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Modern Weather-Based Systems for Plant Disease Forecasting

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Plant diseases are major constraints to agricultural productivity, causing substantial reductions in crop yield, deterioration of produce quality and economic losses to farmers worldwide. Environmental conditions strongly influence pathogen survival, infection, multiplication and dispersal, making weather information an essential component in disease prediction and management. Meteorological parameters such as temperature, relative humidity, rainfall, wind speed, leaf wetness duration, solar radiation and soil moisture play a significant role in determining disease development and epidemic progression. Forecasting approaches based on weather data have evolved from simple empirical and threshold-based systems to advanced mechanistic, simulation, artificial intelligence and geographic information system (GIS) integrated models. These models utilise biological, epidemiological, and environmental information to estimate disease risk, predict epidemic outbreaks and generate timely warnings for management interventions. Their applications in major crops have improved the prediction of diseases such as potato late blight, apple scab, grape downy mildew, rice blast and cereal rusts. The adoption of weather-based forecasting systems supports efficient fungicide scheduling, reduces excessive chemical use, minimises environmental contamination and enhances resource optimisation. The integration of modern technologies, including machine learning, remote sensing and spatial analysis, has further strengthened forecasting precision, thereby contributing to sustainable agriculture, precision crop protection, and climate-resilient farming systems.

Keywords: Plant disease forecasting, Weather parameters, Disease prediction, Precision agriculture, Sustainable crop protection

Introduction

Weather conditions play a critical role in influencing the initiation, progression and spread of plant diseases. Factors such as temperature, relative humidity, rainfall, wind patterns and the duration of leaf wetness provide suitable environments for pathogen survival, infection and transmission. In agricultural systems, disease outbreaks can cause significant reductions in yield, a decline in crop quality and financial difficulties for farmers. To overcome these issues, weather-based disease forecasting models have been designed as predictive tools that use meteorological data to assess disease risk before visible symptoms appear. These models assist in making timely disease management decisions, minimising excessive use of chemicals and improving the overall effectiveness of crop protection.

Various weather-based forecasting models have been developed using different predictive approaches and levels of complexity. Some models are built on historical associations between disease occurrence and environmental factors, while others emphasize the simulation of pathogen life cycle stages under particular weather conditions. In recent years, the integration of advanced technologies, including artificial intelligence, machine learning, remote sensing and geographic information systems, has greatly improved forecasting accuracy and enabled broader disease monitoring. As a result, gaining knowledge about the different categories of weather-based disease forecasting models is important for enhancing disease management strategies, encouraging sustainable agricultural practices and strengthening climate-resilient crop production systems.

Weather parameters influencing plant diseases

Weather variables are fundamental to the development of plant disease forecasting models, as they have a direct influence on pathogen survival, infection processes, reproduction and dissemination. Agricultural forecasting systems frequently consider weather parameters such as temperature, which determines pathogen growth and incubation duration; relative humidity, which creates favourable conditions for spore germination and disease establishment in humid environments; and rainfall, which contributes to spore transport, splash dispersal and the persistence of moisture conditions suitable for disease progression. Leaf wetness duration is also a critical component, since many fungal and bacterial pathogens depend on an adequate period of surface moisture to initiate infection successfully. Moreover, wind speed and direction play an important role in the long-distance spread of airborne spores and the transfer of inoculum across fields. Additional variables commonly included in forecasting model design are solar radiation, which influences canopy microclimate and moisture loss through evaporation, and soil moisture, which is especially relevant in the case of soil-borne pathogens and root-related diseases. These weather parameters are utilised either separately or in combination to create dependable forecasting models that provide early disease warnings and improve crop management efficiency.

Types of weather-based disease forecasting models

Weather-based disease forecasting models can be categorised into several groups according to their prediction approach and the type of data used in agricultural disease management. The main categories include empirical models, mechanistic or process-based models, statistical models, simulation models, threshold or rule-based models, machine learning and artificial intelligence-driven models, as well as Geographical Information Systems (GIS) and remote sensing integrated models. These forecasting models vary in terms of complexity, methodology and their practical application in plant disease prediction and management. A detailed explanation of the different types of weather-based disease forecasting models is presented in the following sections.

Empirical models

Empirical models are data-oriented plant disease forecasting methods developed by analysing observed relationships between environmental conditions and disease occurrence. These models are constructed using historical weather information such as temperature, rainfall, relative humidity, wind speed and leaf wetness duration, together with field observations of disease incidence or severity collected over several growing seasons. Important variables influencing disease development are identified and examined through statistical techniques, including correlation analysis, regression models, probability functions and disease risk indices to formulate prediction thresholds or decision rules. The resulting models are then calibrated and validated with independent datasets to evaluate their accuracy and dependability. In practical use, validated empirical models are linked with real-time weather monitoring systems to issue disease alerts whenever environmental conditions become favourable for disease development, thereby supporting timely management practices such as fungicide application and cultural control measures. Because of their simplicity, minimal computational demand and suitability for operational advisory services, empirical models have been extensively applied in forecasting diseases such as potato late blight, apple scab, powdery mildew and downy mildew.

Mechanistic models

Mechanistic or process-based models are advanced plant disease forecasting systems that predict disease development by simulating the biological interactions among the host, pathogen and environment rather than depending only on statistical relationships. These models use information on pathogen life cycle stages such as spore production, dispersal, germination, infection and survival, along with weather variables including temperature, rainfall, relative humidity, wind speed, solar radiation and leaf wetness duration. Mathematical equations are developed to represent disease processes under different environmental conditions and the models are calibrated and validated using field and experimental data. Because they are based on biological mechanisms, mechanistic models can effectively predict disease outbreaks under varying climatic conditions and management practices. They are widely used for forecasting diseases such as grape downy mildew, wheat rust, potato late blight and apple scab, supporting timely disease management decisions and precision agriculture practices.

Simulation models

Simulation models are computer-based forecasting tools designed to represent plant disease development and epidemic spread under changing environmental and crop conditions. These models combine multiple components, including pathogen characteristics, host susceptibility, weather variables and management practices, within a virtual framework. The process involves identifying important disease stages such as inoculum formation, infection, incubation, lesion growth, sporulation and dispersal, which are mathematically expressed using data obtained from field observations, experiments and scientific literature. Weather factors, including temperature, rainfall, humidity, wind speed and leaf wetness duration, are regularly incorporated due to their direct impact on disease progression. The model operates over defined time intervals, usually hourly or daily, to predict disease initiation, epidemic development and severity under different scenarios. Model calibration is performed by adjusting parameters to align with observed disease patterns, followed by validation using independent datasets from multiple seasons or locations to confirm predictive accuracy. In practical applications, simulation models are widely used to estimate disease risk, forecast epidemic trends and assist decision-making in plant disease management. They are commonly linked with weather forecasting systems and decision support tools to provide real-time alerts, improve fungicide scheduling and assess alternative control strategies. Simulation models have been successfully applied in forecasting diseases such as rice blast, potato late blight, grape downy mildew and cereal rusts, making them valuable tools for precision agriculture and climate-resilient crop protection.

Threshold or rule-based models

Threshold or rule-based models are straightforward decision-support systems applied in plant disease forecasting to estimate disease risk using predefined environmental or epidemiological criteria. These models are based on the concept that disease development takes place only when certain critical conditions, such as suitable temperature, relative humidity, rainfall or leaf wetness duration, are maintained for a required period. The development process involves analysing historical weather and disease records to determine environmental factors that are repeatedly linked with disease outbreaks. From these observations, threshold values or logical decision rules are formulated, for example, issuing a disease alert when temperature remains within a favourable range and leaf wetness persists beyond a specified duration. The established rules are further validated using field data collected from different seasons or geographical locations to confirm their accuracy and reliability. In practical applications, these models are commonly integrated with real-time weather monitoring systems to compare observed conditions with established thresholds and generate warnings whenever disease-conducive conditions are detected. Owing to their simplicity, minimal data requirements and ease of application, threshold or rule-based models are extensively used in forecasting diseases such as potato late blight, apple scab and grape downy mildew within operational advisory systems.

Artificial intelligence (AI)-based models

Artificial intelligence (AI)-based models are advanced data-driven tools used in plant disease forecasting to detect complex patterns and predict disease occurrence through computational learning algorithms. These models function by training algorithms to understand relationships between input variables and disease outcomes from large datasets without the need for explicitly defined biological rules. The process begins with collecting and combining diverse datasets, including weather variables such as temperature, humidity, rainfall and leaf wetness, together with disease incidence records, soil characteristics, crop growth stages and in some cases remote sensing or image-derived data. The data are then pre-processed through cleaning, normalisation, feature selection and division into training, validation and testing datasets. Machine learning and deep learning techniques such as decision trees, random forests, support vector machines, artificial neural networks and convolutional neural networks are subsequently applied to identify patterns linked to disease development. Model performance is assessed using evaluation measures including accuracy, precision, recall and F1-score, followed by optimisation and validation with independent datasets to improve predictive reliability. In practical applications, AI-based models are extensively used to forecast disease outbreaks, classify disease risk and facilitate real-time decision-making by integrating live weather and field information. These models are increasingly incorporated into smart agriculture platforms, mobile applications and decision support systems to provide early warnings, improve disease management strategies and strengthen precision crop protection under changing climatic conditions.

Geographical information system (GIS) and remote sensing integrated models

GIS and remote sensing-based models are spatially focused approaches applied in plant disease forecasting to monitor, assess and predict disease distribution across extensive agricultural regions. These models operate on the principle of identifying spatial and temporal changes in crop health, environmental conditions and factors favourable for disease development using geographic information systems (GIS), satellite imagery, drones and sensor-based technologies. The methodology starts with the collection of spatial datasets such as satellite images, aerial photographs, weather records, soil data, topographic information and field observations of disease occurrence. These datasets are subsequently processed through image correction, georeferencing, normalisation and extraction of important spectral indicators such as the Normalised Difference Vegetation Index (NDVI), canopy temperature and moisture indices related to plant stress. The processed environmental and spatial data are integrated into GIS platforms and analysed using statistical, machine learning or spatial modelling methods to detect disease hotspots, forecast disease spread and delineate risk zones. Model outputs are then validated with field-based ground-truth data to ensure spatial precision and forecasting reliability. In practical applications, GIS and remote sensing-based models are extensively used for early disease detection, large-scale surveillance, epidemic monitoring and the development of spatial risk maps for site-specific disease management. These models are highly valuable in precision agriculture, as they support targeted fungicide application, efficient resource utilisation, and timely interventions by delivering real-time geographic insights into disease dynamics across diverse agroecosystems.

Applications in major crop diseases

Numerous plant disease forecasting models have been developed for major crops to improve disease management and reduce unnecessary fungicide usage. One of the earliest operational systems, the BLITECAST model, was created to predict potato late blight caused by *Phytophthora infestans* using weather factors such as temperature, humidity and leaf wetness duration. The MILLS table is a well-known threshold-based model extensively used for forecasting apple scab caused by *Venturia inaequalis* through the relationship between temperature and leaf wetness duration. In grapevine cultivation, forecasting systems such as DOWNCAST and other mechanistic models are commonly applied to predict downy mildew caused by *Plasmopara viticola*. Likewise, the TOM-CAST model has been used in tomato to forecast early blight and Septoria leaf spot based on disease severity values generated from environmental conditions. Models have also been established for rice blast caused by *Magnaporthe oryzae* by combining weather parameters with crop growth stages. More recently, machine learning techniques, including Random Forest, Support Vector Machine and Artificial Neural Networks, have been introduced for disease prediction in crops such as wheat, soybean and citrus by utilising weather information, historical disease data and remote sensing datasets. These advancements demonstrate the evolution of plant disease forecasting from basic empirical approaches to advanced intelligent decision-support systems in precision agriculture.

Advantages of weather-based forecasting models

Weather-based disease forecasting models offer several advantages in modern crop protection by enabling the early prediction of disease outbreaks and facilitating timely management interventions. Empirical and threshold-based models are simple, cost-effective and suitable for operational advisory systems, whereas mechanistic and simulation models provide a deeper understanding of disease dynamics by incorporating biological processes and environmental interactions. Artificial intelligence-based models enhance prediction accuracy through the analysis of large and complex datasets, while GIS and remote sensing integrated models support large-scale disease surveillance, spatial risk mapping and site-specific management. Collectively, these forecasting approaches reduce unnecessary fungicide applications, lower production costs, minimise environmental contamination and improve crop productivity, thereby contributing significantly to sustainable agriculture and precision disease management.

Conclusion

Weather-based disease forecasting models have become essential tools for improving plant disease management by enabling early prediction of disease outbreaks and supporting timely intervention strategies. The integration of weather variables, biological processes, statistical methods and advanced technologies such as artificial intelligence, machine learning, GIS and remote sensing has significantly enhanced forecasting accuracy and decision-making efficiency. These models not only contribute to reducing crop losses and minimising unnecessary chemical usage but also promote sustainable agricultural practices and precision crop protection. With the increasing challenges posed by climate variability and emerging diseases, the continued development and adoption of advanced forecasting systems will play a crucial role in strengthening resilient and sustainable crop production systems.

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