D visualizations in urban/landscape planning and emphasized communicative value—insight transferable to agriculture when explaining DT-based scenario outcomes to farmers and policymakers [34].

Comparison Tables

Table 1 — Digital Twin Foundations and Reference Architectures

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[2]	DT concept	DT as convergence of sensing + modeling + multimedia	Strong conceptual framing	Not agriculture-specific; limited validation protocols
[3]	DT definition	Standardized DT definition (industry reference)	Clear terminology and scope	High-level; lacks implementation metrics
[13]	DT in engineering	DT for design/production alignment	Links DT to lifecycle engineering	Not tailored to non-stationary natural systems
[14]	DT architecture	Cloud DT reference model for CPS (C2PS)	Architectural clarity	Agriculture needs edge-first variants and field constraints

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[16]	DT values/challenges	DT benefits + enablers + barriers synthesis	Identifies key adoption blockers	Limited domain-specific operational guidance

Table 2 — IoT/Edge/Interoperability Stack Supporting DT in Smart Farming

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[5]	AIoT/IIoT trends	Implementation challenges across IoT/IIoT/AIoT	Practical deployment considerations	Not specific to DT control-loop requirements
[6]	IoT market	Global IoT market context	Supports feasibility argument	Not a technical/peer-reviewed validation source
[7]	Edge computing for IoT	Edge motivations + architectures	Strong survey foundation	Limited agriculture-centric benchmarks
[8]	OPC UA delay	Measured comms delay in OPC UA IoT	Highlights latency impact	Industrial context; needs mapping to farm networks
[32]	LPWA survey	LoRa/NB-IoT connectivity options	Rural applicability	Trade-offs for high-rate data (imaging) remain

Table 3 — Digital Twins in Agriculture: Farm Management to Orchestration

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[17]	Farm management DT	Practical illustrations of DT in farm platforms	Early agricultural DT grounding	Limited scope; early-stage validation
[19]	Next-gen agri digitalization	DT paradigm for future agriculture	Clear motivation and direction	Needs concrete evaluation frameworks
[20]	Smart agriculture DT review	Comprehensive review of DT in smart agri	Broad coverage	Gaps in standardized validation and trust
[21]	Orchestration & applications	Coordinated DT workflows across agri processes	Systems-level orchestration	Implementation complexity; limited cross-farm generalization
[22]	Crop monitoring DT	DT applications in crop monitoring	Application-centric synthesis	Needs integration with explainability + audit mechanisms

Table 4 — Trust Layer: Explainable AI and Blockchain Validation

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[24]	XAI in agriculture	Systematic review of XAI for agri quality assessment	Domain relevance	Focused on spectroscopy; broader tasks need mapping
[25]	LIME	Local, model-agnostic explanations	Flexible across models	Local fidelity issues; explanation stability concerns
[26]	SHAP	Unified feature attribution	Consistency and comparability	Computational cost for complex DT pipelines
[27]	Grad-CAM	Visual explanations for deep nets	Useful for imaging tasks	Less suited for tabular control decisions alone
[29]	Blockchain characteristics	Essential blockchain properties for agri-food	Strong validation framing	Governance + scalability trade-offs in practice

Table 5 — Application Emphasis and Interaction: Control, Sensing, Visualization

Ref	Focus	Core Contribution	Strength	Limitation / Gap
[30]	DRL irrigation	Learning-based irrigation scheduling	High-impact use case	Needs transparent validation and explainability
[31]	RFID sensing	RFID sensing for smart agriculture	Practical sensing integration	Limited for rich physiological/visual signals
[28]	Blockchain traceability	Blockchain for agri product traceability	Provenance and auditability	Often supply-chain centric vs. DT decision logs
[33]	AR/VR plant DT	3D AR/VR plant models as DT artifacts	Improves stakeholder understanding	Requires data fidelity and model standardization
[34]	3D visualization review	Visualization for communicative planning	Trust-building via clarity	Needs translation into agriculture workflows

Research Gap

Despite significant advances in precision agriculture driven by artificial intelligence, IoT, and digitalization, the existing body of literature reveals several critical and unresolved research gaps that limit the practical trustworthiness, scalability, and adoption of AI-driven agricultural decision-support systems.

1. Lack of Trust-Centric Validation Frameworks for AI in Agriculture

Current precision agriculture studies largely emphasize prediction accuracy and operational efficiency, with limited focus on *trust*, *explainability*, and *decision validation*. While digital twins are increasingly used to simulate agricultural processes, most implementations treat the twin as a high-fidelity simulator rather than a formal validation environment for AI decisions. As a result, AI-driven recommendations are rarely stress-tested under diverse hypothetical scenarios before deployment, exposing farmers to operational and economic risks.

2. Fragmented Integration of Digital Twins and Explainable AI

Although digital twins and explainable AI have each been studied extensively, they are typically investigated **in isolation**. Digital twin-based agricultural systems focus on system modeling and optimization, whereas XAI research often evaluates explanation quality without embedding explanations into simulation-based decision loops. This fragmentation prevents stakeholders from *observing how AI reasoning evolves across simulated conditions*, limiting confidence in model behavior under non-ideal or extreme scenarios.

3. Absence of Neuro-Symbolic Reasoning in Agricultural Digital Twins

Most agricultural AI systems rely purely on data-driven machine learning or deep learning approaches, which struggle with generalization under sparse data, rare events, or shifting environmental conditions. Despite theoretical advances in neuro-symbolic AI, its practical adoption within agricultural digital twin environments remains minimal. Existing works rarely encode agronomic rules, causal constraints, or expert knowledge alongside neural models, resulting in systems that lack logical consistency and agronomic interpretability.

4. Insufficient Decision Auditability and Data Provenance

While blockchain has been applied to agricultural supply chains and product traceability, its role in AI decision validation and lifecycle governance remains underexplored. Current studies seldom record model updates, simulation outcomes, explanation traces, or AI-generated decisions in a tamper-resistant manner. This limits post-hoc auditing, regulatory compliance, and accountability—especially critical for high-impact decisions such as irrigation scheduling, disease intervention, and resource allocation.

5. Overdependence on Costly and Risk-Prone Field Experiments

Validation of agricultural AI systems frequently relies on extensive field trials, which are expensive, time-consuming, weather-dependent, and difficult to replicate. Few studies exploit simulation-driven evaluation pipelines that can systematically test AI decisions under controlled yet realistic conditions using digital twins. This gap hinders rapid innovation, comparative benchmarking, and safe pre-deployment assessment.

6. Limited Cross-Domain Generalization and Scenario Robustness

Most existing solutions are optimized for single crops, specific regions, or narrow tasks, with limited discussion on transferability. Without structured simulation environments and knowledge-aware reasoning, AI models often fail to adapt to unseen climatic conditions, soil variations, or management practices. Robustness across scenarios remains an open challenge.

Conclusion

This literature-driven analysis highlights that, while precision agriculture has rapidly advanced through artificial intelligence, IoT, and data-driven automation, trust, transparency, and validation remain fundamental bottlenecks preventing large-scale real-world adoption. Existing agricultural AI systems largely prioritize predictive performance, yet often neglect interpretability, explainability, and systematic validation—factors that are critical for farmer confidence, regulatory acceptance, and sustainable decision-making.

The review demonstrates that digital twins provide a powerful foundation for simulation-driven evaluation by enabling safe, repeatable, and cost-effective testing of agricultural strategies across diverse scenarios. However, most current digital twin implementations in agriculture function primarily as monitoring or optimization tools rather than as formal validation environments for AI-driven decisions. This limits their ability to assess robustness, failure modes, and behavioral consistency prior to deployment.

Further, the survey reveals that neuro-symbolic AI remains largely absent from operational precision agriculture systems. Purely data-driven models struggle under sparse data, non-stationary environmental conditions, and rare events—common characteristics of agricultural domains. Integrating symbolic agronomic knowledge with neural learning offers a clear pathway toward more robust, logically consistent, and explainable decision-making, yet practical implementations within digital twin ecosystems are still scarce.

The growing body of work on explainable AI underscores its importance in transforming black-box predictions into human-understandable insights. Nevertheless, explanations are rarely embedded into closed-loop simulation workflows, preventing stakeholders from observing how AI reasoning changes under varying environmental and operational conditions. Similarly, although blockchain technologies have proven effective for agricultural traceability, their application to AI decision auditability—covering data provenance, model updates, simulation outcomes, and decision logs—remains underexplored.

Collectively, the literature indicates a clear need for integrated, trust-centric precision agriculture frameworks that unify digital twins, neuro-symbolic AI, explainable AI, and blockchain-based validation. Such simulation-driven ecosystems can significantly reduce dependence on costly and risky field trials, enable transparent pre-deployment testing, and support accountable, auditable agricultural decision-making.

In conclusion, advancing precision agriculture beyond experimental success toward dependable real-world adoption requires a paradigm shift—from performance-centric AI models to simulation-validated, explainable, and verifiable decision systems. The convergence of digital twins with knowledge-aware AI, interpretable analytics, and secure validation mechanisms represents a promising and necessary direction for building resilient, trustworthy, and sustainable AI-powered agriculture systems.

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