CHAPTER

2

DEVELOPMENT OF FOREWARNING MODELS FOR PLANT DISEASES: A SYSTEMS-BASED APPROACH FOR SUSTAINABLE CROP PROTECTION

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Abstract

The intensification of agricultural production in the face of climate variability and pathogen evolution has heightened the urgency for sustainable plant disease management strategies. This chapter explores the development and application of forewarning models for plant diseases within a systems-based framework. These predictive tools, integrating host-pathogen-environment interactions, enable early warning and informed intervention, thus minimizing crop loss and chemical overuse. The chapter outlines key model types, empirical, mechanistic and hybrid and discusses the integration of environmental monitoring, disease biology, host susceptibility and vector dynamics into predictive systems. Real-world applications, such as forecasting late blight in potatoes and rice blast, demonstrate the effectiveness of these models in enhancing decision support and aligning with integrated pest management (IPM) principles. The discussion also addresses challenges in data availability, regional customization and adoption barriers, while highlighting emerging technologies such as machine learning, IoT and mobile-based advisories. By promoting proactive disease management, forewarning models contribute significantly to sustainable, resilient and climate-smart agriculture.

***Keywords**: Forewarning, plant disease, Epidemiological Model, Integrated pest management*

Introduction

Plant diseases pose one of the most significant threats to global food security, affecting not only crop yields but also the quality, safety and economic value of agricultural produce (Savary *et al.,* 2019). The consequences of plant disease outbreaks, ranging from regional famines to long-term yield stagnation, underscore the importance of effective disease control strategies. Traditionally, disease management in agriculture has been largely reactive, often relying on the visual detection of symptoms followed by blanket chemical treatments. This approach, while sometimes effective in the short term, leads to unsustainable practices such as overuse of fungicides, development of pathogen resistance and severe ecological disruption.

In an era where agricultural systems are increasingly vulnerable to climate variability, globalization of trade and changing pest dynamics, there is a critical need to transition toward proactive and preventive disease management approaches. A proactive system anticipates the onset of disease before it causes economic damage, allowing for timely, targeted and environmentally responsible interventions. This transition is vital not only for enhancing crop productivity but also for promoting long-term agricultural sustainability and resilience.

The foundation of proactive plant disease management lies in the development and deployment of disease forewarning models predictive systems that simulate disease occurrence based on climatic, biological and agronomic data. These models are designed to detect risk factors and simulate disease pressure before symptoms are visible in the field. They provide valuable insights into when and where diseases are likely to occur, thus enabling pre-emptive decisions on disease control measures such as fungicide application, resistant variety deployment and crop rotation planning (McDonald *et. al.,* 2016)**.**

This paradigm shift from reactive response to predictive planning represents a transformation in agricultural thinking. Rather than waiting for a problem to emerge, the systems-based approach embraces early detection, system modelling and risk-based decision-making. The integration of modern data analytics, sensor technology and mobile decision support platforms has further accelerated the adoption of forecasting systems at both regional and farm levels (Mahlein *et.al.*, 2016).

The intensifying threat of plant diseases, driven by climate variability, global trade *and* changing agro-ecosystems, underscores the urgency for transitioning from reactive to proactive plant health strategies. Traditional plant disease management often relies heavily on calendar-based pesticide applications, which not only elevate environmental and economic costs but also promote resistance development among pathogens. Forewarning models represent a paradigm shift in this landscape by enabling early detection and predictive management of potential outbreaks before clinical symptoms manifest. These models align with the goals of sustainable agriculture namely, minimizing chemical inputs, preserving ecosystem services and improving productivity per unit of environmental resource. The development of such systems necessitates an integrated, multidisciplinary approach involving plant pathology, meteorology, data science *and* farmer-centric communication strategies. A systems-based methodology wherein diverse components such as disease ecology, real-time weather data and machine learning algorithms are synergistically embedded enhances the reliability and adaptability of these models across crop types and agro-climatic zones (Bhati *et al.*, 2021; Dutta *et al.*, 2020). As a result, forewarning models not only optimize crop protection strategies but also advance resilience against emergent and re-emergent plant diseases under a changing climate.

This chapter explores the conceptual foundations, components, methodologies and real-world applications of disease forewarning models. By adopting a systems-based lens, we aim to illustrate how predictive modelling can bridge the gap between science and practice, enabling a more sustainable and resilient form of crop protection.

Components of the P-H-V-E System and Their Role in Disease Forewarning Models

The P-H-V-E system comprising Pathogen, Host, Vector and Environment was foundational to the construction of effective plant disease forewarning models (Figure 1). Each component plays a distinct yet interconnected role in the epidemiological dynamics that lead to disease outbreaks. The pathogen component includes factors such as virulence, inoculum potential, reproduction cycles and survival strategies. Highly virulent and polycyclic pathogens, for instance, require more intensive monitoring and frequent forecasting updates. The host element captures the crop's genetic susceptibility or resistance, growth stage, density and ontogenic resistance all of which determine its vulnerability to infection and influence the timing and accuracy of forecasts. The environment, particularly weather variables like temperature, relative humidity, rainfall and leaf wetness, critically modulates both host susceptibility and pathogen activity. Most forecasting models rely heavily on environmental inputs as triggers for prediction algorithms. For vector-borne diseases, the vector component is equally vital. Insect vectors such as aphids or whiteflies not only mediate disease transmission but also respond to environmental cues, adding complexity to disease progression. Understanding vector dynamics, population size, mobility and feeding behaviour enables models to forecast not just primary infections but also secondary spread. By integrating data from all four components, P-H-V-E-based models offer a systems-level perspective, making predictions more robust, temporally precise and spatially relevant (Table 1). This integrated approach is essential for timely interventions and effective deployment of control measures in sustainable agriculture.

Table 2.1. Components of the P-H-V-E System and Their Role in Disease Forewarning Models

Component	Key Factors	Role in Forecasting Models
Pathogen (P)	Virulence level - Reproduction type (polycyclic/monocyclic) - Inoculum load	Determines disease potential, outbreak scale, and epidemic velocity
Host (H)	Resistance genes - Growth stage - Plant density - Ontogenic resistance	Influences susceptibility window and risk of infection
Environment (E)	Temperature - Relative humidity - Rainfall - Leaf wetness duration	Governs pathogen development, spore dispersal, and survival; forms the basis for weather-driven prediction
Vector (V)	Population dynamics - Movement patterns - Transmission efficiency	Critical in vector-borne diseases; affects speed and spatial pattern of pathogen spread
Human Factor (optional)	Planting date - Irrigation practices - Crop management decisions	Modifies exposure risks and can be integrated into models to optimize intervention strategies

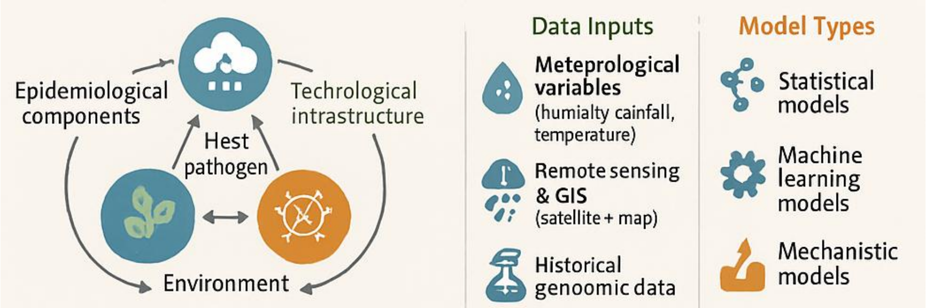

Figure 2.1. System based forewarning Conceptual Framework and Key Components of Disease Forewarning

Systems-Based Forewarning: Conceptual Framework

A systems-based forewarning model in plant pathology can be conceptualized as a dynamic, data-intensive and predictive framework that integrates biological, environmental and technological elements to facilitate timely and spatially resolved decisions. Central to this model is the epidemiological triad host, pathogen and environment which governs the initiation and spread of plant diseases. Unlike reductionist approaches that isolate one factor, systems thinking views the crop production ecosystem holistically, incorporating feedback loops and interactions. Modern models assimilate continuous data from IoT-based sensors, remote sensing imagery, meteorological stations and even farmer-reported observations. They also draw on statistical and mechanistic models that simulate the disease triangle under various scenarios. These data flows are aggregated and analysed through decision support systems (DSSs), which apply machine learning algorithms or rule-based systems to issue disease forecasts, risk maps and action thresholds. This holistic integration ensures that models remain adaptable and locally relevant, while still maintaining generalizability across diverse ecological settings. Ghosh & Kumpatla (2022) and Chakraborty & Chandran (2022) emphasize that such systems-based approaches foster sustainability by reducing pesticide dependency, improving biodiversity conservation *and* promoting knowledge-based interventions tailored to specific farming communities.

Key Components of Plant Disease Forewarning Models

The core of a forewarning system lies in its ability to translate multidimensional input data into actionable disease risk forecasts. At the heart of these systems are real-time and historical data on environmental variables such as temperature, humidity, rainfall and wind velocity, all of which critically influence pathogen development, dispersal and infection potential. These climatic drivers are captured through networks of in-field sensors, automated weather stations and satellite imagery and are complemented by agronomic factors including crop variety, planting date, irrigation schedules and soil nutrient status. Additionally, high-resolution drone images and hyperspectral data provide spatial intelligence on vegetation stress and canopy anomalies. A second critical component is disease surveillance data, which involves both expert monitoring and participatory tools like mobile apps for farmer disease reporting.

These datasets are processed through sophisticated models ranging from logistic regression and time-series forecasting to deep learning classifiers and ensemble models that recognize patterns and anomalies indicative of imminent outbreaks. Lata & Saini (2022) highlighted the role of convolutional neural networks (CNNs) in detecting disease symptoms from leaf imagery with high accuracy, while Chergui & Kechadi (2022) explored big data analytics in aggregating multi-source crop health information. Collectively, these components constitute a digital ecosystem for anticipatory disease management.

Model Development and Validation Process

Developing robust forewarning models requires a multi-phased and iterative process involving data preprocessing, model construction, training and validation. Initially, raw data gathered from diverse sensors and databases undergo preprocessing steps such as de-noising, outlier correction, normalization and feature selection. Temporal alignment of weather and disease data is critical to capturing causality and time-lag effects. The next step involves choosing appropriate modelling techniques. Statistical models like logistic regression are effective for binary classification (disease/no disease), while machine learning algorithms such as decision trees, support vector machines (SVM) and deep learning models like CNNs or LSTMs can handle nonlinear relationships and high-dimensional data. Mechanistic models, like the BLASTCAST system for rice blast, use biological rules and disease cycles to simulate outbreak likelihood under given weather conditions (Bhati *et al*., 2021). Once developed, models are trained on historical multi-year, multi-location datasets and validated using k-fold cross-validation or independent real-time data. Validation metrics such as accuracy, sensitivity, specificity, F1-score and ROC-AUC are used to assess model performance. According to Tripathy *et al*. (2012), hybrid systems that blend epidemiological understanding with AI adaptability outperform single-method approaches in both reliability and interpretability. This rigorous validation ensures scalability and resilience under future agro-climatic uncertainties.

Applications and Case Studies

Several real-world applications demonstrate the success, adaptability and scalability of forewarning models in managing economically important crop diseases across diverse agro-ecological zones. These systems have evolved from basic rule-based methods into sophisticated digital tools embedded in integrated pest and disease management frameworks. In the United Kingdom, the SIMBLIGHT1 model exemplifies a successful regional system for managing potato late blight. This model utilizes hourly meteorological inputs particularly temperature, humidity and rainfall to forecast disease risk levels. Farmers receive timely advisories that guide fungicide application, reducing both overuse and crop loss while supporting environmentally conscious practices.

In Southeast Asia, particularly in rice-intensive regions, BLASTCAST has been widely adopted for rice blast management. This model correlates leaf wetness duration, humidity, and air temperature with the infection cycle of *Pyricularia oryzae*, offering real-time disease risk advisories.

Field trials have shown significant reductions in yield losses and input costs, empowering smallholder farmers with science-backed decision-making tools (Bhati *et al.,* 2021).

India offers several notable innovations. For instance, microclimate-based decision support systems (DSSs) have been developed for cotton disease management, particularly targeting bollworm and bacterial blight. These systems incorporate in-field data such as canopy temperature, soil moisture, and pest surveillance to produce high-resolution forecasts that guide targeted intervention (Madasamy *et al.,* 2020). Similarly, a weather-based pest forecasting model developed by Tripathy *et al*. (2012) predicts groundnut thrips dynamics by combining wireless sensor networks and regression tree algorithms. These systems help optimize insecticide application timing, ensuring economic savings and ecological sustainability. These models are increasingly embedded in digital platforms such as mobile apps and web dashboards, making them accessible to even resource-poor farmers. Participatory interfaces enable feedback loops between users and system developers, improving model customization and trust.

In East Africa, GIS-integrated risk mapping systems have been developed to manage wheat rusts, particularly stem rust (*Puccinia graminis*). These systems combine remote sensing data, wind trajectory analysis, and pathogen surveillance to produce spatial risk forecasts. This approach supports national and regional surveillance networks and guides cross-border response strategies, especially in Ethiopia, Kenya, and Uganda (Ghosh & Kumpatla, 2022*)*.

Earlier established models such as BLITECAST in the USA and NEGFRY in Denmark have also shown high utility in forecasting potato late blight under temperate conditions. These models use a combination of environmental inputs and pathogen development stages to trigger fungicide application only when necessary. In tomato production, the TOM-CAST system has gained traction in North America for managing early blight, using disease severity values (DSVs) to optimize fungicide use with up to 50% reduction in applications. For grapevine diseases, the PLASMO model used in Italy simulates the life cycle of downy mildew and integrates phenology with rainfall and humidity inputs. Adoption of PLASMO in vineyard DSSs has led to significant chemical savings without compromising disease control (Table 2).

Incorporation of AI and machine learning techniques is now emerging as a powerful direction. For instance, Proteus, a beta regression model developed in India, uses microclimate data to predict late blight risk with high spatial specificity. Meanwhile, mobile-based platforms are experimenting with neural networks and decision trees for pest management in chickpea, rice and maize across Africa and South Asia.

These diverse applications clearly demonstrate that forewarning models are not only scientifically robust but also socio-technically adaptable. They reinforce the importance of localization, farmer engagement and institutional support in driving widespread adoption. As these tools evolve through integration with mobile technologies, geospatial analytics, and participatory interfaces, they are set to become central to the future of climate-smart, sustainable crop protection.

Table 2.2. Key Forewarning Models for Plant Disease Prediction

Model Name	Target Disease & Crop	Country/ Region of Origin	Model Type	Key Features / Parameters	Reference
Dutch Rules (1926)	Late Blight of Potato (*Phytophthora infestans*)	Netherlands	Empirical	Minimum temp >10°C, dew, rain, cloudiness	Van Everdingen (1926)
Beaumont Period (1947)	Late Blight of Potato	UK	Rule-based	Two days with RH >75% and min temp >10°C	Beaumont (1947)
Smith Period (1956)	Late Blight of Potato	UK	Rule-based	RH ≥90% for 11 hrs/day for 2 days; temp ≥10°C	Smith (1956)
BLITECAST	Late Blight of Potato	USA	Simulation/Empirical	Uses RH, temp, rainfall to issue spray warnings	Wallin (1962), Hyre (1954)
FAST	Early Blight of Tomato (*Alternaria solani*)	USA	Simulation	Combines dew and rain sub-models; calculates severity indices	Madden et al. (1978)
TOM-CAST	Early Blight of Tomato	USA	Simplified simulation	Modified FAST model; uses dew-based DSV (Disease Severity Values)	Pitblado & Gossen (1992)
PLASMO	Downy Mildew of Grapes (*Plasmopara viticola*)	Italy	Mechanistic simulation	Simulates grape phenology + mildew infection stages	Rosa et al. (1995)
NEGFRY	Late Blight of Potato	Denmark	Hybrid	Integrates BLITECAST + negative prognosis; includes cultivar & irrigation	Hansen et al. (1995)
EPIBLAST	Rice Blast (*Pyricularia oryzae*)	India/Asia	Simulation	Uses temperature, RH, rainfall, wetness hours	Kim and Yoshino, (1995)
JHULSACAST	Late Blight of Potato	India	Empirical + Rule-based	Hill-specific model using rainfall, temperature, RH	Singh et al. (2000)
AI-Based Systems	Rice Blast, Grape Mildew, Tomato Mosaic	Global	AI/ML	Uses neural networks, decision trees, and satellite input	Mahlein (2016)

Sustainable Crop Protection Integration

Forewarning models play a transformative role in sustainable crop protection by enabling decision-making that is both environmentally responsible and economically efficient. These models form a critical pillar of Integrated Pest Management (IPM), allowing stakeholders to intervene only when disease thresholds are met, thereby minimizing unnecessary pesticide applications. Moreover, by linking real-time forecasts with automated advisory systems (e.g., SMS, mobile apps), farmers are empowered with timely, location-specific alerts that support better planning. The models also enable seed companies and policymakers to allocate resistant varieties, adjust planting schedules *and* manage supply chains more proactively. Singh *et al*. (2016) argue that weather-based forewarning tools facilitate more rational spray schedules, helping in resistance management and reducing the cost burden on smallholders. Furthermore, these systems contribute to climate-smart agriculture by reducing greenhouse gas emissions associated with pesticide production and application. As more models incorporate economic injury levels and environmental externalities, they can serve as regulatory benchmarks for policy formulation, promoting agroecological sustainability and global food security.

Role of Epidemiological Modelling

Epidemiological models are foundational to disease forewarning systems, as they formalize the mechanisms by which pathogens infect and spread across host populations. These models are commonly categorized as simple threshold-based models**,** spore dispersal simulations and SEIR-type compartmental models susceptible, exposed, infectious *and* removed borrowed from human epidemiology. Such frameworks allow researchers to simulate infection rates under various conditions, thereby enabling what-if scenario testing. A key feature is the ability to include incubation periods, latency and secondary infection dynamics. For instance, in modelling *Puccinia s*pp. in wheat, researchers have demonstrated how latent and infectious periods shift with temperature, enabling precise forecasting windows. These models are also evolving to integrate pathogen mutation rates and spatial heterogeneity**,** which are critical under global warming scenarios. Bhati *et al*. (2021) and Sigvald (2012) emphasized the importance of linking these epidemiological dynamics with sensor feedback for real-time adaptation of forecasts, creating a living system responsive to both biological and environmental cues.

Remote Sensing and GIS in Disease Surveillance

Remote sensing and Geographic Information Systems (GIS) offer transformative tools for spatial disease monitoring and prediction. These technologies enable the detection of early stress signals in crops over large geographic areas using multispectral or hyperspectral satellite and drone imagery. For instance, reflectance anomalies in the red-edge band are often early indicators of foliar infections. GIS platforms layer this spatial data with weather variables and topographic features to create disease risk maps, which inform both macro (policy) and micro (field-level) interventions. These tools are particularly effective in detecting outbreaks of fast-spreading airborne pathogens like rusts or late blight. Ghosh &

Kumpatla (2022) demonstrated the utility of NDVI-based indices and thermal maps in forecasting rice sheath blight and wheat stripe rust. The spatial outputs are increasingly being integrated with GPS-guided farm machinery and irrigation systems for site-specific management. The convergence of satellite, UAV *and* field sensor data in GIS environments enables a 4D (space-time) view of pathogen dynamics that is essential for pre-emptive action.

Machine Learning and Artificial Intelligence Applications

AI and machine learning are revolutionizing the landscape of plant disease forewarning through automated pattern recognition, feature selection *and* real-time adaptive learning. Supervised models like random forests, support vector machines (SVM) and gradient boosting machines (GBM) are widely used for classifying infected vs. healthy plant tissue using structured data. Meanwhile, deep learning models - particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs) excel at processing unstructured data such as leaf images, video *and* sensor streams. Lata & Saini (2022) and Madasamy *et al*. (2020) applied CNNs with MobileNet architectures to achieve over 90% accuracy in classifying diseases in cotton and tomato crops. Ensemble methods further improve robustness by aggregating multiple model predictions. Emerging areas include transfer learning, graph neural networks and explainable AI (XAI), which allow for model reuse across crops and transparency in decision-making. These AI-enhanced systems are now embedded in cloud-based dashboards and farmer-facing mobile applications for scalable deployment.

Integration with Decision Support Systems (DSS)

The utility of any forewarning model ultimately depends on its effective translation into actionable guidance for farmers, policymakers and supply chain actors. This is where Decision Support Systems (DSS) play a vital role. DSS platforms integrate predictive models with user interfaces, visualization tools and alert systems to recommend optimal actions such as fungicide application, crop rotation or resistant variety selection. Advanced DSS are modular and cloud-based, enabling real-time updates and user customization. For instance, the e-Agromet DSS in India integrates disease models with agro-advisory services across 150 districts. DSS may also include economic components such as cost-benefit analyses, suggesting whether the disease risk justifies intervention. The best systems are bidirectional, allowing farmers to feedback disease observations, which further refine model predictions. Dutta *et al*. (2020) emphasize that open-source, multilingual DSS platforms are key to ensuring equitable access and usability across socio-economic strata.

Participatory Epidemiology and Farmer Integration

Forewarning models are most effective when co-developed and validated with the end user's farmers, extension workers *and* local agro-ecological experts. Participatory approaches in epidemiology, sometimes called "citizen phytopathology," involve structured data collection by farmers via mobile apps, disease diaries or farmer field schools. These community-generated datasets provide invaluable ground-truth data for model calibration and validation. Moreover, participatory modeling workshops allow stakeholders to define local thresholds, action plans and socio-cultural factors affecting model adoption. Singh *et al*. (2016) documented improved adoption and model accuracy when farmers were involved in the deployment of weather-based pest forewarning systems. Integrating indigenous knowledge systems (IKS), particularly in marginal farming regions, enhances model interpretability and acceptance. Dube *et al*. (2024) advocate for combining scientific and traditional indicators for climate-linked disease outbreaks to improve early warning efficacy and trust.

Technological Infrastructure: IoT, Sensors and Drones

Modern forewarning systems increasingly rely on a technological triad: in-field sensors, Internet of Things (IoT) communication and aerial imagery. IoT-based systems connect distributed sensors that continuously monitor parameters like leaf wetness, canopy temperature *and* soil moisture. These data streams are fed into cloud-based platforms via wireless protocols (e.g., LoRa, ZigBee), enabling remote diagnostics and alerts. Drones complement this network by capturing high-resolution aerial data that can detect disease patches missed by ground sensors. Dasari *et al*. (2024) highlight how LoRa-based sensor stations integrated with weather models can provide 48-hour advance alerts for paddy blast. Additionally, edge computing devices installed on farms allow for preliminary data processing on-site, reducing reliance on continuous internet connectivity. Together, these technologies enable precision forewarning with unprecedented temporal and spatial granularity.

Ethics, Privacy and Open Access in Data-Driven Systems

As forewarning models become increasingly data-driven, ethical considerations around data ownership, privacy *and* access become paramount. Smallholder farmers often lack control over the data collected from their fields, raising concerns about exploitation or surveillance. Furthermore, proprietary models developed by private firms may restrict access or demand subscription fees, limiting their benefits to resource-poor farmers. Open-source models and community-curated databases (e.g., Plant Village, Open Weather Map) offer a more democratic alternative. Transparent data policies, participatory consent protocols *and* data anonymization techniques are essential to foster trust and ensure equitable benefits. Chergui & Kechadi (2022) emphasize that the future of agricultural AI must be rooted in “data justice” ensuring that vulnerable stakeholders derive value from the data ecosystems they help create.

Climate Change and Resilience Modelling

Climate change introduces non-stationarity into disease dynamics, disrupting historical patterns and rendering traditional models obsolete. Rising temperatures, erratic rainfall *and* increased frequency of extreme events create conducive conditions for disease emergence, host susceptibility shifts and geographic range expansions. Forewarning systems must evolve to incorporate climate adaptation modules that use downscaled GCM data to simulate future disease risk zones. For example, rust diseases in wheat and coffee are predicted to move to higher altitudes under warming scenarios. Tripathy *et al*. (2012) and Sigvald (2012) argue for ensemble modelling approaches that combine historical data, real-time weather and climate forecasts for robust prediction. Models must also account for co-infection dynamics, where multiple pathogens exploit stressed crops, requiring multi-pathogen forecasting capacity.

Challenges and Future Directions

Despite their promise, forewarning models face significant barriers that must be overcome to realize their full potential. Data scarcity and poor infrastructure in developing regions limit the accuracy and granularity of predictions. Many models lack interoperability or transferability across different crops, regions, or socio-economic contexts. Farmers' trust remains a key barrier, especially where digital literacy is low or advisory systems are not localized. Additionally, the complexity of multi-pathogen ecosystems, coupled with evolving climatic patterns, presents difficulties in capturing non-linear disease dynamics. Sigvald (2012) and Chakraborty & Chandran (2022) have pointed out that most models are insufficiently robust to incorporate long-term climate change projections or pathogen evolution. Looking ahead, future research should focus on climate-resilient modelling, explainable AI to enhance transparency and the integration of pathogen genomics for real-time threat analysis. The use of blockchain technology for traceability and trust, as well as UAV-based imagery for ultra-high-resolution monitoring, are other frontiers. Building global disease forecasting networks with participatory citizen science models will be vital for long-term resilience and adaptive management in agriculture.

Conclusion

The development of forewarning models for plant diseases, when anchored in systems-based thinking, offers a scientific, scalable and sustainable strategy for modern crop protection. These models not only enhance productivity by enabling pre-emptive interventions but also align with global goals of climate resilience, agroecological sustainability and equitable technology access. Going forward, integration of genomics, AI ethics and climate-aware modelling will define the next generation of disease forecasting platforms. The convergence of participatory science, edge computing and global disease intelligence networks could usher in a new era of anticipatory agriculture capable of mitigating risks and adapting dynamically to ecological and socio-economic shifts.

Disclosure Statement

The authors reported no potential conflict of interest.

References

1. Beaumont, A. (1947). The dependence on the weather of the dates of outbreak of potato blight epidemics. *Transactions of the British Mycological Society*, *31*(1-2), 45–53. https://doi.org/10.1016/S0007-1536(47)80007-9

2. Bhati, H. P., Charaya, M. U., & Upadhyay, A. (2021). Plant disease forecasting: Past practices to emerging technologies. In S. Nehra (Ed.), *Plant disease: Management strategies* (pp. 1–30).
3. Chergui, N., & Kechadi, M. T. (2022). Data analytics for crop management: A big data view. *Journal of Big Data*, *9*(1), 1–20. https://doi.org/10.1186/s40537-022-00668-2
4. Dasari, S., Sowmya, N., & Gowrisankar, R. (2024). Weather based forewarning systems for important pests and diseases in major crops. *International Journal of Plant & Soil Science*, *36*(10), 545–557. https://doi.org/10.9734/ijpss/2024/v36i105062
5. Dube, T., Huhn, A. L., Nobre, G. G., & Moyo, E. N. (2024). Incorporating indigenous knowledge systems-based climate services in anticipatory action in Zimbabwe: An ex-ante assessment. *Frontiers in Climate*, *6*, Article 1301908. https://doi.org/10.3389/fclim.2024.1301908
6. Ghosh, P., & Kumpatla, S. P. (2022). GIS applications in agriculture. In *Geographic information systems and applications in environmental planning* (pp. 231–254). IntechOpen. https://doi.org/10.5772/intechopen.104786
7. Hansen, J. G., Andersson, B., & Hermansen, A. (1995). NEGFRY—A system for scheduling chemical control of late blight in potatoes. In *Proceedings of the workshop on potato late blight* (pp. 201–208). Boole Press Ltd.
8. Hyre, R. A. (1954). Progress in forecasting late blight of potato and tomato. *Plant Disease Reporter*, *38*, 245–253.
9. Kim, C. K., & Yoshina, R. (1995). Epidemiological studies of rice blast disease caused by *Pyricularia oryzae* Cavara VI: Measurement of sporulation on blast lesions of naturally infected leaf. *Japanese Journal of Phytopathology*, *61*(2), 89–92.
10. Lata, K., & Saini, S. (2022). A review of deep learning approaches for plant disease detection and classification. In *Artificial intelligence and smart agriculture technology* (pp. 209–222). CRC Press. https://doi.org/10.1201/9781003299059-12
11. Madasamy, B., Balasubramaniam, P., & Dutta, R. (2020). Microclimate-based pest and disease management through a forewarning system for sustainable cotton production. *Agriculture*, *10*(12), Article 641. https://doi.org/10.3390/agriculture 10120641
12. Madden, L. V., Pennypacker, S. P., & MacNab, A. A. (1978). FAST, a forecast system for tomato early blight. *Plant Disease Reporter*, *62*, 576–581.
13. Mahlein, A. K. (2016). Plant disease detection by imaging sensors—Parallels and specific demands for precision agriculture and plant phenotyping. *Plant Disease*, *100*(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE
14. McDonald, B. A., & Stukenbrock, E. H. (2016). Rapid emergence of pathogens in agro-ecosystems: Global threats to agricultural sustainability and food security. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *371*(1709), Article 20160026. https://doi.org/10.1098/rstb.2016.0026
15. Pitblado, R. E., & Gossen, B. D. (1992). Development of TOM-CAST, a disease forecaster for tomatoes. *Canadian Journal of Plant Pathology*, *14*(4), 295–295.

16. Rosa, M., Gozzini, B., Orlandini, S., & Seghi, L. (1995). A computer program to improve the control of grapevine downy mildew. *Computers and Electronics in Agriculture*, *12*(4), 311–322. https://doi.org/10.1016/0168-1699(95)00007-Q
17. 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
18. Singh, B. P., Ahmad, I., Sharma, V. C., & Shekhawat, G. S. (2000). JHULSACAST: A computerized forecast of potato late blight in western Uttar Pradesh. *Journal of the Indian Potato Association*, *27*(1-2), 1–7.
19. Singh, J., Das, D. K., Vennila, S., & Rawat, K. S. (2018). Weather based forewarning of pest and disease: An important adaptation strategies under the impact of climate change scenario: A brief review. *International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR)*, *1*(10), 6–21. https://doi.org/10.31426/ijamsr.2018.1.10.1012
20. Singh, P., Shahi, B., Singh, K. M., & Kendra, K. V. (2015, October). *Sustainable strategies for climate-smart insect-pest management by extension systems* [Paper presentation]. ISEE Golden Jubilee National Seminar on Strategy To Drive Skill-Based Agriculture Development For Sustainability And Rural Employability, Gwalior, India.
21. Smith, L. P. (1956). Potato blight forecasting by 90 per cent humidity criteria. *Plant Pathology*, *5*(3), 83–87. https://doi.org/10.1111/j.1365-3059.1956.tb00825.x
22. Tripathy, A. K., Adinarayana, J., & Merchant, S. N. (2012). Data mining and wireless sensor network for groundnut pest thrips dynamics and predictions. *Journal of Emerging Trends in Computing and Information Sciences*, *3*(4), 438–445.
23. Van Everdingen, E. (1926). The relation between weather conditions and potato blight (*Phytophthora infestans*). *Tijdschrift over Plantenziekten*, *32*(5), 129–140.
24. Wallin, J. R. (1962). Summary of recent progress in predicting late blight epidemics in United States and Canada. *American Potato Journal*, *39*(8), 306–312.