Physical Education, Health and Social Sciences

https://journal-of-social-education.org

E-ISSN: 2958-5996

P-ISSN: 2958-5988

Digital Plant Twins for Real-Time Prediction of Disease Progression Under Climate Change Scenarios

Dr. Nadia Jabeen *[1], Osama Akbar[2], Mohammad Ayoob[3], Abdulrehman Niazi[4]

1 Department of Agriculture, Hazara University Mansehra, KPK. nadia_khan909090@yahoo.com nadia.agri@hu.edu.pk ORCID ID: 0000-0001-6617-8301

2 Department of Plant Breeding and genetics, University of Agriculture Faisalabad osamashahwani0@gmail.com

3 Department of Plant Breeding and Genetics, University of Agriculture Faisalabad ayoubkhoso992@gmail.com

4 Department of Plant Breeding and Genetics, University of Agriculture Faisalabad abdulrehmanniazi493@gmail.com

DOI: https://doi.org/10.63163/jpehss.v4i1.1695

Abstract

Plant diseases account for 20–40% of global crop losses annually, a burden exacerbated by climate change-driven shifts in temperature, precipitation, and atmospheric CO_2 that destabilize host-pathogen-environment dynamics. Traditional reactive management strategies and static empirical models are inadequate for predicting disease progression under these evolving conditions. This review examines the integration of Digital Twin (DT) technology with hybrid mechanistic-AI modeling frameworks for real-time prediction and mitigation of plant disease outbreaks. We present a comprehensive analysis of the four-tier DT architecture encompassing IoT sensor networks, edge-cloud communication, hybrid modeling engines, and automated actuation systems that enables continuous bidirectional synchronization between physical crop systems and their virtual counterparts. The core analytical engine employs Physics-Informed Neural Networks (PINNs) coupled with spatiotemporal SEIR reaction-diffusion equations, embedding biophysical governing laws directly into neural network loss functions to achieve robust predictions on sparse field data while maintaining interpretability. Deep learning vision pipelines incorporating EfficientNet, Vision Transformers, and YOLO architectures provide automated lesion detection and severity quantification, with model lightweighting enabling edge deployment for low-latency inference. Despite technical advances, implementation bottlenecks persist, including data interoperability challenges, computational latency constraints, and the prevalence of unidirectional "Digital Shadows" rather than fully autonomous closed-loop systems. Future directions emphasize multi-agent AI orchestration, standardized communication protocols, and PINN-based surrogate modeling to reduce computational overhead. This review synthesizes current knowledge on digital plant twins, identifies critical research gaps, and proposes pathways toward climate-resilient, precision agricultural systems capable of proactive disease management.

Keywords: Digital Twin, Plant Disease Prediction, Climate Change, Physics-Informed Neural Networks, SEIR Models, Precision Agriculture, Deep Learning, IoT Sensing

1. Introduction

Plant diseases pose a severe threat to global food security, agricultural sustainability, and economic stability, causing an estimated 20% to 40% loss in annual crop production worldwide. The cascading economic and social ramifications of these crop losses are further intensified by rapid global population growth, which necessitates a projected 25% to 70% increase in agricultural yield to ensure global food sufficiency (Savary & Willocquet, 2020). Historically, crop protection strategies have relied heavily on reactive chemical pesticide applications, post-symptomatic visual evaluations, and static empirical forecasting models. However, these conventional management frameworks are increasingly rendered ineffective by the rising frequency of extreme weather events, microclimate instability, and shifting phytopathogen ranges driven by anthropogenic climate change (Méndez et al., 2026).

To overcome the limitations of static diagnostic tools, the agricultural sector is undergoing a paradigm shift toward precision farming enabled by Digital Twin (DT) technology. Originating in industrial manufacturing and aerospace engineering, a Digital Twin is defined as a high-fidelity, dynamic virtual representation of a physical asset, biological organism, or complex system that continuously mirrors its real-world counterpart across its operational lifecycle (GrieveJones et al., 2020). Applied to plant pathology and crop management, a Digital Plant Twin integrates multi-source physical data streams derived from Internet of Things (IoT) sensor networks, spectral remote sensing, and automated phenotyping platforms with advanced biophysical, functional-structural, and epidemiological models (Verdouw et al., 2021).

A foundational distinction must be drawn between a passive "Digital Shadow" and an interactive, fully integrated "Digital Twin". A Digital Shadow encompasses a unidirectional flow of information where physical field states are recorded, processed, and visualized in a virtual environment without automated operational feedback. In contrast, a fully realized Digital Plant Twin establishes continuous, bidirectional synchronicity between the physical crop environment and its digital virtual counterpart (Grieves & Vickers, 2017). The virtual model continuously assimilates real-time observational data to update internal parameters, simulates disease progression under dynamic environmental shifts, and automatically transmits optimized prescriptive controls back to physical farm infrastructure. These actuation mechanisms include variable-rate precision sprayers, automated drip irrigation valves, and controlled-environment climate systems (Wolfert et al., 2017).

The integration of Digital Plant Twins into plant pathology is essential for predicting complex, non-linear disease progression under climate change scenarios. Concurrent shifts in ambient temperature, atmospheric carbon dioxide concentration, relative humidity, and precipitation patterns fundamentally alter host-pathogen-environment dynamics (Chakraborty & Newton, 2011). By coupling physics-informed machine learning, spatial reaction-diffusion differential equations, and deep neural diagnostic architectures, Digital Plant Twins enable continuous real-time parameter identification, early physiological stress detection, and proactive disease mitigation before visible epiphytotic outbreaks manifest (Ahmed et al., 2026).

2. Climate Change Dynamics and the Shifting Plant Disease Triangle

The fundamental framework of plant pathology rests upon the classical "Disease Triangle," which posits that an epidemic outbreak requires the simultaneous convergence of a susceptible host plant, a virulent pathogen, and a conducive environment. Climate change perturbs every vertex of this triangle simultaneously, introducing dynamic environmental interactions that invalidate historical empirical forecasting models (Savary et al., 2019).

Within this triadic interaction, atmospheric perturbations modify the microclimate surrounding host tissues, while rising global temperatures alter both pathogen metabolic rates and host immune signaling pathways. Concurrently, volatile precipitation patterns dictate pathogen spore survival and mechanical dispersal mechanisms, creating a complex biophysical environment that requires dynamic, real-time computational tracking (Oerke, 2006).

2.1 Atmospheric Carbon Dioxide Perturbations

Global atmospheric CO_2 concentrations have increased substantially above pre-industrial baselines, altering crop canopy architecture and intra-canopy microclimates. Elevated CO_2 levels stimulate photosynthetic activity and vegetative biomass production in C_3 crops, leading to denser foliage and higher leaf area indices. These dense leaf canopies restrict internal airflow and trap moisture, resulting in prolonged leaf wetness duration and consistently high relative humidity within the crop canopy (Tilman et al., 2011). Such humid microenvironments create optimal conditions for fungal spore germination, appressorium formation, and bacterial penetration for foliar pathogens such as *Botrytis cinerea* and rust species (*Puccinia* spp.). Additionally, elevated atmospheric CO_2 alters host structural and biochemical defenses, causing changes in leaf cuticle thickness, stomatal conductance, and leaf carbohydrate accumulation, which can heighten susceptibility to both biotrophic and necrotrophic pathogens (Bebber et al., 2014).

2.2 Thermal Optima Dynamics and Immunological Breakdown

Temperature is a primary environmental variable governing pathogen development rates, infection efficiency, vector survival, and geographical distribution. Plant pathosystems operate within specific thermal ranges; for instance, *Xanthomonas oryzae* colonization in rice reaches maximum virulence at daytime temperatures of 35°C and nighttime temperatures of 27°C, whereas *Globodera pallida* root nematode infection peaks at 15°C (Kritzinger et al., 2018). Atmospheric warming accelerates pathogen metabolic processes, shortens generation times, and drives poleward and higher-altitude shifts in pathogen geographic ranges, exposing previously unexposed crop populations to novel disease pressures (Aditya et al., 2026).

Importantly, elevated temperatures directly affect the molecular immune responses of host plants. High ambient temperatures even transient exposures to temperatures between 28°C and 35°C can compromise Effector-Triggered Immunity (ETI) governed by plant Nucleotide-binding Leucine-rich Repeat (NLR) resistance receptors (Kamilaris & Prenafeta-Boldú, 2018). Thermal stress suppresses the transcript and protein accumulation of crucial NLRs, including N gene-mediated viral resistance in tobacco, $Mi-1$-mediated nematode resistance in tomato, and TSW-mediated virus resistance in pepper. Although specific NLR proteins, such as potato $Rx1$ or rice $Xa7$, display thermal stability or enhanced ETI via salicylic acid-independent pathways at higher temperatures, the thermal vulnerability of host immune defenses underscores the need for continuous microclimate and physiological monitoring (Jones et al., 2020).

2.3 Precipitation Volatility and Moisture Dynamics

Shifted precipitation regimes characterized by prolonged drought periods punctuated by intense rainfall events drastically modify pathogen dispersal mechanisms and host stress levels. Free water accumulation on leaf surfaces is required for the motility of oomycete zoospores (*Phytophthora* spp.) and bacterial chemotaxis toward stomata. High-velocity wind and raindrop splash act as physical vectors, aerosolizing and dispersing fungal conidia across agricultural fields. Conversely, drought stress debilitates host physiological status, impairing basal defense pathways and increasing vulnerability to opportunistic necrotrophic stem and root pathogens (Gao & Zhu, 2026).

Table 1: Multi-Factor Impacts of Climate Change Variables on Plant Pathosystems and Immune Defense Mechanisms

Climate Parameter	Direct Pathogen Response	Direct Host Plant Response	Net Pathosystem Impact
Elevated Atmospheric CO_2	Increased sporulation capacity, higher conidial germination rates, and accelerated reproduction cycles.	Increased total biomass, denser leaf canopy architecture, modified cuticle thickness, and elevated leaf carbohydrate levels.	Dense crop canopies trap moisture and reduce airflow, elevating intra-canopy humidity and promoting foliar fungal outbreaks.
Increased Ambient Temperature	Faster metabolic development, expanded latitudinal range, enhanced overwintering, and faster vector propagation.	Suppression of specific NLR resistance proteins (*e.g.*, *Mi-1*, *N*, *TSW*), compromised ETI, and altered phenological timing.	Mismatches between crop developmental stages and pathogen emergence; severe disease outbreaks due to thermally suppressed host immunity.
Precipitation Instability & High Humidity	Enhanced water-borne motility (*zoospores*), increased splash dispersal of bacterial and fungal propagules.	Waterlogging stress, root hypoxia, stomatal closure, and impaired structural surface defenses.	Increased incidence of aqueous apoplastic microenvironments, promoting bacterial blights and oomycete infections.

3. Multilayer Architecture of Agricultural Digital Twins

To effectively capture, process, and act upon climate-driven phytopathological dynamics, Digital Plant Twins employ a hierarchical, four-tier functional architecture. This multi-tiered structure ensures seamless bidirectional flow, moving from physical field sensing up to high-performance computational models, and back down to automated field execution equipment (Hossain et al., 2024).

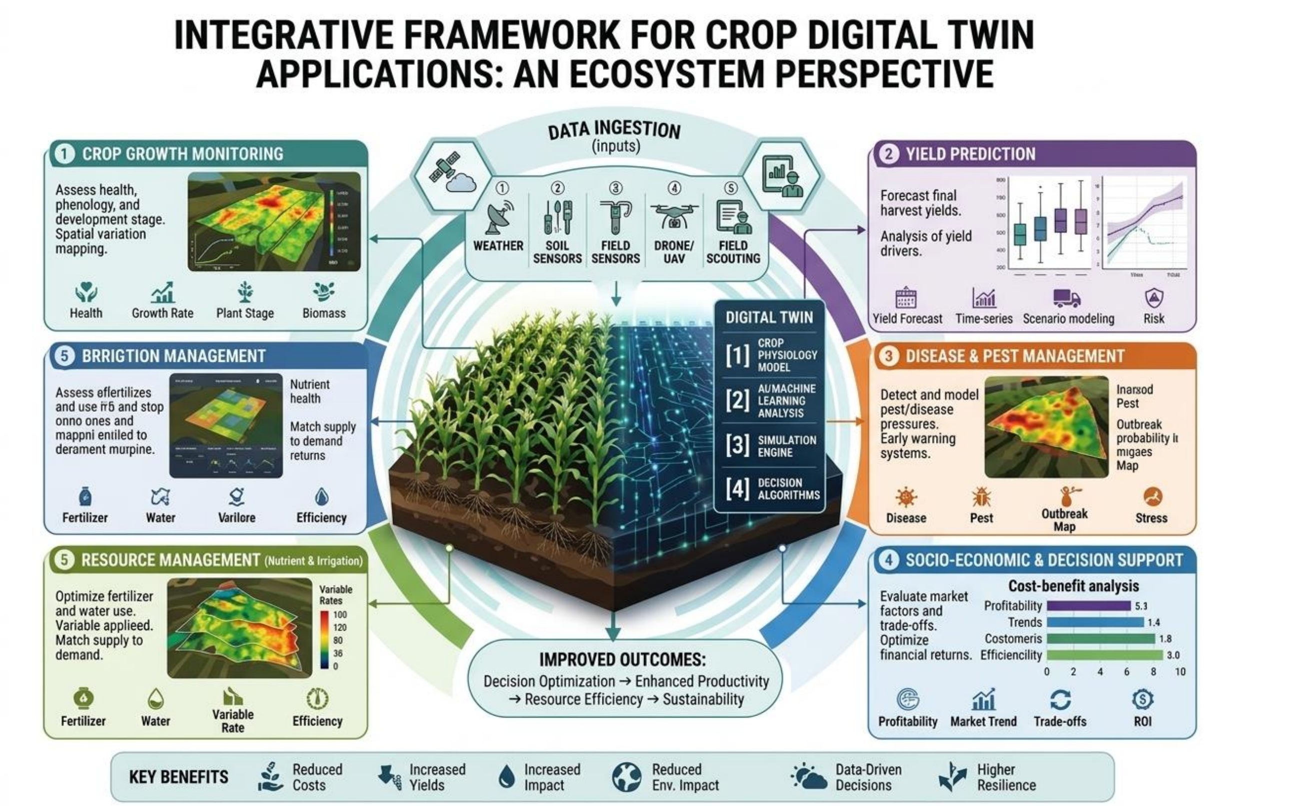
The architectural continuum begins at the physical baseline with the Perception and Data Acquisition Layer, which captures multi-modal environmental, physiological, and spatial data. These raw sensor streams are ingested by the Network and Edge-Cloud Communication Layer, where distributed edge computing nodes perform preliminary signal filtering, data aggregation, and protocol translation before streaming sanitized data to central repositories (Farda et al., 2026). Central computation occurs within the Modeling and Simulation Layer, which combines biophysical crop engines, spatial epidemiological partial differential equations, and deep learning diagnostic architectures to evaluate crop health and run predictive scenarios. Finally, the Application, Decision Support Systems, and Actuation Layer translates simulation trajectories into spatial prescription maps and direct control commands sent back to automated field equipment, establishing a fully closed-loop digital twin ecosystem (Iqbal & Naqvi, 2025).

3.1 Perception and Data Acquisition Layer

The perception layer forms the physical interface of the Digital Plant Twin architecture, collecting multi-scale environmental and plant status data from fields or controlled greenhouse environments. Stationary micro-meteorological stations measure ambient air temperature, relative humidity, barometric pressure, solar radiation, and wind velocity vectors. Soil-embedded IoT probe arrays continuously track volumetric water content, soil temperature, electrical conductivity, and plant-available nutrient concentrations across root-zone profiles. In-situ foliage contact sensors measure leaf wetness duration and canopy surface temperature (Fernández et al., 2025).

Airborne and remote sensing modalities augment in-situ probes by capturing field-scale spatial heterogeneity. Unmanned Aerial Vehicles (UAVs) equipped with Real-Time Kinematic (RTK) positioning units gather high-resolution spatial imagery. Multispectral sensors track light reflectance across specific wavebands to construct vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE), identifying chlorophyll degradation and structural canopy stress (Liu et al., 2023). Thermal Infrared (TIR) imaging measures canopy surface temperature variations, identifying pre-symptomatic stomatal closure caused by vascular pathogen blockade or root stress before visible leaf chlorosis appears. Light Detection and Ranging (LiDAR) sensors generate 3D spatial point clouds, providing precise structural measurements of leaf area index, leaf angle distribution, and vertical canopy geometry (Cai et al., 2025).

Figure 1. Integrative Architecture and Ecosystem Applications of Agricultural Crop Digital Twins



3.2 Network and Edge-Cloud Communication Layer

The network layer provides a reliable, low-latency communication bridge connecting physical sensors to digital processing hubs. Raw telemetry data from distributed IoT nodes are transmitted via long-range, low-power wireless communication protocols including LoRaWAN, NB-IoT, and cellular 5G networks. Edge computing nodes situated directly at the field margin process raw data streams locally, applying exponential moving averages and filtering algorithms to remove sensor noise, missing packets, and drift anomalies. Edge preprocessing reduces network bandwidth consumption, enabling fast local diagnostic inference while streaming curated datasets to cloud platforms for full-scale twin state synchronization (Bădoi et al., 2026).

3.3 Modeling and Simulation Layer

The modeling layer is the core analytical engine of the Digital Plant Twin, where multi-source data streams are merged with digital simulation models. This computational layer integrates process-based crop growth models, dynamic 3D Functional-Structural Plant (FSP) engines, spatial disease reaction-diffusion differential equations, deep visual diagnostic networks, and Physics-Informed Neural Networks (PINNs). By continuously calibrating internal model states against real-time sensor inputs, the modeling layer simulates pathogen infection kinetics, calculates future outbreak probabilities under changing weather conditions, and evaluates potential mitigation strategies (Uddin & Koo, 2024).

3.4 Application, Decision Support Systems, and Actuation Layer

The top architectural tier translates virtual model predictions into operational field interventions. Interactive user interfaces and Decision Support Systems (DSS) display spatial risk heatmaps, diagnostic summaries, and proactive intervention recommendations to farm managers. In automated closed-loop configurations, the application layer communicates directly with physical farm infrastructure (Mănescu, 2025). Upon predicting a localized disease outbreak, the Digital Twin auto-generates variable-rate prescription maps and dispatches autonomous sprayers or agricultural drones to apply targeted, localized crop protection treatments. In controlled-environment greenhouses, the layer directly adjusts climate control systems, altering ambient temperature, reducing humidity levels, or shifting supplementary LED lighting spectra to inhibit pathogen sporulation (Giovannetti, 2026).

Table 2: Multi-Modal Data Streams Across Sensing Layers in Agricultural Digital Twins

Sensing Modality	Primary Measured Parameters	Spatial & Temporal Resolution	Functional Role in Disease Prediction
Multispectral & Hyperspectral Imaging	Spectral reflectance wavebands, NDVI, NDRE, Photochemical Reflectance Index.	Field-scale; spatial resolution millimeter-to-centimeter via UAVs; weekly to daily flights.	Identifies physiological stress, chlorophyll degradation, and early tissue necrosis prior to visual manifestation.
Thermal Infrared (TIR) Sensors	Surface canopy temperature, leaf-to-air temperature differential, transpiration rates.	Individual plant to field scale; real-time stationary probes or high-resolution UAV maps.	Detects pre-symptomatic stomatal closure and transpiration declines caused by vascular or root pathogens.
LiDAR Point Clouds	3D canopy geometry, leaf area index (LAI), leaf tilt angles, canopy height.	Individual plant to field scale; millimeter-level structural point clouds.	Maps internal canopy structural density, enabling simulation of microclimatic airflow and localized humidity buildup.
In-Situ Microclimate IoT Probes	Air temperature, relative humidity, barometric pressure, leaf wetness duration.	Sensor node scale; continuous high-frequency streaming (minute-to-hour intervals).	Provides real-time microclimatic boundary conditions required for pathogen spore germination models.
Soil Sensing Networks	Volumetric water content, soil temperature, electrical conductivity, N-P-K levels.	Root-zone scale; continuous real-time telemetry.	Evaluates root-zone abiotic stress, predicting host vulnerability to soilborne fungal and bacterial pathogens.

4. Hybrid Mechanistic-AI Modeling: Integrating PINNs and SEIR Dynamics

Accurate prediction of plant disease progression under variable climate conditions requires robust computational modeling frameworks. Historically, predictive phytopathology relied on either purely mechanistic biophysical models or purely empirical machine learning models. However, both paradigms exhibit distinct operational limitations when applied independently to dynamic agricultural environments (Fan et al., 2026).

4.1 The Need for Hybrid Paradigms

Purely data-driven deep learning models excel at extracting complex non-linear patterns from multi-dimensional sensor streams. However, these empirical models function as black-box estimators that require vast amounts of annotated training data and frequently fail when predicting outside their training distribution a key drawback under shifting climate regimes (Reichstein et al., 2019). Conversely, purely mechanistic biophysical models (such as process-based differential equation systems) incorporate established biological principles and offer strong interpretability. Yet, they are computationally intensive, difficult to calibrate for real-time field data, and sensitive to unmeasured environmental variations (Shi et al., 2025).

To resolve these limitations, Digital Plant Twins employ hybrid mechanistic-AI frameworks powered by Physics-Informed Neural Networks (PINNs). PINNs embed physical, chemical, and biological governing laws directly into the loss functions of deep neural networks, combining empirical observational data with explicit governing differential equations (Karniadakis et al., 2021).

4.2 Spatiotemporal SEIR Epidemic Formulation

A core mathematical framework for modeling plant disease transmission is the spatiotemporal SEIR (Susceptible-Exposed-Infectious-Removed) reaction-diffusion system. Within a two-dimensional spatial canopy domain $\Omega \subset \mathbb{R}^2$ over time $t \in [0, T]$, the total host tissue biomass density N is divided into four dynamic state compartments: susceptible tissue (S), latent or exposed infected tissue (E), actively sporulating infectious tissue (I), and rotted or removed tissue (R) (Li & Hu, 2026):

$$\frac{\partial S}{\partial t} = D_S \nabla^2 S - \beta(T, RH, CO_2) \frac{SI}{N}$$

$$\frac{\partial E}{\partial t} = D_E \nabla^2 E + \beta(T, RH, CO_2) \frac{SI}{N} - \sigma(T) E$$

$$\frac{\partial I}{\partial t} = D_I \nabla^2 I + \sigma(T) E - \gamma(T) I$$

$$\frac{\partial R}{\partial t} = D_R \nabla^2 R + \gamma(T) I$$

In these spatial partial differential equations, D_S, D_E, D_I, and D_R denote spatial diffusion coefficients representing airborne spore dispersal, vector movement, or passive canopy contact. The parameter $\beta(T, RH, CO_2)$ represents the infection transmission rate, explicitly parameterized as a function of ambient temperature (T), relative humidity/leaf wetness (RH), and carbon dioxide concentration (CO_2). The parameter $\sigma(T)$ defines the temperature-dependent incubation transition rate from latency to active infectiousness, while $\gamma(T)$ denotes the tissue removal or death rate (Willard et al., 2022).

4.3 PINN Architecture and Composite Loss Formulation

In a PINN-enabled Digital Plant Twin, a deep neural network $\hat{\mathbf{y}}(x, y, t; \theta)$, parameterized by trainable weights and biases θ, is configured to approximate the true disease state vector $\mathbf{y} = [S, E, I, R]^T$ across space and time. Partial derivatives of the neural network outputs with respect to spatial coordinates (x, y) and time t are calculated efficiently via automatic differentiation (Tagarakis et al., 2024).

The overall training loss function $\mathcal{L}_{\text{total}}(\theta)$ comprises four distinct optimization terms:

$$\mathcal{L}_{\text{total}}(\theta) = w_{\text{data}} \mathcal{L}_{\text{data}}(\theta) + w_{\text{PDE}} \mathcal{L}_{\text{PDE}}(\theta) + w_{\text{BC}} \mathcal{L}_{\text{BC}}(\theta) + w_{\text{IC}} \mathcal{L}_{\text{IC}}(\theta)$$

The data loss term $\mathcal{L}_{\text{data}}(\theta)$ measures the mean squared error between neural network predictions and observational field sensor measurements across N_d sampled points:

$$\mathcal{L}_{\text{data}}(\theta) = \frac{1}{N_d} \sum_{i=1}^{N_d} \| \hat{\mathbf{y}}(x_i, y_i, t_i; \theta) - \mathbf{y}_{\text{observed}}(x_i, y_i, t_i) \|^2$$

The physics loss term $\mathcal{L}_{\text{PDE}}(\theta)$ enforces biological consistency by penalizing residuals of the SEIR differential equations evaluated across N_r unlabelled collocation points distributed throughout the spatial canopy domain (Keramioti et al., 2026):

$$\mathcal{L}_{\text{PDE}}(\theta) = \frac{1}{N_r} \sum_{j=1}^{N_r} \left\| \mathcal{R}_{\text{SEIR}} \left(\hat{\mathbf{y}}(x_j, y_j, t_j; \theta) \right) \right\|^2$$

Where $\mathcal{R}_{\text{SEIR}}$ represents the system of differential equation residuals. The boundary condition loss term $\mathcal{L}_{\text{BC}}(\theta)$ enforces homogeneous Neumann boundary conditions ($\nabla \mathbf{y} \cdot \mathbf{n} = 0$) along physical field borders $\partial\Omega$, ensuring zero net loss of tissue mass across field boundaries. Finally, the initial condition loss term $\mathcal{L}_{\text{IC}}(\theta)$ constrains state variable predictions at $t = 0$ to match baseline crop health measurements (Escribà-Gelonch et al., 2024).

Table 3: Comparative Evaluation of Computational Modeling Approaches in Phytopathology

Parameter / Capability	**Process-Based Biophysical Models**	**Purely Data-Driven Deep Learning**	**Hybrid PINN Digital Twins**
Data Requirement	Low; requires precise manual calibration of physical parameters.	Extremely High; demands vast annotated image/telemetry datasets.	Moderate; uses biophysical loss constraints to train effectively on sparse field data.
Extrapolation Capability	High; anchored in established differential equations.	Poor; struggles when exposed to out-of-distribution climate shifts.	High; bounded by fundamental mass conservation and biological principles.
Computational Latency	High; numerical PDE solvers require minutes to hours per iteration.	Extremely Low; sub-second forward-pass inference post-training.	Low; surrogate neural evaluation executes in under 100 milliseconds.
Parameter Calibration	Offline; relies on manual or iterative numerical fitting.	Non-existent; parameters are hidden within non-interpretable neural weights.	Online; continuous dynamic inverse parameter calibration using stream data.
Noise Robustness	Sensitive to boundary condition noise and missing input variables.	Vulnerable to adversarial noise, glare, and sensor drift artifacts.	High; differential residual loss terms filter out unphysical sensor noise.

5. Early Detection, Deep Learning, and Explainable AI Integration

To provide high-resolution diagnostic inputs to the modeling engine, Digital Plant Twins integrate vision-based deep learning pipelines for automated disease identification, lesion segmentation, and spatial spot-localization. The diagnostic pipeline processes raw leaf or canopy images captured by field cameras or drones through deep feature extractors, evaluates disease severity, and generates visual explainability maps for agronomic review (Wang, 2024).

5.1 Deep Neural Architectures for Visual Diagnostics

Modern diagnostic vision systems utilize advanced convolutional and attention-based neural backbones to process high-resolution RGB, multispectral, and hyperspectral crop imagery. Deep Convolutional Neural Networks (CNNs) such as VGG, ResNet, DenseNet, and EfficientNetB3 extract spatial feature hierarchies, fine leaf textures, and subtle color shifts indicative of early fungal lesions or bacterial blights. EfficientNetB3 employs compound scaling to balance network depth, width, and image resolution, achieving high diagnostic accuracy while maintaining computational efficiency (Cuomo et al., 2022).

Vision Transformers (ViTs) further improve diagnostic performance by dividing leaf images into non-overlapping spatial patches and applying self-attention mechanisms to capture long-range contextual relationships across the leaf surface (Raissi et al., 2019). Advanced hybrid architectures combining CNN feature extractors with Transformer cross-attention modules (such as PDLC-ViT) achieve diagnostic accuracies exceeding 99% on benchmark datasets by evaluating both localized lesion margins and broader leaf-scale symptom patterns. For spatial disease localization, single-stage object detectors (YOLOv8/v9, SSD) and two-stage frameworks (Faster R-CNN) draw bounding boxes around individual lesions in real time, enabling precise automated quantification of disease severity (Tang et al., 2026).

5.2 Edge Optimization and Model Lightweighting

Deploying deep diagnostic models onto solar-powered field gateways, smart cameras, or agricultural drones requires neural network compression. Structural pruning, weight quantization (converting 32-bit floating-point parameters to 8-bit integer representations), and knowledge distillation significantly reduce computational complexity and memory footprints. Lightweight network architectures such as MobileNetV2 and MobileNetV3 utilize depthwise separable convolutions and inverted residual blocks to compress model sizes down to approximately 1.5 million parameters. These optimized models execute low-latency diagnostic inference directly on edge hardware, eliminating the need for constant cloud connectivity (Méndez et al., 2026).

5.3 Overcoming Domain Shift in Field Environments

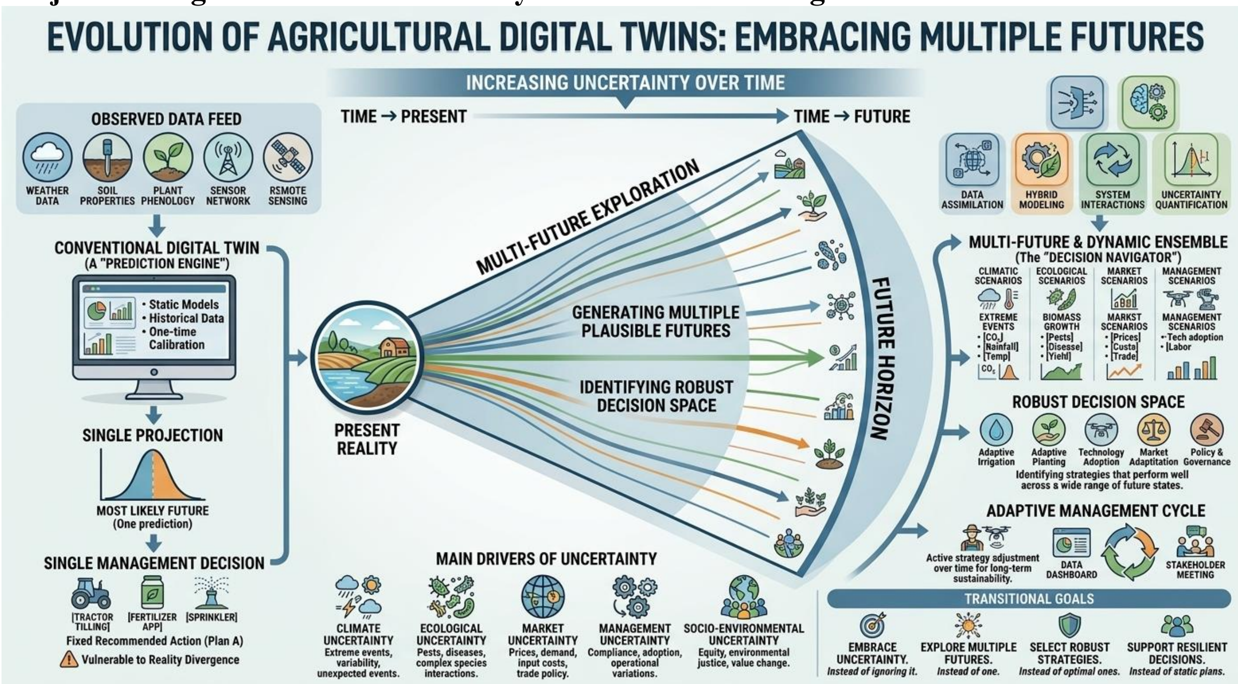
A key challenge facing computer vision models in smart agriculture is "domain shift". Neural networks trained on laboratory-curated datasets (*e.g.*, PlantVillage, featuring detached leaves against uniform backgrounds under controlled lighting) often suffer significant performance degradation when deployed in operational fields. Real-world agricultural fields introduce complex variable backgrounds, dynamic sun shadows, overlapping leaves, dust accumulation, direct solar glare, and dual-disease co-infections (Savary & Willocquet, 2020).

Digital Plant Twins address domain shift by utilizing generative adversarial data augmentation, domain adaptation techniques, and synthetic image synthesis. Training diagnostic models on diverse field datasets (*e.g.*, PlantDoc, FieldPlant) that capture varying lighting, weather conditions, and growth stages ensures robust performance under real-world operating conditions (Wolfert et al., 2017).

6. Implementation Bottlenecks, Edge Computing, and Future Directions

Despite the technical benefits of Digital Plant Twins, transitioning these complex computational platforms from experimental field trials to widespread commercial deployment introduces technical, operational, and architectural challenges (Kritzinger et al., 2018).

Figure 2. Evolutionary Paradigm Shift in Agricultural Digital Twins: From Static Single-Projection Engines to Multi-Future Dynamic Decision Navigators



6.1 Unidirectional Digital Shadows Versus Closed-Loop Digital Twins

Most commercial smart agriculture platforms currently marketed as digital twins operate only as "Digital Shadows". These platforms establish one-way data pipelines that collect field sensor metrics and stream them to cloud dashboards for manual review. Fully autonomous closed-loop Digital Twins capable of continuously evaluating predictive simulations and directly controlling physical farm equipment without human intervention remain limited in open-field crop production (Gao & Zhu, 2026).

Moving from a passive Digital Shadow to an active Digital Twin requires mitigating the risks of "contextual mismatch". An AI-generated recommendation that appears mathematically optimal within a virtual model may prove agronomically incorrect if it ignores localized soil variations, specific crop growth stages, or equipment constraints. To ensure operational safety, advanced Digital Plant Twins incorporate a "generation-simulation-verification" workflow. Candidate control actions proposed by AI algorithms are first tested within biophysical simulation engines and verified against agronomic safety constraints before automated execution commands are sent to field machinery (Ahmed et al., 2026).

6.2 Data Interoperability, Standardization, and Hardware Latency

Agricultural field environments are technologically fragmented. Distributed IoT sensors, UAV cameras, satellite feeds, and tractor ISOBUS networks frequently use proprietary data formats, custom communication protocols, and non-standard metadata schemas. Achieving true Digital Twin integration requires the adoption of universal open-data standards and interoperable API frameworks across equipment manufacturers (Kamilaris & Prenafeta-Boldú, 2018).

Additionally, running multi-scale biophysical simulations in real time introduces computational latency challenges. High-fidelity physics models, such as 3D fluid dynamics or molecular kinetics simulations, require hours to days per compute run, making them impractical for real-time control. Replacing compute-heavy numerical solvers with PINN surrogate neural networks reduces evaluation times by up to four orders of magnitude, enabling sub-100-millisecond execution times suitable for real-time closed-loop edge control (Bebber et al., 2014).

6.3 Multi-Agent AI Orchestration

The future evolution of Digital Plant Twins lies in agentic multi-system orchestration. Rather than relying on isolated single-purpose algorithms, future platforms will deploy networks of autonomous AI agents. Specialized sub-agents focused on microclimate forecasting, visual leaf diagnostics, economic market analysis, and resource scheduling will interact within a unified orchestration framework. By querying knowledge bases, executing code-based simulations, and evaluating operational trade-offs, agentic Digital Twins will manage complex agricultural ecosystems with high precision, adaptability, and climate resilience (Wolfert et al., 2017).

Conclusion

The integration of Digital Plant Twins represents a transformative paradigm shift in plant disease management, moving beyond reactive, symptom-based interventions toward predictive, climate-adaptive strategies. By synthesizing multi-modal IoT sensor data, high-resolution remote sensing, and hybrid mechanistic-AI modeling, these platforms enable continuous monitoring of host-pathogen dynamics under shifting environmental conditions. The application of Physics-Informed Neural Networks coupled with spatiotemporal SEIR epidemiology provides a robust computational framework that balances the pattern-recognition capabilities of deep learning with the biological interpretability of differential equation models, ensuring reliable predictions even under novel climate scenarios. However, the transition from research prototypes to widespread commercial deployment faces significant challenges, including sensor interoperability, computational latency for real-time control, and the current prevalence of unidirectional digital shadows rather than fully autonomous closed-loop systems. Future research must prioritize the development of standardized open-data architectures, lightweight PINN surrogate models for edge deployment, and multi-agent AI orchestration frameworks capable of managing complex agricultural ecosystems holistically. As climate change continues to reshape pathogen distributions and host susceptibility, Digital Plant Twins offer a promising pathway toward sustainable intensification of agriculture, enabling proactive disease mitigation, reduced chemical inputs, and enhanced global food security. The convergence of digital infrastructure, computational modeling, and biological understanding will be essential for realizing the full potential of this technology in the coming decade.

References

Aditya, B. R., Marchiningrum, A. U., & Ginanjar, Y. (2026). Digital twin for agricultural land monitoring system. *Pertanika Journal of Science and Technology, 34*(1). https://doi.org/10.47836/pjst.34.1.01

Ahmed, S., Bijarani, M. A., Keerio, I. K., & Jhatial, M. J. (2026). IoT-based smart farming system with convolutional neural networks for real-time plant disease detection. *Lahore Garrison University Research Journal of Computer Science and Information Technology, 10*(1). https://doi.org/10.54692/lgurjcsit.v10i1.195

Bădoi, C. I., Kartal Çetin, B., Çetin, K., Karataş, Ç., Özbek, M. E., & Şahin, S. (2026). A hierarchical framework leveraging IIoT networks, IoT hub, and device twins for intelligent industrial automation. *Applied Sciences*, *16*(2), 645.

Bebber, D. P., Ramotowski, M. A. T., & Gurr, S. J. (2014). Crop pests and pathogens move polewards in a warming world. *Nature Climate Change, 3*(11), 985–988. https://doi.org/10.1038/nclimate1990

Cai, H., Jiang, J., Wang, C., Yang, S., & Du, W. (2025). A reconfigurable digital twin framework for plant factories: crop modeling, environmental anomaly detection, and system reconfiguration. *The International Journal of Advanced Manufacturing Technology*, *141*(1), 295-322.

Chakraborty, S., & Newton, A. C. (2011). Climate change, plant diseases and food security: An overview. *Plant Pathology, 60*(1), 2–14. https://doi.org/10.1111/j.1365-3059.2010.02411.x

Cuomo, S., Di Cola, V. S., Giampaolo, F., Rozza, G., Raissi, M., & Piccialli, F. (2022). Scientific machine learning through physics-informed neural networks: Where we are and what's next. Journal of Scientific Computing, 92, 88. https://doi.org/10.1007/s10915-022-01939-z

Escribà-Gelonch, M., et al. (2024). Digital twins in agriculture: Orchestration and applications. Journal of Agricultural and Food Chemistry, 72(19). https://doi.org/10.1021/acs.jafc.4c01934

Fan, A., Wang, L., Jia, S., Wang, C., Ji, T., Sánchez-Molina, J. A., ... & Wang, H. (2026). Forecasting Models for Plant Diseases: Advances, Applications and Future Perspectives. *Agronomy*, *16*(16), 1603.

Farda, B., Sabbi, E., Fares, R., Djebaili, R., Mignini, A., Mitra, D., & Pellegrini, M. (2026). Shifting disease dynamics: effect of climate change on plant pathogens and their management in field crops. *Journal of Plant Biochemistry and Biotechnology*, *35*(1), 57-79.

Fernández, R., Navas, E., Rodríguez-Nieto, D., Rodríguez-González, A. A., & Emmi, L. (2025). DigiHortiRobot: An AI-driven digital twin architecture for hydroponic greenhouse horticulture with dual-arm robotic automation. *Future Internet*, *17*(8), 347.

Gao, M., & Zhu, L. (2026). Pattern dynamics and practical application of infectious disease reaction-diffusion systems based on higher-order networks and physics-informed neural networks. *Chaos, 36*(6), 063110. https://doi.org/10.1063/5.0311452

Giovannetti, A. (2026). Integrating Modeling & Simulation and Artificial Intelligence for Training and Decision-Support in Complex Systems.

Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary perspectives on complex systems* (pp. 85–113). Springer.

Hossain, M. M., Sultana, F., Mostafa, M., Ferdus, H., Rahman, M., Rana, J. A., ... & Al Sabbir, M. A. (2024). Plant disease dynamics in a changing climate: impacts, molecular mechanisms, and climate-informed strategies for sustainable management. *Discover Agriculture*, *2*(1), 132.

Iqbal, M. U., & Naqvi, S. A. H. (2025). Climate change impacts on fruit crops and mechanisms of stress-induced disease dynamics for resilience strategies. *Applied Fruit Science*, *67*(5), 381.

Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology, 29*, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3, 422–440. https://doi.org/10.1038/s42254-021-00314-5

Keramioti, E., Hafiane, A., & Oikonomou, E. (2026). Physics-informed artificial intelligence remote sensing models in agriculture: Review and potential research outlook. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.7243392

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine, 51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

Li, J., & Hu, Q. (2026). Beyond data-driven: Integrating scientific knowledge and machine learning for crop prediction. European Journal of Agronomy, 180, 128261. https://doi.org/10.1016/j.eja.2026.128261

Liu, J., Wang, L., Wang, Y., Xu, S., & Liu, Y. (2023). RETRACTED: research on the interface of sustainable plant factory based on digital twin. *Sustainability*, *15*(6), 5010.

Mănescu, D. C. (2025). Big data analytics framework for decision-making in sports performance optimization. *Data*, *10*(7), 116.

Méndez, I., et al. (2026). Does climate change increase disease severity caused by crop pathogens? A systematic review. *Plant Disease*.

Mushtaq, N., Hashem, A. F., Irfan, M., & Mohamud, L. A. (2026). Design and evaluation of Bayesian optimized hybrid deep learning model for forecasting crop yields using climate dynamics. Scientific Reports, 16, 19782.

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of Agricultural Science, 144*(1), 31–43. https://doi.org/10.1017/S0021859605005708

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. Nature, 566, 195–204. https://doi.org/10.1038/s41586-019-0912-1

Savary, S., & Willocquet, L. (2020). Modeling the impact of crop diseases on global food security. *Annual Review of Phytopathology, 58*, 313–341. https://doi.org/10.1146/annurev-phyto-010820-012856

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution, 3*, 430–439. https://doi.org/10.1038/s41559-018-0793-y

Shi, Y., Han, L., Zhang, X., Sobeih, T., Gaiser, T., Thuy, N. H., Behrend, D., Srivastava, A. K., Halder, K., & Ewert, F. (2025). Deep learning meets process-based models: A hybrid approach to agricultural challenges. arXiv. https://arxiv.org/abs/2504.16141

Tagarakis, A. C., Benos, L., Kyriakarakos, G., et al. (2024). Digital twins in agriculture and forestry: A review. Sensors, 24(10), 3117. https://doi.org/10.3390/s24103117

Tang, R., Wu, L., Wang, Z., Zhu, L., Sun, A., Ru, Q., & Ju, B. (2026). Physics-informed neural networks for real-time updating and synchronisation in digital twins: A focused review. Digital Twins and Applications.

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences, 108*(50), 20260–20264. https://doi.org/10.1073/pnas.1116437108

Uddin, R., & Koo, I. (2024). Real-time remote patient monitoring: a review of biosensors integrated with multi-hop IoT systems via cloud connectivity. *Applied Sciences*, *14*(5), 1876.

Verdouw, C., Kruize, J. W., Robbemond, R. M., Wolfert, J., Beulens, A. J. M., & Parent, M. (2021). Digital twins in smart farming. *Agricultural Systems, 189*, 103046. https://doi.org/10.1016/j.agsy.2020.103046

Wang, L. (2024). Digital twins in agriculture: A review of recent progress and open issues. Electronics, 13(11), 2209. https://doi.org/10.3390/electronics13112209

Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2022). Integrating physics-based modeling with machine learning: A survey. ACM Computing Surveys, 55(11), 1–34. https://doi.org/10.1145/3514228

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming A review. *Agricultural Systems, 153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.015