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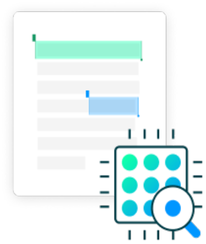

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Review Article
Weather Based Forewarning Systems for Important Pests and Diseases in Major Crops

ABSTRACT

An essential tool used in modern agriculture is the Weather-Based Pest Forewarning Model, which uses meteorological data to forecast the incidence and severity of common diseases and insect pests. In order to, forecast pest and disease outbreaks, this model incorporates important meteorological variables including temperature, humidity, rainfall, and wind patterns. This enables the implementation of preemptive and focused control techniques. These forewarning systems provide timely insights by utilizing sophisticated modelling techniques and historical data analysis. This allows farmers to minimize crop losses, optimize pesticide usage, and take preventive steps. By reducing environmental effects and increasing agricultural output, the use of these models makes a substantial contribution to sustainable agriculture. Even with their potential, these models' accuracy and usability still need work because of issues including data availability, localizing the model to the situation, and the effects of climate change. To fully realize the benefits of weather-based forewarning systems in integrated pest and disease control, more research and development is necessary.

Keywords: Forecasting, Disease outbreak, weather, Insect pests, sustainability.

1. INTRODUCTION

For suitable, proactive, and current planning especially in the uncertain field of agriculture reliable and timely forecasts are essential. One of the greatest threats to world agriculture is the presence of insect pests and diseases, which can seriously reduce yields and compromise food security[1]. Timely corrective actions can be applied to reduce yield loss; this is possible if both the duration and severity of the pest and disease outbreak are known in advance. Therefore, factors influencing agricultural output as well as pest and disease outbreaks must be studied [2,3]. The development of pests and diseases, as well as crop growth, is significantly influenced by the weather.

Conventional approaches to managing pests and diseases have frequently depended on preventative measures, like the liberal use of chemical pesticides. On the other hand, over time, these techniques may prove to be unsustainable, environmentally harmful, and inefficient. The creation of weather-based pest forewarning models has become a proactive strategy for managing agricultural pests and illnesses in response to these difficulties[4,5].

Novel devices such as weather-based pest forewarning models are made to forecast the onset and spread of key insect pests and diseases in agricultural systems. A forewarning is a warning that a large-scale insect infestation or disease that might harm the crop financially is likely to occur[6]. It is crucial to the integrated pest control program because it is a tool for ensuring to be ready for unforeseen circumstances. Crop protection uses weather-based pest and disease forecasting models. Both biological and climatic data are needed for the creation and use of these models, and the predicted spread of disease or pests is the model's output [7,8].

These models predict disease prevalence and pest outbreaks by using meteorological data, including temperature, humidity, rainfall, and wind patterns. There is ample evidence linking weather patterns to pest dynamics [9]. For example, temperature has a direct impact on insect pest development rates, while rainfall and humidity can foster the growth of plant diseases. Comprehending these correlations facilitates the creation of forecasting models that have the ability to accurately predict pest and disease challenges[10,11].

These models provide farmers early warnings by analyzing the connection between insect behaviour and weather, which enables farmers to put effective pest management plans into action. The transition towards precision agriculture is represented by weather-based pest forewarning models, which enable targeted and timely interventions based on scientific forecasts[12]. By reducing the need for widespread pesticide applications, these models lessen their negative effects on the environment and encourage the use of more sustainable farming methods. Furthermore, because changing weather patterns can affect the distribution and behaviour of diseases and pests, they offer an essential tool for adjusting to the problems faced by climate change[13]. In light of the growing stresses that biotic and abiotic factors place on agricultural systems globally, it is imperative that we implement Weather-Based Pest Forewarning Models[14,15].

2. CRITERIA FOR SUCCESSFUL INSECT PEST AND DISEASE FORECASTING SYSTEM

For integrated pest management (IPM) to be effective, a forecasting system for diseases and insect pests must be successful. The following are the main factors that make it successful [16,17]:

- Prediction Accuracy: Using meteorological data and other pertinent information, the system must forecast pest and disease outbreaks with accuracy and dependability.
- Timeliness: Farmers should be able to take preventive or control action before the pest or disease outbreak reaches a critical level if predictions are provided promptly.
- User-Friendliness: Farmers, extension agents, and other stakeholders should be able to easily use and access the system. This entails offering recommendations that are actionable and maintaining an intuitive interface.
- Cost-Effectiveness: By minimising the usage of chemical pesticides and lowering crop losses, the forecasting system should be economical for users.
- Adaptability: The system must be able to adjust to various crops, geographical areas, and pest or disease kinds. Additionally, it must to be able to learn from fresh information and advance with time.

- Integration with IPM Practices: To promote ecologically friendly and sustainable pest and disease control, the forecasting system should complement and strengthen current IPM techniques.
- Data Availability and Quality: Accurate forecasting depends on having access to high-quality, current data on crop state, insect populations, and weather.
- Stakeholder Engagement: In order for implementation to be successful, farmers, researchers, extension agencies, and legislators need to collaborate and cooperative.

By meeting these criteria, a pest and disease forecasting system can significantly improve agricultural productivity and sustainability.

3. DIFFERENT TYPES OF FOREWARNING SYSTEMS

The variables of interest in a pests and diseases forewarning system could include the maximum number of pests or the severity of the disease, the pest population or the severity of the disease at the most destructive stage of the crop, the time of the pests' or diseases' first appearance, the time of maximum number of pests or disease severity, maximum time for pests or disease severity exceeding the threshold limit, the degree of damage, weekly pest monitoring etc[18,19]. If data are available for 15–20 years at regular intervals, a thorough investigation can be conducted for several criteria.

However, different model types can be used to construct forewarning systems, depending on the data available. There are two sorts of models that can be used to predict pests and diseases: "Between year models" and "Within year models" [20].

3.1 Between year models: These models were created with data from prior years. It was assumed that the current year represents a component of the composite population of the prior years, and as such, the associations established using the data from those years will also apply to the current year. By inserting the data from the current year into a model built using the prior years' data, one might get the forecast for diseases and pests.

3.2 Within year models: If there are 10–12 data points between the time of the disease or pest's first appearance and its maximum severity, or the population of the disease or pest, and no historical data is available, a forecast of the maximum disease severity or pest population can be made using the within-year growth model and current season data. Using partial crop season data, the technique consists of fitting a suitable model to the pattern of disease development / pest population and forecasting the maximum value based on this model.

4. VARIOUS FOREWARNING SYSTEMS USED FOR INSECT PESTS AND DISEASES IN MAJOR CROPS

4.1 EPIPRE (EPidemics PREdiction and PREvention): A collaborative project called EPIPRE (EPidemic PREdiction and PREvention) aims to control diseases and pests in wheat under supervision. It functions according to the specific field. Basic information and field observations are kept in a data bank from each wheat field. The central staff receives field observations from farmers and enters them into the data bank. Simulated models that are simplified are used to update field data every day. Three main options are made based on the calculation and usage of expected impact and loss: "treat," "don't treat," or "make another field observation." Information is sent by mail between the central staff and the farmers. Puccinia striiformis marked the beginning of EPIPRE in 1978 [21].

In 1981, guidance was given for P. striiformis, P. recondita, Erysiphe graminis, Septaria spp., and the cereal aphids, Sitobion avenae, Metopolophium dirhodum, and Rhopalosiphum padi. Since then, the number of insects and diseases that are taken into consideration has expanded. Using explanatory simulation models as a tool, predictive approaches have been established for each of these diseases and pests. The knowledge of numerous input relations and some external elements, such as temperature, which control the majority of the processes involved in the dynamics of pest and disease populations, forms the basis of these explanatory models[22, 23]. Simplified decision rules have been designed and implemented in the guidance system, eliminating the requirement for changing the forcing variables, based on a sensitivity analysis conducted with these models.

4.2 COMPUTER CENTRE FOR AGRICULTUTRAL PEST FORECASTING (CIPRA)

Based on hourly meteorological data, the CIPRA is an easy-to-use software program that can forecast the growth of pests (insects and diseases), crops (phenology), and some postharvest diseases. As a result, this program lets users decide when to apply plant protection measures most effectively in real time. The software is based on weather forecasts in addition to weather data from several automated stations located around Quebec[24, 25]. The creation of a centralised computer network makes real-time meteorological data accessible. Next, using bioclimatic models produced through scientific means, the odds of pest development are computed.

More than 130 forecasting models for diseases, insect pests, crop phenology, and postharvest physiological disorders for more than 25 distinct crops are included in the CIPRA, all housed within a shared computer infrastructure. CIPRA is a tool that is always changing since new bioclimatic models or indicators are added to it every year. The CIPRA is a great tool for decision support regarding crop protection and production in Canada, as it is now the largest collection of real-time bioclimatic forecasting models in use in the country.

4.3 Weather based pest forewarning model for major insect pests of rice [26].

Narayanasamy et al., 2017 made an attempt to predict the population occurrence of Yellow Stem Borer (YSB), Brown Planthopper (BPH) and Rice Leaffolder (RLF). The information pertaining to the weekly light trap captures of YSB, RLF, and BPH in the Cauvery delta zone was gathered from the Directorate of Rice Research, Hyderabad's progress report, spanning 17 years, from 1990 to 2007. In order to determine the abundance of the targeted insect pests, light traps were placed in the rice fields[27]. The number of insects captured each week was calculated by counting those that were captured overnight and tallied in the morning. The daily data is used to calculate the weekly cumulative abundance of insect pests, weekly averages of rainfall, maximum and lowest temperatures, morning and evening relative humidity, and sunshine hours. YSB, BPH, and RLF forewarning models were developed using these data.

Generalized Linear Model (GLiM) was developed for YSB, BPH and RLF for predicting the population at a given time. The chi square test findings showed that, in addition to meteorological parameters, there are numerous other elements that influence the quantity of light trap catches of insects. When creating the model, combining the weather parameters with the other factors (variety, soil, fertiliser treatment, etc.) might improve the equation's predictability[28].

The experiment's findings showed that, for both YSB and BPH, the trend in the observed and expected pest counts is nearly the same. Regarding the leaf folder, there was a discrepancy in the trends observed and predicted. If the weather is included in the model development process along with other elements like variety, soil, fertiliser application, etc., the predictability of these equations can be further enhanced.

4.4 Development of forewarning model for rice yellow stemborer over West Bengal

In 2016, Rajalakshmi D et al. studied at the India Meteorological Department's Agricultural Meteorology Division in Pune to create a rice yellow stem borer forewarning model utilising pheromone trap data. For the years 2003 through 2014, daily weather and pest data were gathered and converted to pentads for additional study. When creating a forewarning model, the pentad with the highest incidence in the chosen years (125 Days After Sowing (DAS) was taken into account[29].

The maximum moth population is highly correlated with pentad of 80 DAS for maximum temperature and bright sunshine hours, 55 DAS for minimum temperature, 50 DAS for morning and evening relative humidity, 100 DAS for rainfall, and 55 DAS for soil temperature at a depth of 5 cm, according to the results of a correlation study. The years 2013 and 2014 underwent validation. In order to predict the same pest during the peak infection (125 DAS), weather variables from 1 DAS, 30 DAS, 60 DAS, 75 DAS, 80 DAS, and 95 DAS were used. The models' dependability was determined by calculating the root mean square error (RMSE) and its percentage. They have been divided into three categories: fair, good, and poor, based on the values. It was discovered that the weather variables from 80 DAS and 60 DAS were both good and 75 DAS were reasonable; in contrast, every other combination had an extremely high error rate and classified as being poor.

4.5 Cucurbit Downy Mildew (CDM) ipmPIPE forecasting system

The propagation of CDM spores over North America is predicted by this system. Growers, extension specialists, researchers, and other agricultural professionals who keep an eye out for the presence of CDM in commercial cucurbit fields and sentinel plots provide data for the model[30, 31, 32]. To estimate when conditions will be favourable for the spread of inoculum and plant infection, this data is supplemented with information from meteorological forecasts and models on the movement of particles in the atmosphere [33,34]. The North American Plant Disease Forecast Centre at North Carolina State University is in charge of the initiative. The real-time maps produced by the CDM forecast system indicate areas where infections are likely to occur[35,36]. Certain cucurbit crops that are cultivated and pathogen biotypes that may be resistant to fungicide treatments might be taken into account when adjusting the risk levels. When compared to calendar-based spray programs, growers are predicted to save two to three fungicide applications annually by utilising the approach. The user can view the maps on the CDM ipmPIPE website, and based on their geographic location, they can receive alerts via email or text.

4.6 BLIGHTCAST

With the use of temperature, relative humidity (RH), and rainfall information, the forecast model BLIGHTCAST was created to estimate the possible severity of late blight on tomatoes and potatoes[37,38]. Severity levels are specifically calculated using total 24-hour rainfall and the highest and lowest temperatures at which the relative humidity is greater than 90%. The severity values that accumulate over time are used to suggest whether fungicides should be used and to show the probability of infection by the late blight pathogen. Penn State University first offered BLIGHTCAST as a phone-in service. The BLIGHTCAST model's derivatives can now be found on a number of platforms, such as regional forecasting systems and standalone weather monitoring software [39].

4.7 Pacific Northwest late blight warning system

Although this model employs long-range meteorological (rain) forecasts to predict the possibility of late blight outbreaks on a regional scale, the Pacific Northwest late blight warning system also gives projections on the severity of late blight[40,41]. The system notifies growers when a preliminary fungicide spray is required. On the basis of canopy development, weather projections, and the likelihood of late blight outbreaks, recommendations are made for additional applications.

5. ADVANTAGES

Proactive Pest Management: By using these models, farmers can lessen their dependency on reactive control techniques by anticipating pest issues and taking preventive action. **Decreased Pesticide Use:** These models assist in optimising pesticide treatments by properly forecasting pest outbreaks, which lowers environmental contamination and chemical inputs. **Cost savings:** Prompt actions predicated on model projections can avert crop losses and lower pest management expenses.

Sustainable Agriculture: By reducing the negative environmental effects of pest control and protecting beneficial creatures, the integration of weather-based forewarning models into integrated pest management (IPM) techniques fosters sustainable agriculture.

6. LIMITATIONS

Weather-Based Pest Forewarning Models have multiple challenges in spite of their potential

Data Accessibility: The precision of these models is contingent upon the availability of current, high-quality meteorological and pest data. This kind of information may be hard to get by or inaccurate in many places, particularly in developing nations.

Model Adaptation: Since pest dynamics can differ greatly between areas and crops, models must be tailored to particular local circumstances. This necessitates ongoing model validation and calibration.

Climate Change: The past weather-pest correlations may change as a result of shifting climatic patterns, which could have an impact on forecast accuracy. In order to take these changes into account, models must be updated often.

Technology Access: It's possible that smallholder farmers don't have as much access to the knowledge and tools needed to apply these models efficiently. A necessity exists. Initiatives aimed at increasing capacity are required to guarantee wider adoption.

7. CONCLUSION

Weather-Based Forewarning Models, which provide a proactive strategy to safeguard crops from insect pests and diseases constitute a noteworthy breakthrough in pest management. These models can accurately anticipate pest outbreaks by utilising meteorological data, which makes early and focused responses possible. However, issues with data availability, model adaptability, and climate change must be resolved if these models are to be truly helpful. To fully realise the potential of these models in sustainable agriculture, more research and development is needed, as is work to make them available to all farmers.

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