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Plant Disease Forecasting: A Comprehensive Review

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ABSTRACT

Plant diseases are increasingly becoming a significant constraint on crop production, with their incidence rising each year worldwide. Consequently, managing crop diseases has grown more challenging. In response, the use of fungicides has escalated in recent years. Forecasting has emerged as an essential preventive tool for managing epidemic diseases. By employing forecasting techniques, fungicides can be applied precisely and at optimal times, effectively limiting disease spread. Climate change is a major contributor to these epidemics, as temperature fluctuations can exacerbate the spread of pests and diseases. This has resulted in severe economic losses, including famine, and has weakened the economies of numerous nations. Most forecasting efforts have concentrated on airborne diseases, which pose a substantial threat to food security. Crop diseases can lead to significant yield losses, degrade produce quality, and, in severe cases, cause total crop failure. These effects directly impact the availability and affordability of food, posing challenges for both producers and consumers. To mitigate these challenges, plant disease forecasting plays a pivotal role in disease management. Its primary goal is to provide timely and accurate predictions of disease outbreaks, enabling farmers to take proactive measures to protect their crops and minimize losses.

Introduction

Plant pathogens responsible for major crop diseases significantly reduce yields, productivity, and food security, ultimately impacting a country's GDP and the overall health of its agricultural systems. Early detection and effective treatment of these diseases are critical to minimizing losses and supporting sustainable agricultural practices (Ristaino et al., 2021). According to the Food and Agriculture Organization (FAO), plant diseases and pests account for 20–40% of global losses in agricultural productivity and food security. Prompt disease control is therefore essential to reducing these losses on a global scale (Pierce and Nowak, 1999). Advancements in early warning systems and predictive analytics have revolutionized plant disease forecasting. Modern systems now integrate diverse data sources, including weather and environmental conditions, to deliver accurate and timely forecasts of potential disease outbreaks. These advancements have significantly enhanced disease control strategies, enabling farmers to make informed decisions and take preventive measures more effectively (Hasanaliyeva et al., 2022).

This article explores the environmental data, forecasting models, and practical applications of plant disease forecasting systems. It also

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examines the causes of epidemics and the use of prophylactic sprays for managing various diseases. The Plant Disease Forecasting System operates similarly to weather forecasting but is specifically designed to predict plant disease outbreaks. This innovative tool estimates the likelihood and location of disease occurrences, assisting farmers and growers in implementing preventative measures to minimize damage and protect crops. Plant diseases pose a substantial threat to agricultural productivity, often resulting in reduced yields, financial losses, and compromised food security. Effective disease management is therefore essential to maintaining healthy crops and ensuring sustainable food production. By adopting preventive strategies, farmers can better safeguard their crops against the adverse effects of plant diseases (Chattopadhyay et al., 2011).

Plant disease forecasting is a critical management tool designed to predict the emergence and severity of plant diseases. By leveraging historical and anticipated weather data specific to a region, these systems provide farmers with early warnings, enabling timely adjustments to crop protection strategies (Bhupathi and Sevugan, 2021). Accurate and timely predictions can significantly reduce financial costs, minimize productivity losses, and mitigate environmental impacts. Although severe infections are rare, favorable climatic conditions can trigger devastating crop losses. Forecasting systems play a vital role in anticipating and managing such outbreaks (Rehman et al., 2016).

Plant disease forecasting is a component of applied epidemiology, used to detect early signs of disease in specific areas. It provides data to implement timely remedial measures and prevent losses. Forecasting considers various predictive factors, including weather conditions, relative humidity, leaf wetness, dew, weather during the intercrop period and crop season, disease presence in young crops, and inoculum levels in the air, soil, or planting material (Shakya et al., 2015). This strategy is especially important in controlling plant diseases when genetic resistance is unavailable. Forecasting systems reduce economic losses, prevent epidemics, and support effective prophylactic measures by using weather data to identify disease risks and implement early control steps. This proactive approach enhances disease management, promotes crop health and yield, and encourages environmentally responsible agricultural practices (Juroszek and Von Tiedemann, 2011).

Short-range forecasting allows for the anticipation of devastating diseases, helping farmers avoid costly plant protection operations. Prophylactic spraying, for instance, can effectively reduce seed-borne diseases like sorghum smut. Advanced long-term forecasting enables farmers to select resistant crop varieties over susceptible ones (Kim et al., 2017). Plant diseases are significant contributors to famines and epidemics. While many fungicides have been developed, some diseases remain challenging to manage. These challenges are exacerbated by the evolution of virulent pathogen strains and fungicide resistance, which can lead to recurring infections even after chemical treatments (Luck et al., 2011). Diseases also reoccur in various genotypic forms, and pathogen aggressiveness combined with ineffective control measures results in substantial yield losses.

Effective management strategies include forecasting, cultural practices, biological control, varietal resistance, and chemical methods. Among these, forecasting stands out as the most effective approach for managing plant diseases. It provides immediate and accurate insights into disease risks and favorable conditions, enabling farmers to take proactive measures to protect their crops (Richard et al., 2022). The primary sources of plant disease infections include soil, seeds, and infected plant debris. Consequently, cultural practices such as flooding, fallowing, and crop rotation are effective strategies for managing soil-borne diseases like fusarium wilt and root rot, as they reduce the inoculum load in the soil. Among the various management approaches, host resistance remains the most effective. Although a range of fungicides—contact, systemic, and translaminar—has been tested on plants, pathogens continue to demonstrate remarkable adaptability to changes in both host genotypes and fungicide formulations (Hwang et al., 2008). In contrast, biological management is gaining importance due to its environmentally friendly nature.

Forecasting plays a pivotal role in preventing or mitigating epidemics, with numerous disease forecasting models developed worldwide to protect crops (Lahlali et al., 2022). These systems aim to control diseases by predicting their intensity or likelihood of outbreak (Agrios, 2005). A key objective of forecasting systems is to minimize the reliance on chemical interventions by providing timely and accurate predictions that allow proactive measures to be taken in an environmentally safe manner. Various modeling techniques are utilized to predict plant diseases (Taylor et al., 2003). Many forecasting models incorporate image processing and meteorological data, with a significant focus on potato late blight disease. These models analyze data from crops, pathogens, and weather—or a combination of the three—to predict disease emergence and changes in severity.

At the core of plant disease forecasting lies the "disease triangle," which illustrates the interaction between the environment, host, and pathogen. Understanding these factors is essential for accurately and efficiently predicting disease outbreaks (Francl, 2001). Forecasting systems consider a range of variables, including weather patterns, crop health, and environmental conditions, to assess the likelihood and potential severity of disease epidemics. By analyzing these indicators, scientists can provide precise predictions about disease risks, enabling farmers to take timely preventive measures. Armed with this information, farmers can stay ahead of potential outbreaks, protecting their crops and reducing losses (Grünwald et al., 2000).

Plant disease forecasting system: early detection, data collection, and analysis techniques for disease prediction

Early detection and predictive analysis empower farmers to implement preventive measures in advance, reducing reliance on reactive solutions and increasing the likelihood of successful crop protection. By forecasting disease onset, farmers can take timely actions such as applying fungicides or adjusting irrigation practices to mitigate potential crop damage. Integrating predictive analysis with sustainable farming techniques enables disease management while preserving soil health and biodiversity (Javaid et al., 2022).

Effective disease forecasting begins with comprehensive data collection, which includes monitoring weather patterns, crop health, and disease prevalence. Data acquisition methods range from on-site field observations to advanced technologies like automated sensors and satellite imaging, ensuring accuracy and thoroughness (Javaid et al., 2022). At the core of any plant disease forecasting system lies an extensive disease database. This database stores critical information on disease patterns, symptoms, and potential epidemics. When integrated with management systems, it provides farmers with timely, actionable insights for disease prevention and control (Popkova et al., 2022). Technologies such as drones and remote sensors play a pivotal role in disease surveillance. These tools collect real-time data on crop health and disease prevalence, offering farmers immediate updates and practical recommendations for disease management. Such innovations help prevent severe yield losses and enhance decision-making (Raj et al., 2021).

The interpretation of collected data relies on advanced modeling and analytical methods. These approaches use numerical analysis and scientific algorithms to identify patterns, correlations, and risk factors associated with disease outbreaks. This analysis enables farmers to make data-driven decisions and implement targeted interventions (Buja et al., 2021). Weather is a critical factor in disease development. Monitoring weather data—such as temperature, humidity, and rainfall—facilitates the creation of predictive models that assess the likelihood of disease outbreaks under favorable conditions (Sparks et al., 2014).

In addition to weather data, monitoring crop health and phenotypic characteristics provides valuable insights into disease susceptibility. Observing indicators such as leaf color, growth patterns, and stress levels enables early detection of disease, allowing farmers to take timely preventive measures (Zheng et al., 2023). Remote sensing and satellite imaging have revolutionized agricultural monitoring, enabling farmers to oversee vast areas from above. These technologies capture images at multiple wavelengths, detecting subtle changes in crop health and identifying potential disease hotspots with precision (Mandal et al., 2022).

Machine learning and artificial intelligence (AI) have elevated data analysis to unprecedented levels. By training algorithms on large datasets of historical information, these technologies can identify patterns and generate accurate forecasts of disease outbreaks. Such forecasting models empower farmers to implement timely interventions and protect their crops from various diseases (Chemura et al., 2017). Weather plays a crucial role in the development and spread of plant diseases. Specific weather patterns create favorable conditions for certain diseases, such as fungal infections that thrive in cold, moist environments or hot, humid climates. By analyzing the relationship between weather conditions and disease dynamics, plant disease forecasting systems provide farmers with essential insights to take proactive measures (Mandal et al., 2022).

In addition to weather, other environmental factors significantly influence disease transmission. Soil moisture, air humidity, and the presence of pathogens in the surrounding environment contribute to the spread of plant diseases. Agricultural practices like crop rotation and ensuring proper air circulation can mitigate these risks. Incorporating such environmental factors into forecasting models enhances their accuracy and applicability, helping farmers better predict and manage outbreaks (Raji et al., 2015). Climate data and models are vital components of precise plant disease forecasting systems. Using a combination of climate models, satellite imagery, and historical weather data, scientists can identify patterns and trends in disease emergence. This analysis enables the creation of predictive models that estimate outbreaks based on current and future weather conditions. These tools provide farmers with actionable insights, allowing them to make informed decisions for effective disease management (Coakley, 1988).

Information needed for disease forecasting

A solid understanding of epidemiology is essential for precise plant disease forecasting. Accurate predictions require detailed knowledge of several factors, including the prevalence of susceptible cultivars in the region, the host's response to pathogen activity at different growth stages, and the distribution and abundance of the host in specific locations. Additional critical elements include the quantity of primary (initial) inoculum present in the soil, air, or planting material, as well as the spread of inoculum, infection processes, spore germination rates, incubation periods, and sporulation on infected hosts. The re-dispersal or dissemination of spores, inoculum potential, density, and survival stages in seeds, soil, and air are also vital considerations (Francl, 2001). Environmental factors such as temperature, humidity, light intensity, and wind velocity significantly influence disease development. These variables interact within the framework of the "disease triangle," which represents the relationship between the host, pathogen, and environmental conditions. By studying this interaction, forecasting models can be developed to minimize yield losses caused by various diseases. For example, a forecasting model for potato late blight might incorporate favorable conditions such as specific temperature ranges and wind speeds to predict disease outbreaks and guide preventive measures (Fig. 1).

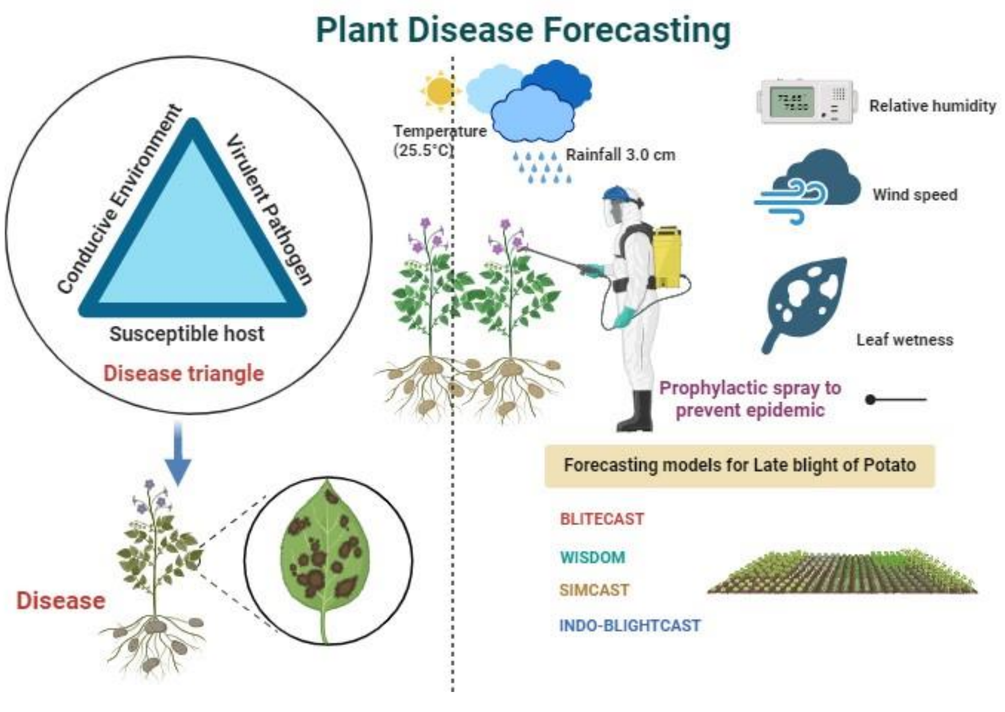

Fig. 1. A forecasting model for late blight of potato based on specific temperature, relative humidity, and leaf wetness suitable for disease development.

Forecasting models for different plant diseases

Forecasting models have been developed for a wide range of plant diseases, with significant emphasis on managing and preventing the spread of early and late blight in potatoes. Over the years, numerous models have been created to address key diseases, as summarized in Table 1. Among these is the computer simulation program EPIDEM, introduced in 1969. EPIDEM simulates each stage of a pathogen's life cycle in relation to environmental conditions. Its primary goal is to prevent early blight epidemics in potatoes and tomatoes caused by *Alternaria solani*.

Table 1. Information on forecasting and simulation models developed for major plant diseases, including late blight of potato, early blight of tomato and potato, fire blight of apple, and rice blast, highlights the contributions of various scientists in creating tools for effective disease prediction and management.

S. No	Forecasting models	Used against	Reference
1.	BLITECAST	Late blight of potato (*Phytophthora infestans*)	Krause et al. (1975)
2.	EPIPHTORA		Gurevich (1979)
3.	SIMPHYT		Stephan and Gutsche (1980)
4.	Phytoprog		Gujer (1991)
5.	WISDOM		Stevenson (1993)
6.	PhytoPRE		Forrer et al. (1993)
7.	PHYTEB		Gutsche (1993).
8.	JHULSACAST		Singh et al. (2000)
9.	SIMCAST		Grunwald et al. (2002)
10.	EGY-BLIGHTCAST		Afifi et al. (2009)
11.	BLIGHT Pro		Small et al. (2015)
12.	INDO-BLIGHTCAST		Singh et al. (2016)
13.	BLIGHTSIM		Narouei-Khandan et al. (2020)
14.	EPIDEM	Early blight (*Alternaria solani*) on tomato and potato	Waggoner and Horsfall (1969)
15.	FAST	Early blight (*Alternaria solani*) on tomato	Madden et al. (1978)
16.	PLANT-Plus	Early blight (*Alternaria solani*) in potato	Raatjes et al. (2004)
17.	TOMCAST	*Alternaria,* (Septoria, anthracnose) in tomato	Cowgill et al. (2005)
18.	EPIMAY	Southern corn (*Bipolaris maydis*) leaf blight	Stirm et al. (1971)
19.	EPICORN		Massie (1973)
20.	EPIPRE	Yellow rust (*Puccinia striformis*) in winter wheat	Reinink (1986)
21.	BARSIM-I	Leaf rust (*Puccinia triticina*) of Barley	Teng (1980)
22.	EPIGRAM	Powdery mildew (*Blumeria graminis* f.sp. *hordei*) of barley	Aust et al. (1983)
23.	PLAM	Leaf spot (*Cercosporidium personatum*) of Groundnut	Olatinwo et al. (2012)
24.	CERCOS	*Cercospora* blight of celery	Berger (1973)
25.	MYCOS	*Mycosphaerella* blight of chrysanthemum	McCoy (1976)
26.	MARYBLYT	Fire blight (*Erwinia amylovora*) on apples and pear	Lightner and Steiner (1992)
27.	EPIVEN	Apple scab (*Venturia inaequalis*) on apples	Kranz (1979)
28.	A- Scab		Rossi et al. (2007)
29.	MELCAST	Watermelons (Anthracnose, gummy stem blight), Muskmelons (*Alternaria*)	Keinath et al. (2007)
30.	BLASTCAST	Rice blast (*Pyricularia oryzae*)	Ohta et al. (1982)
31.	BLASTAM		Hayashi (1988)
32.	BLASTL		Ishiguro and Hashimoto (1991)
33.	BLASTSIM. 2-a	Rice blast (*Pyricularia oryzae*) for tropical rice	Calvero and Teng (1991)
34.	EPIBLAST	Rice blast (*Pyricularia oryzae*)	Kim and Kim (1993)
35.	BLASTMUL		Ashizawa et al. (2005)

Late blight of potato

Potatoes (*Solanum tuberosum* L.) are globally recognized as the most important tuber crop. However, their production is severely threatened by *Phytophthora infestans*, an oomycete pathogen that causes significant damage to potato plants. This fungus can lead to severe infections, resulting in foliage loss and tuber rotting, which cause substantial yield losses. The devastating impact of *Phytophthora infestans* was tragically illustrated during the Irish famine of 1845, when an outbreak of late blight triggered a catastrophic epidemic, leading to widespread food shortages and loss of life.

To combat this persistent threat, researchers have developed various forecasting models aimed at predicting and preventing similar epidemic diseases in potato crops. These models consider environmental factors such as nighttime temperature, humidity, leaf wetness, and dew to provide early warnings and guidance for farmers. Disease outbreaks are most likely to occur in environments with temperatures ranging from 10 to 22°C, humidity levels above 75%, and gloomy or foggy weather conditions. The late blight pathogen is closely associated with these conditions and is influenced by factors such as relative humidity, light intensity, fog, rainfall, dew, and wind speed (Bhattacharyya et al., 1983). It is estimated that seven to fourteen d of favorable conditions typically precede the onset of potato late blight, characterized by a five-d average temperature of 25.5°C and cumulative rainfall exceeding 3.0 cm over the preceding ten d.

Farmers can now leverage advanced computerized models, such as Phytoprog, Indo-BlightCast, and LightCAST, to receive early warnings of late blight outbreaks across different regions. For example, Syngenta operates the Blightcast system in the UK, while the Indian Meteorological Department collaborates with the Central Potato Research Institute (CPRI) in Shimla and the All India Coordinated Research Project (AICRP) in New Delhi to develop the Indo-BlightCast model. In West Germany, forecasting relies on the Phytoprog model (Singh et al., 2016).

A noteworthy advancement is the INDO-BLIGHTCAST late blight forecasting model, developed by CPRI in Shimla, India. This model uses meteorological data and historical records of late blight outbreaks across four distinct regions in the Indo-Gangetic plains to predict disease occurrence accurately. It calculates the mean overnight relative humidity (RH) and physiological d (P-d) accrued over a seven-d period. Late blight is forecasted to appear within 15 d if the cumulative effective temperature (P-d) and RH exceed 52.5 and 525, respectively, for seven consecutive d (Singh et al., 2016).

In Egypt, Afifi et al. (2009) developed EGY-BLIGHTCAST, the first computer model tailored to address late blight disease in the country's potato-growing regions. These regions are particularly susceptible to *P. infestans* due to their cool and humid climates. EGY-BLIGHTCAST relies on data from automated agro-weather stations to evaluate the daily infection potential of late blight, analyzing the 24-h microclimate. The model integrates and refines prediction techniques based on observations from multiple growing seasons, providing a more accurate and cost-effective solution for managing the disease. This targeted approach reduces the need for fungicide applications compared to traditional spray schedules, minimizing environmental and health impacts while maintaining effective disease control.

Similarly, earlier advancements in predictive modeling include BLITECAST, an automated forecasting algorithm developed by Krause et al. (1975) and Krause and Massie (1975) at Pennsylvania State University. This model combined Wallin's (1962) severity ratings and Hyre's (1947) concept of blight-favorable d, enabling growers to receive tailored advice based on meteorological data from their fields. By integrating these forecasting techniques, BLITECAST has significantly advanced the field of plant pathology, offering growers actionable recommendations to manage late blight effectively.

PHYTEB is a forecasting model for *Phytophthora infestans* that predicts the symptomatic stages of hosts, including the latent period, pre-infection stage, number of infections, and the amount of dead tissue. This model comprises two sub-models, SIMPHYT-1 and SIMPHYT-2. SIMPHYT-1 is capable of predicting the start of an outbreak seven to ten d in advance. Conversely, SIMPHYT-2 accelerates the spread of the epidemic by incorporating two cultivar classes and various fungicide application techniques. According to Gutsche (1993), PHYTEB is a valuable tool for anticipating and managing outbreaks of *P. infestans* in crops.

The late blight forecasting model, known as SIMPHYT, is a sophisticated tool designed to predict the first appearance date of *P. infestans*. SIMPHYT-1 utilizes a risk rating and crop emergence date to provide these forecasts. Additionally, SIMPHYT-2 is an intricate expert system that predicts *P. infestans* epidemics on a plot-specific basis. This system offers recommendations based on various factors, including weather conditions, crop data, and fungicide properties. Another component of the system, SIMPHYT-3, functions as an infection pressure model and determines the optimal interval for fungicide spraying in a given area. These models have undergone years of validation, demonstrating their effectiveness in reducing fungicide loads on potato crops. As a result of their success, the SIMPHYT models have been integrated into warning systems across Germany, Austria, and Luxembourg (Erich et al., 2003).

A comprehensive review of 15 years of weather data (1997–2012) was conducted in the province. Arora et al. (2012) developed JHULSACAST, a model to predict late blight in western Uttar Pradesh, providing valuable insights for anticipating late blight development in Punjab. The model indicated that if specific temperature and relative humidity conditions persisted for a given duration, late blight would manifest ten d later. The updated model demonstrated a high level of accuracy in predicting the onset of late blight under Punjabi conditions.

Forrer et al. (1993) developed PhytoPRE, a sophisticated computer-based information and decision support system to manage potato late blight in Switzerland. PhytoPRE includes an epidemiological forecast model, a set of decision rules, and an information system. PHYTEB, a component of this system, accurately predicts the presence of *P. infestans* and effectively controls the symptomatic stages of hosts, including the latent period, pre-infection, number of infections, and the amount of dead tissue. PHYTEB consists of two sub-models, SIMPHYT-1 and SIMPHYT-2. SIMPHYT-1 predicts that the outbreak of potato late blight will occur seven to ten d earlier than previously anticipated. On the other hand, SIMPHYT-2, as described by Gutsche (1993), accelerates the spread of epidemics across two cultivar classes and integrates various fungicide application strategies.

The Netherlands has also developed a tool called PROPHY to assist farmers in making informed decisions about their crops. PROPHY recommends applying a fungicide ten d after the potato crop reaches a height of 15 cm, particularly when cultivating more resistant varieties. To determine the timing of additional treatments, PROPHY considers both weather conditions and the level of fungicide protection already present in the crops. Ideal conditions for the growth of *P. infestans*, a harmful pathogen, include a d with at least six h of relative humidity and at least two h of rain or leaf wetness between 8:00 PM the previous d and 12:00 AM on the evaluation d. According to Schepers (1995), the temperature range required for optimal growth of *P. infestans* is between 8 and 25°C.

Accurate data on temperature, relative humidity, soil moisture content, crop prevalence, and cultivar vulnerability are crucial for the effective operation of the SIMBLIGHT 1 model (Kleinhenz et al., 2007). This model calculates a cumulative risk score for different emergence date groups and alerts authorities when the score surpasses a predetermined threshold, signaling the onset of an epidemic.

The BLIGHTSIM model, developed by Narouei-Khandan et al. (2020), represents a groundbreaking advancement in predicting potato late blight. It simulates the response of *Phytophthora infestans* to variations in dtime temperature and humidity, particularly those associated with climate change. BLIGHTSIM uses relative humidity and hourly temperature as its primary input variables. The model was calibrated using growth chamber data that covered a complete infection cycle and was subsequently validated with field data from Ecuador. Across all datasets analyzed, BLIGHTSIM demonstrated a consistently strong fit, highlighting its reliability.

Analysis of growth chamber data for a single infection cycle revealed that the area under the disease progress curve (AUDPC) is significantly influenced by both the average temperature and its amplitude. This finding underscores the importance of these variables in understanding disease dynamics. BLIGHTSIM's integration into a potato growth model could enable researchers to explore the impact of daily temperature fluctuations on late blight development under various climate change scenarios, offering valuable insights for future disease management strategies.

Early blight disease in potato

Alternaria solani is the causative agent of early blight disease in potatoes, which leads to significant leaf loss. In 1969, Waggoner and Horsfall developed the EPIDEM model to predict the occurrence of early blight in potato crops. This forecasting model adjusts the progression of various fungal stages based on weather conditions, covering processes such as the formation of conidiophores and spores, spore dispersal by wind or rain, deposition, germination, penetration, incubation, and lesion growth. The model incorporates key meteorological variables, including temperature, relative humidity, wind speed, sunshine, and precipitation, evaluated on a three-hour basis.

The PLANT-Plus system provides a sophisticated forecasting strategy for managing fungicide applications based on disease risk, climatic variables, observed meteorological conditions, and plant growth factors. This decision support system (DSS), developed by Dacom Plant Service in Emmen, the Netherlands, enables fungicide treatments to be tailored to the level of disease risk. By leveraging weather forecasts and fungal life-cycle models to predict the onset of infections, PLANT-Plus aids in scheduling fungicide applications. This targeted approach reduces costs and minimizes the frequency of fungicide sprays while maintaining effective disease control (Raatjes et al., 2004).

Early blight of tomato

In 1978, Madden et al. introduced a forecasting system called FAST, designed to predict outbreaks of *Alternaria solani* in tomatoes. Over time, researchers have refined this system to include an automated forecasting technique for tracking *A. solani* severity during epidemics. FAST generates spray schedules for tomatoes, typically implemented two to four weeks after the onset of early blight. In addition to weekly spray schedules, the system offers a transplanting timetable, identifies optimal environmental conditions for tomato cultivation, and evaluates the effectiveness of spray schedules compared to a non-sprayed control. However, despite implementing effective fungicide applications, no significant changes in disease outcomes were observed.

The FAST system relies on weekly calendars and timetables, integrating two empirical models: one based on apparent infection rates and the other on final disease severity. It incorporates daily environmental parameters such as hours of leaf wetness, maximum and minimum disease levels, and comparisons with non-sprayed controls. Analysis of factors like rainfall, temperature fluctuations during wet periods, and humidity levels exceeding 90% revealed that fewer fungicide treatments were needed under certain conditions. These insights contributed to developing weekly timetables that consistently provided effective disease control.

Rice blast

Rice blast, caused by *Pyricularia grisea*, is a major epidemic disease affecting all parts of the rice plant. A typical sign of infection is the appearance of small brown spots on the neck, node, and leaf, which leads to the production of chaffy grains during the reproductive phase, significantly reducing crop yield. Among the various forecasting models developed worldwide to monitor rice blast, the correlative information method is widely employed. This method predicts disease outbreaks based on temperature and relative humidity (RH). Severe infections are forecasted when the minimum temperature ranges between 20 and 26 °C and RH exceeds 90% (Calvero et al., 1991).

In 1991, Ishiguro and Hashimoto developed the BLASTL model in Japan to optimize the timing of fungicide applications, aiming to minimize leaf blast incidence. The BLASTAM system, which operates using real-time weather data provided by AMeDAS via telephone modem, evaluates whether conditions are favorable for leaf blast infections. BLASTAM enables users to predict the onset of a leaf blast epidemic and the rapid increase in lesion numbers. Key data inputs for these predictions include leaf wetness hours, the mean temperature during leaf wetness periods, and the average temperature over the previous five d. These parameters help forecast potential outbreaks and determine the optimal timing for fungicide applications.

In Korea, Kim and Kim (1993) developed the EPIBLAST forecasting technique to address the challenge of predicting rice blast disease. This system provides quantitative predictions regarding the frequency of leaf blast outbreaks by integrating meteorological and plant physiological factors. Input variables include temperature, relative humidity, precipitation, dew period, and wind velocity, along with plant conditions such as the proportions of dead, diseased, and healthy leaves. EPIBLAST also accounts for critical epidemiological processes, including the incubation period, penetration, sporulation, conidia release and spread, and inoculum potential. By synthesizing these factors, EPIBLAST offers accurate predictions of leaf blast risk, guiding effective management strategies to protect rice crops and ensure optimal production.

Early tikka leaf spot of groundnut

Cercospora arachidicola is the pathogen responsible for groundnut early leaf spot, an airborne disease spread through wind-borne spores and conidia. Under favorable conditions, the disease can spread rapidly, reducing the plant's photosynthetic activity and ultimately leading to significant yield losses. Effective management and control of early leaf spot require a thorough understanding of the critical climatic factors that facilitate the disease's development. To achieve this, a prediction and forecasting model utilizing the high-resolution Weather Research and Forecasting (WRF) model has been proposed. This model relies on temperature and relative humidity data as its primary inputs. By integrating short-term weather parameter predictions, producers can make informed decisions, optimizing the timing and application of fungicides to minimize the disease's impact on crops. In addition to early leaf spot, groundnut resistance to late leaf spot disease is also influenced by temperature and the duration of leaf wetness (Rao et al., 2004). This further underscores the importance of incorporating weather forecasting into comprehensive disease management strategies for groundnuts.

Fire blight on apples and pear

The software application MARYBLYT is specifically designed to forecast key epidemiological events and evaluate the risk status of fire blight, aiding in the selection of appropriate chemical treatments. By incorporating multiple data inputs such as rainfall, minimum and maximum temperatures, and phenological factors, MARYBLYT provides accurate fire blight risk predictions. This integration of diverse data supports effective and timely disease management strategies (Lightner and Steiner, 1992).

Yellow/stripe rust of wheat and barley

The EPIPRE model, developed by Reinink et al. (1986), was designed to manage diseases and pests in wheat. From 1981 to 1984, 27 experiments were conducted to evaluate and refine the EPIPRE system for pest and disease management. These studies led to adjustments in the system's recommendations for controlling *Septoria* spp. Following these modifications, there was minimal difference in net yields and the type and number of pesticide applications compared to conventional guidance. The EPIPRE model demonstrated effectiveness in managing a range of pests and diseases, including powdery mildew, cereal aphids, stripe rust, and leaf rust. Additionally, its implementation resulted in a lower reduction in pesticide usage compared to previous years, highlighting its potential for more targeted and sustainable pest and disease management in wheat (Reinink et al., 1986).

Cercospora blight of celery

The CERCOS early forecasting system is designed to prevent the global spread of early blight in celery caused by *Cercospora apii*. Recent "low-risk" fungicides, particularly strobilurins such as azoxystrobin and a combination of pyraclostrobin and boscalid, have demonstrated significant effectiveness in managing this disease. When used alongside forecasting models like the Berger model, these newer fungicides achieved an 81% reduction in the area under the early blight disease curve compared to the older fungicide chlorothalonil. This finding highlights the greater effectiveness of these modern fungicides in controlling early blight and reducing yield losses (Raid et al., 2008).

Powdery mildew of wheat and barley

The MEHLTAU forecasting model, developed by Friedrich and Boyle (1997), was designed to control powdery mildew in winter wheat caused by *Erysiphe graminis*. This model employs spore traps placed in the field to monitor the daily distribution of spores, focusing on the periodicity of spore dispersal, airborne conidial concentrations, and the washing-off of conidia. These factors are heavily influenced by the timing and amount of precipitation. By incorporating climatic data, the MEHLTAU model forecasts disease outbreaks before they escalate during the onset of spring epidemics. This early warning system enables the implementation of appropriate management strategies, including timely fungicide applications, to prevent further disease spread. As a result, the model helps maintain wheat health by preserving its photosynthetic capacity and overall vitality. However, the model's accuracy relies on the proper functioning and placement of spore traps; malfunctioning equipment or incorrect placement can lead to inaccurate data collection and faulty forecasts.

Septoria leaf spot of tomato

The TOMCAST method, short for "Tomato Disease Forecasting System," is a forecasting tool used to manage septoria leaf spot, a disease caused by *Septoria lycopersici* that significantly impacts tomatoes in Brazil. The system is designed to optimize fungicide application timing, aiming to control the disease more effectively while reducing reliance on routine chemical treatments. TOMCAST calculates disease severity values (DSVs) based on key environmental factors, including temperature and leaf wetness duration. According to Avila et al. (2020), the updated TOMCAST model determines the timing of fungicide applications by assessing the DSV for each treatment. This method achieves disease control comparable to weekly fungicide applications but with fewer treatments, resulting in more efficient fungicide use and improved disease management.

Watermelons (anthracnose, gummy stem blight) and muskmelons (alternaria)

Alternaria leaf blight, caused by the fungus *Alternaria cucumerina*, poses a significant threat to muskmelons, while watermelons show relative resistance. In muskmelons, the disease can cause considerable damage, leading to earlier ripening and reduced fruit quality. Another critical disease, Gummy Stem Blight (GSB), caused by the fungus *Didymella bryoniae*, affects a wide range of cucurbits, including watermelons, muskmelons, squash, and pumpkins. As noted by Keinath et al. (2007), GSB can severely impact plant health, resulting in substantial yield losses.

Anthracnose, caused by the fungus *Colletotrichum orbiculare*, is yet another severe disease affecting watermelons and muskmelons. It significantly reduces yields and marketability due to its widespread effects on various parts of the plant.

To help growers manage these diseases, the MELCAST system was developed as a forecasting tool for diseases such as Alternaria leaf blight, anthracnose, and GSB. It optimizes fungicide applications by leveraging environmental data—specifically hourly leaf moisture and temperature. This approach not only improves disease control but also minimizes unnecessary fungicide use (Keinath et al., 2007).

The MELCAST models, developed through controlled-environment research and validated in field studies, translate leaf wetness and temperature data into Environmental Favorability Index (EFI) values. Fungicide applications are then scheduled based on these EFI values rather than on fixed intervals (e.g., weekly or biweekly). This technique, known as scheduling by epidemiological time, ensures that treatments are responsive to actual disease risk conditions.

MELCAST can be customized to local conditions by incorporating site-specific weather data and sensor information, ensuring its effectiveness across various growing environments. However, the accuracy and reliability of sensors used to measure leaf wetness and temperature are critical, as inconsistencies in data quality can affect the system's performance. Additionally, the interface and data presentation of MELCAST might pose challenges for less tech-savvy users, potentially hindering its use in practice.

Limitations in plant disease forecasting

Research on plant disease forecasting has made significant strides, but there are still limitations and areas for improvement. Some limitations that challenge plant disease forecasting models include: i) data quality and availability; ii) complexity of disease dynamics; iii) model accuracy and reliability (forecasting models are based on assumptions and simplifications, which may not account for all local variations or unforeseen changes in environmental conditions); iv) rapid changes in climate; v) economic constraints; and vi) scale and adaptability, whereby many models are developed for specific crops or regions and may not be easily adaptable to different contexts or crops.

Conclusions

In conclusion, plant disease forecasting serves as a vital tool in mitigating crop losses and facilitating the timely implementation of preventive measures. These systems rely heavily on mathematical and statistical models that incorporate both weather forecasts and historical data to predict disease outbreaks effectively. Despite their importance, several challenges limit their widespread effectiveness, including the dependence on precise and reliable climatic data, the high costs associated with implementation, and the variability of local environmental conditions. To address these limitations and improve the utility of forecasting systems, it is critical to focus on strategies such as enhancing data collection methods, integrating advanced modeling techniques like machine learning, and designing solutions tailored to specific regional conditions. Additionally, fostering collaboration among plant pathologists, climatologists, and data scientists can drive innovation and adaptation of these tools, enabling them to respond to the growing challenges posed by climate change, the emergence of new pathogens, and advancements in agricultural technologies. By prioritizing these improvements, plant disease forecasting can become more accurate, accessible, and impactful in safeguarding global food security.

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Conflict of Interest

The authors indicate no conflict of interest in this work.

References

Afifi MA, Zayan SA. 1973. Implementation of EGY-

BLIGHTCAST the first computer simulation model for potato late blight in Egypt. Phytopathology 63(9), 1161.

Agrios GN. 2005. Plant Pathology. Elsevier Academic Press, 952.

Arora RK, Ahmad I, Singh BP. 2012. Forecasting late blight of potato in Punjab using JHULSACAST model. Potato Journal 39(2).

Ashizawa T, Sasahara M, Ohba A, Hori T, Ishikawa K, Sasaki Y, Kuroda T, Harasawa R, Zenbayashi KS, Koizumi S. 2005. Evaluation of a leaf blast simulation model (BLASTMUL) for rice multilines in different locations and cultivars, and effective blast control using the model. Rice is Life: Scientific perspectives for the 21st century, 477-479.

Aust HJ, Hau B, Kranz J. 1983. Epigram-a simulator of barley powdery mildew/Epigram-ein Simulator des Gerstenmehltaus. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz. Journal of Plant Diseases and Protection 35, 244-250.

Avila M, Lourenco JV, Quezado-Duval AM, Becker WF, de Abreu-Tarazi MF, Borges LC, dos Reis Nascimento A. 2020. Field validation of TOMCAST modified to manage Septoria leaf spot on tomato in the central-west region of Brazil. Crop Protection 138, 105333.

Bhattacharyya SK, Phadtare SG, Khanna RN, Srivastava DS, Singh DS, Prasad B. 1983. Efficacy of some fungicides in controlling late blight of potato in India. Crop Protection 142, 105-109.

Bhupathi P, Sevugan P. 2021. Application of hyperspectral remote sensing technology for plant disease forecasting: An applied review. Annals of the Romanian Society for Cell Biology 25(6), 4555-4566.

Buja I, Sabella E, Monteduro AG, Chiriacò MS, De Bellis L, Luvisi A, Maruccio G. 2021. Advances in plant disease detection and monitoring: From traditional assays to in-field diagnostics. Sensors 21(6), 21-29.

Calvero SB, Teng PS. 1991. BLASTSIM. 2-a model for tropical leaf blast-rice pathosystem. Pest Management Council of the Philippines, Manila (Philippines). Conference 22.

Chattopadhyay C, Agrawal R, Kumar A, Meena RL, Faujdar K, Chakravarthy VK, Kuma Goyal P, Meena PD, Shekhar C. 2011. Epidemiology and development of forecasting models for White rust of *Brassica juncea* in India. Archives of Phytopathology and Plant Protection 44(8), 751-763.

Chemura A, Mutanga O, Dube T. 2017. Separability of coffee leaf rust infection levels with machine learning methods at Sentinel-2 MSI spectral resolutions. Precision Agriculture 18, 859-881.

Coakley SM. 1988. Variation in climate and prediction of disease in plants. Annual Review of Phytopathology 26(1), 163-181.

Cowgill WJ, Tietjen WH, Johnston SA, Nitzsche PJ. 2005. Early blight forecasting systems: evaluation, modification, and validation for use in fresh-market tomato production in Northern New Jersey. HortScience 40(1), 85-93.

Dubey SC. 2005. Role of weather on development of cercospora leaf spot (*Cercospora arachidicola*) on groundnut (*Arachis hypogaea*). The Indian Journal of Agricultural Sciences 75(4).

Erich J, Kleinhenz B. 2003. decision support systems for the control of late blight (*Phytophthora infestans*) of potato. Predavanj in Referatov 187.

Forrer HR, Gujer HU, Fried PM. 1993. PhytoPRE-a comprehensive information and decision support system for late blight in potatoes. Phytoparasitica 34-38.

Francl LJ. 2001. The disease triangle: a plant pathological paradigm revisited. The Plant Health Instructor 10.

Friedric S, Boyle C. 1997. Simulation of infection probability of powdery mildew in winter wheat. IFAC Proceedings Volumes 30(26), 243-248.

Grünwald NJ, Rubio-Covarrubias OA, Fry WE. 2000. Potato late-blight management in the Toluca Valley: Forecasts and resistant cultivars. Plant Disease 84(4), 410-416.

Grünwald N, Montes GR, Saldaña HL, Covarrubias OR, Fry WE. 2002. Potato late blight management in the Toluca Valley: Field validation of SimCast modified for cultivars with high field resistance. Plant Disease 86(10), 1163-1168.

Gujer HU. 1991. Integrated control of potato late blight (*Phytophthora infestans*) in Switzerland: concept and first results 1. EPPO Bulletin 21(1), 61-66.

Gurevich BI, Filippov AV, Tverskoi DL. 1979. Forecasting the development of harmfulness of potato late blight under different meteorological conditions on the basis of a simulation model “Epiphtora.” Mikologiia i fitopatologiia, 34-38.

Gutsche V. 1993. PROGEB—a model-aided forecasting service for pest management in cereals and potatoes 1. EPPO Bulletin 23(4), 577-581.

Hasanaliyeva G, Ammour M, Yaseen T, Rossi V, Caffi T. 2022. Innovations in disease detection and forecasting: a digital roadmap for sustainable management of fruit and foliar disease. Agronomy 12(7), 1707.

Hayashi T, Koshimizu Y. 1988. Computer program BLASTAM for forecasting occurrence of rice leaf blast. Bull Tohoku Nat Agric Exp Stn 78, 123-138.

Hwang SF, Strelkov SE, Turnbull GD, Manolii V, Howard RJ, Hartman M, Laflamme P. 2008. Soil treatments and amendments for management of clubroot on canola in Alberta. Canadian J. Plant Science 91, 999-1010.

Hyre RA. 1954. Progress in forecasting late blight of potato and tomato. Plant Disease Reporter 38, 245-253.

Ishiguro K, Hashimoto A. 1991. Computer-based forecasting of rice blast epidemics in Japan. In International Rice Research Conference, Seoul (Korea Republic), IRRI. 24-39.

Javaid M, Haleem A, Singh RP, Suman R. 2022. Enhancing smart farming through the applications of Agriculture 4.0 technologies. International Journal of Intelligent Networks 3, 150-164.

Juroszek P, Von Tiedemann A. 2011. Potential strategies and future requirements for plant disease management under a changing climate. Plant Pathology 60(1), 100-112.

Keinath AP, Everts KL, Langston DB, Egel DS, Holmes GJ. 2007. Multi-state evaluation of reduced-risk fungicides and Melcast against Alternaria leaf blight and gummy stem blight on muskmelon. Crop Protection 26(8), 1251-1258.

Kim CK, Kim CH. 1993. The rice leaf blast simulation model EPIBLAST. In Systems approaches for agricultural development: Proceedings of the International Symposium on Systems Approaches for Agricultural Development, 2-6 December 1991, Bangkok, Thailand. Springer Netherlands 309-321.

Kim Y, Roh JH, Kim HY. 2017. Early forecasting of rice blast disease using long short-term memory recurrent neural networks. Sustainability 10(1), 34.

Kleinhenz B, Falke K, Kakau J, Rossberg D. 2007. SIMBLIGHT1–A new model to predict the first occurrence of potato late blight. EPPO Bulletin 37(2), 339-343.

Kranz J. 1979. Simulation of Epidemics Caused by *Venturia inaequalis* (Cooke) Aderh. 1. EPPO Bulletin 9(3), 235-241.

Krause RA, Massie L B, Hyre RA. 1975. Blitecast: a computerized forecast of potato late blight. Plant Disease Reporter 59, 95.

Krause RA, Massie LB. 1975. Predictive systems: modern approaches to disease control. Annual Review of Phytopathology 13(1), 31-47.

Lahlali R, Ezrari S, Radouane N, Kenfaoui J, Esmaeel Q, El Hamss H, Belabess Z, Barka EA. 2022. Biological control of plant pathogens: A global perspective. Microorganisms 10(3), 596.

Lightner GW, Steiner PW. 1992. An update on version 4.1 of the MARYBLYT™ computer program for predicting fire blight. In VI International Workshop on Fire Blight 338, 131-136.

Luck J, Spackman M, Freeman A, Tre, Bicki P, Griffiths W, Finlay K, Chakraborty S. 2011. Climate change and diseases of food crops. Plant Pathology 60(1), 113-121.

Madden L, Pennypacker SP, MacNab AA. 1978. FAST, a forecast system for *Alternaria solani* on tomato. Phytopathology 68(9),1354-1358.

Mandal N, Adak S, Das DK, Sahoo RN, Kumar A, Viswanathan C, Mukherjee J, Gakhar S. 2022. Characterization of rice blast disease using greenness index, canopy temperature and vegetation indices 81-89.

McCoy RE. 1976. MYCOS, a computer simulator of Ascochyta blight of Chrysanthemum. In Proceedings of the Florida State Horticultural Society 89, 296-298.

Narouei-Khandan HA, Shakya SK, Garrett KA, Goss EM, Dufault NS, Andrade-Piedra JL, Asseng S, Wallach D, Bruggen AHV. 2020. BLIGHTSIM: A new potato late blight model simulating the response of *Phytophthora infestans* to diurnal temperature and humidity fluctuations in relation to climate change. Pathogens 9(8), 659.

Ohta K, Chib S, Shimad K. 1982. Simulation of rice leaf blast using BLASTCAST, a plant disease simulator. Annual Report of the Society of Plant Protection of North Japan 9-11.

Olatinwo R, Prabha TV, Paz JO, Hoogenboom G. 2012. Predicting favourable conditions for early leaf spot of peanut using output from the weather research and forecasting (WRF) model. International Journal of Biometeorology

56, 259-268.

Pande S, Rajesh TR, Kishore GK. 2004. Effect of temperature and leaf wetness period on the components of resistance to late leaf spot disease in groundnut. Plant Pathology Journal 20(1), 67-74.

Pierce FJ, Nowak P. 1999. Aspects of precision agriculture. Advances in Agronomy 67, 1-85.

Popkova EG, Sozinova AA, Sofiina EV. 2022. Model of agriculture 4.0 based on deep learning: Empirical experience, current problems and applied solutions. In Smart Innovation in Agriculture, 333-346.

Raatjes P, Hadders J, Martin D, Hinds H. 2004. PLANT-Plus: Turn-key solution for disease forecasting and irrigation management. In Decision Support Systems in Potato Production 169-186. Wageningen Academic.

Raid R N, Pernezny K, Havranek N, Sanchez J, Saddler B. 2008. Weather-based forecasting systems reduce fungicide use for early blight of celery. Crop Protection 27(3-5), 396-402.

Raj M, Gupta S, Chamola V, Elhence A, Garg Atiquzzaman M, Niyato D. 2021. A survey on the role of the Internet of Things for adopting and promoting Agriculture 4.0. Journal of Network and Computer Applications 187, 103-107.

Raji SN, Subhash N, Ravi V, Saravanan R, Mohanan CN, Nita S, Kumar TM. 2015. Detection of mosaic virus disease in cassava plants by sunlight-induced fluorescence imaging: A pilot study for proximal sensing. International Journal of Remote Sensing 36(11), 2880-2897.

Rehman A, Jingdong L, Khatoon R, Hussain I, Iqbal MS. 2016. Modern agricultural technology adoption its importance, role and usage for the improvement of agriculture. Life Science Journal 14(2), 70-74.

Reinink K. 1986. Experimental verification and development of EPIPRE, a supervised disease and pest management system for wheat. Netherlands Journal of Plant Pathology 92, 3-14.

Richard BA, Fitt BD. 2022. Control of crop diseases through integrated crop management to deliver climate-smart farming systems for low- and high-input crop production. Plant Pathology 71(1), 187-206.

Ristaino J, Anderson PK, Bebber DP, Brauman KA, Cunniffe NJ, Fedoroff NV, Finegold C, Garrett KA, Gilligan CA, Jones CM, Martin MD. 2021. The persistent threat of emerging plant disease pandemics to global food security. Proceedings of the National Academy of Sciences 118(23), 20-25.

Rossi V, Giosue S, Bugiani R. 2007. A-scab (apple-scab), a simulation model for estimating risk of *Venturia inaequalis* primary infections. EPPO Bulletin 37(2), 300-308.

Schepers H. 1995. ProPhy: a computerized expert system for control of late blight in potatoes in the Netherlands. In Proceedings XIII International Plant Protection Congress 48.

Shakya SK, Goss EM, Dufault NS, Van Bruggen AC. 2015. Potential effects of diurnal temperature oscillations on potato late blight with special reference to climate change. Phytopathology 105(2), 230-238.

Singh BP, Govindakrishnan PM, Ahmad I, Rawat S, Sharma S, Sreekumar J. 2016. INDO-BLIGHTCAST–a model for forecasting late blight across agroecologies. International Journal of Pest Management 62(4), 360-367.

Sing B, Ahmad I, Sharma VC, Shekhawat CS. 2000. JHULSACAST: A computerized forecast of potato late blight in western Uttar Pradesh. Potato Journal 27(2), 25-34.

Singh VK, Pundhir VS. 2013. Forecasting models for potato late blight management-a review. Agricultural Reviews 34(2), 87-96.

Small IM, Joseph L, Fry WE. 2015. Development and implementation of the BlightPro decision support system for potato and tomato late blight management. Computers and Electronics in Agriculture 115, 57-65.

Sparks AH, Forbes GA, Hijmans J, Garrett KA. 2014. Climate change may have limited effect on global risk of potato late blight. Global Change Biology 20(12), 3621-3631.

Stephan S, Gutsche V. 1980. Ein algorithmisches modell zur simulation der phytophthora-epidemie (SIMPHYT). Archives of Phytopathology and Plant Protection 16(3), 183-192.

Stevenson WR. 1993. IPM for potatoes: a multifaceted approach to disease management and information delivery. Plant Disease 24, 84-88.

Stirm WL, Bauer M, Loewe O. 1971. Predicting southern corn leaf blight development in 1971 by computer simulator EPIMAY. In Proceedings of the Indiana Academy of Science (81) 325-329.

Taylor MC, Hardwick NV, Bradshaw NJ, Hall AM. 2003. Relative performance of five forecasting schemes for potato late blight (*Phytophthora* *infestans*) and accuracy of infection warnings and reduction of unnecessary, theoretical, fungicide applications. Crop Protection 22(2), 275-283.

Teng PS, Blackie MJ, Close RC. 1980. Simulation of the barley leaf rust epidemic: Structure and validation of BARSIM—I. Agricultural Systems 5(2), 85-103.

Waggoner PE, Horsfall, J. 1969. Epidemic: a simulator of plant disease written for a computer. Bulletin. Connecticut Agricultural Experiment Station, 698.

Wallin JR. 1962. Summary of recent progress in predicting late blight epidemics in United States and Canada. American Potato Journal 39, 306-312.

Zadoks JC. 1981. EPIPRE: a disease and pest management system for winter wheat developed in The Netherlands 1. EPPO Bulletin 11(3), 365-369.

Zheng Q, Huang W, Xia Q, Dong Y, Ye H, Jiang H, Chen S, Huang S. 2023. Remote sensing monitoring of rice diseases and pests from different data sources: A review. Agronomy 13(7), 1851.