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

ABSTRACT

In present - day agriculture, weather based forewarning systems have become a vital tool in combating pests and diseases. Thesesystems forecast the occurrence and severity of important insect pests and diseases using the meteorological data provided. The data regarding important meteorological variables like temperature, rainfall, humidity, wind speed, and wind patterns are integrated in these systems. As forewarning systems use highly developedartificial intelligence technology, historical data analysis and pest-weather correlations to provide precise and timely insights to the farmer community, which enable them to take appropriate control measures when required and help in reducing crop losses and optimising the pesticide usage.These will help to schedule pesticide applications as needed, ultimately reducing the quantity of pesticides sprayed and their detrimental impact on the environment and other beneficial organisms and increasing the overall agricultural output, which is very important in sustainable agriculture. To unlock the full potential of these systems, issues regarding data availability, localizing the systems to particular regions, and the effects of climate change should be addressed.

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 systems 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 systems 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 a very important tool in integrated pest management programs as it is very essential to predicting unforeseen circumstances [7,8].

Past works in this area of research suggest that there is always a relation between the weather patterns and pest occurrence. These systems predict the outbreaks using data of various meteorological parameters like temperature, rainfall, humidity, and wind patterns [9].For example, temperature is the most important physical factor which determines the duration of the various stages in the insect life cycle.By taking into account all these correlation data,forecasting systems have the capability to accurately predict the insect pests and diseases that occur in crops [10,11].

Using forewarning systems in agriculture, which provide timely warnings of occurrence and outbreaks by correlating the weather parameters with the insect behaviour and severity of disease, helps in taking the proper crop protection measures whenever needed, and it is also a very big step towards precision agriculture[12].Precise and timely application of pesticide sprays not only reduce the number of sprays but also lessen their ill effects on the surrounding environment, and this encourages the use of sustainable farming methods. Furthermore, rapid changes in the climate also affect the distribution and behaviour of pests and diseases; these systems provide an opportunity to overcome the problems caused by climate change[13].As of now, both biotic and abiotic factors play a crucial role in agricultural losses, so it is very important to incorporate weather based forewarning systems in agriculture as they help in predicting these factors to a major extent [14,15].

2. CRITERIA FOR SUCCESSFUL INSECT PEST AND DISEASE FORECASTING SYSTEM

The following are the criteria that make the forecasting systems successful [16,17]:

- Prediction Accuracy: The predictions provided by the systems should be accurate, and this depends mainly on the quality of the data provide to the systems.
- Timeliness: Timely prediction of occurrence and outbreaks of pests and disease before they reach the threshold level is very important as it plays a crucial role in taking preventive control measures.
- User-Friendliness: The user interface should be simple and offer easily understandable recommendations, which can be very helpful to the farmers and make the work of extension workers easy.
- Cost-Effectiveness: Cost of production decreases as these systems help in minimizing the usage of pesticides and also lower the agricultural losses.
- Adaptability: The systems should be up to date, and they should be able to adapt to different kinds of crops, weather patterns, pests, diseases, and regions.
- Integration with IPM Practices: Implementing the forewarning systems in the IPM programs should be environment-friendly and promote the sustainable control of both pests and diseases.
- Data Availability and Quality: The success of a forewarning system mainly depends on the quality and quantity of the past and current data one can provide on meteorological parameters, insect population, disease occurrence and crop growth.

- Community Involvement: For the systems to be successful, it requires continued and cooperative learning among the farmer community, researchers, and extension workers.

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" [3,20].

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. These between year models are further divided into different types.

i. **Regression models:** This model is the simplest of all the models, and it assumes a simple linear relation between the past data of the variable and the future data. It is so simple and cannot be used more often because relationships between many weather variables can be non-linear [3].

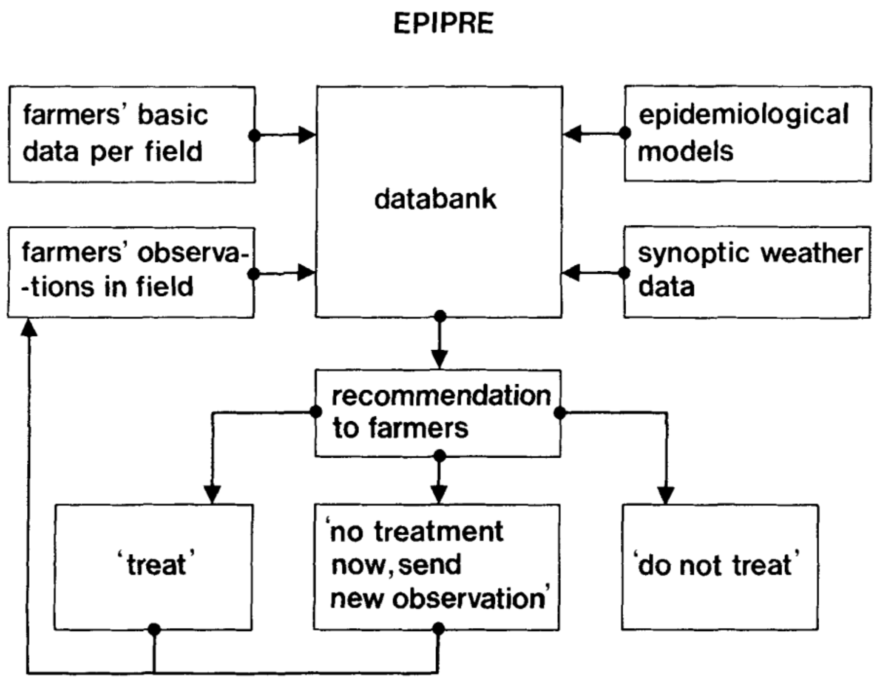
ii. **Complex Polynomial model:** The main aspect of this technique is that it selects the structure of the model without using prior information about the relation of independent variables with dependent variables. It assumes a non-linear relation between the predicted variable and the target variable [3].

iii. **Artificial Neural Networks:**These learn from the examples and capture the subtle relations among the data, even if the underlying relations are unknown and hard to describe. They infer the unseen part of a population often correctly, even if the data is noisy. To do this, it requires large amounts of data and deep learning power, which is the major problem [3].

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 (EPidemicsPREdiction and PREvention): A collaborative project called EPIPRE (EPidemicPREdiction 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

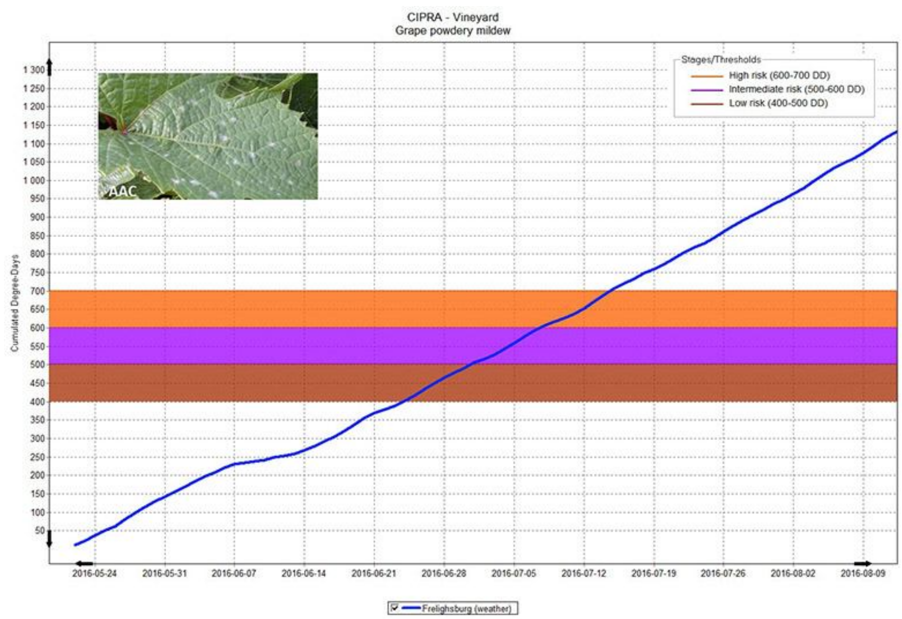
Fig 1: Block diagram of EPIPRE[42]

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, *Sitobionavenae, Metopolophiumdirhodum,* and *Rhopalosiphumpadi*. 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 systems[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 systems.

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 scientificmeans, the odds of pest development are computed.More than 130 forecasting systems for diseases, insect pests, crop phenology, and postharvest physiological disorders for more



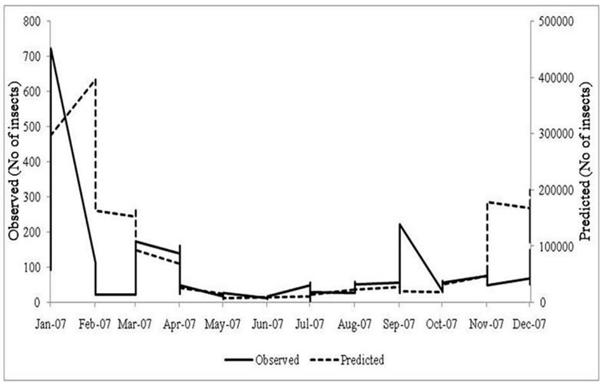
than 25 distinct crops are included in the CIPRA, all housed within a shared computer infrastructure. CIPRA is a tool that is always changing since new bioclimatic models or indicators are added to it every year. The CIPRA is a great tool for decision support regarding crop protection and production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

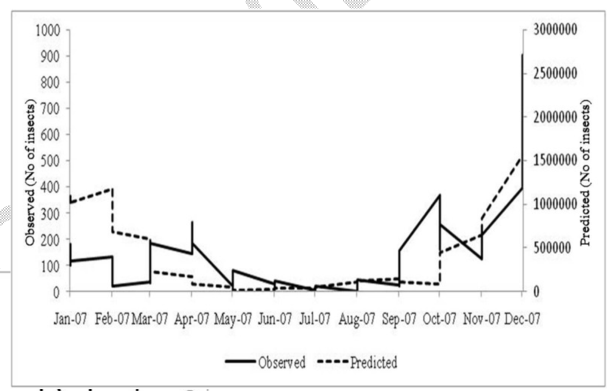
Fig 2: Sample graph from CIPRA software predicting the occurrence of Grapevine powdery mildew. Horizontal axis indicates the date while vertical axis indicates the number of cumulative degree days. Horizontally coloured strips across the graph indicate the level of the stages and thresholds of the organism.

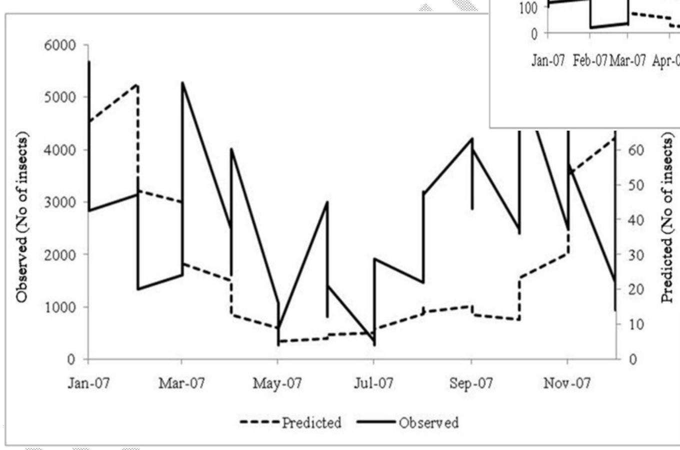
4.3 Weather based pest forewarning model for major insect pests of rice [26].

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 systems 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.

Fig 3: Observed and predicted light trap catches of YSB **Fig 4:** Observed and predicted light trap catches of BPH

Fig 5: Observed and predicted light trap catches of Leaf folder

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 systems' 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 were goodand from 60 DAS and 75 DAS were both reasonable; in contrast, every other combination had an extremely high error rate and classified as being poor.

Table No. 1 Validation of Forewarning model

Validation	Obs.pest	1DAS	30DAS	60DAS	75DAS	80DAS	95DAS	Selected_wth
2013	0	-2.6	-1.8	-2.8	0.6	0.8	-2.8	-1.8
2014	0.9	-15.6	0.9	1.8	0.0	1.2	-1.7	-2.8
RMSE		5.3	3.0	1.5	1.5	**1.0**	4.2	3.4
RMSE%		98.2	55.5	27.7	27.0	**19.1**	77.0	61.8
Category		**Poor**	**Poor**	**Fair**	**Fair**	**Good**	**Poor**	**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 systems 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 systems, farmers can lessen their dependency on reactive control techniques by anticipating pest issues and taking preventive action. **Decreased Pesticide Use:** These systems assist in optimising pesticide treatments by properly forecasting pest outbreaks, which lowers environmental contamination and chemical inputs. **Cost savings:**Timely predictions help in avoiding the losses caused by the various pests and diseases and also in lowering the cost of crop protection practices.

Sustainable Agriculture: Accurate prediction of pest occurrence helps farmers to plan their sprayings whenever necessary, which eventually reduces the amount of pesticide sprays and their ill effects on the environment and other beneficial organisms. Incorporatingweatherbased forewarning systems into integrated pest management (IPM)helps promote sustainable agriculture.

6.LIMITATIONS

Even though they have great potential, there are some challenges that one has to face while using these systems.

Data Accessibility: The success of these systems depends mainly on the quality of the meteorological and pest data we provide and also on the obtainability of the current data. However, it is very difficult to obtain all the necessary data or the data obtained can be inaccurate, mainly in under developed and developing nations.

Model Adaptation: Occurrence and outbreak of pests and diseases fluctuate widely between types of crops and areas, so these systems should be altered according to the particular circumstances.

Climate Change: Accuracy of prediction may be affected due to rapid shifting of climate because this brings changes in the past pest and weather correlations. So as to avoid any mishaps, these systems should be updated to the date.

Access to the technology: As these systems need more technical knowledge, smallholder farmers may face difficulties while accessing them and using them efficiently in their fields. Initiatives should be taken to educate the farmers regarding usage of these systems.

7. CONCLUSION

Forewarning systems based on weather are very useful to farmers, as they use different artificial intelligence techniques to predict the outbreaks of pests and diseases based on the meteorological data accurately and early. This precise and timely prediction provides an opportunity to the farmers to safeguard their crops by well planning their pest management strategies according to the pest outbreaks. So far, weather based forewarning systems are considered an excellent breakthrough in the field of agriculture; however, there are still issues regarding the adaptability of these systems to different climatic zones and the availability of data. If these issues are resolved, these systems can be truly helpful to the farmer community and in the sustainable agriculture.

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