

Epidemiology and forecasting of insect-pests and diseases for value-added agro-advisory

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सार – मॉडल का अभिप्राय संक्षिप्त और संगठित ज्ञान के अभिग्रहण से है। एक सिस्टम के भिन्न-भिन्न अवयवों के बीच इन अभिव्यक्तियों में दर्शाया गया है। अच्छी तरह से जाँचा परखा गया मौसम आधारित मॉडल हानिकारक कीटों और बिमारियों के बारे में अग्रिम चेतावनी देने के लिए प्रभावशाली वैज्ञानिक उपकरण हो सकता है क्योंकि इससे समय पर पौधों की सुरक्षा के उपाय किए जा सकते हैं। इस उद्देश्य के लिए भिन्न-भिन्न प्रकार की तकनीकें विकसित की गई हैं। इसमें सबसे साधारण तकनीक अनुभव पर आधारित नियमों की श्रेणी की है जोकि अनुभव पर आधारित है। यद्यपि इनका कोई वैज्ञानिक आधार नहीं है परन्तु संकट की शीघ्र चेतावनी पहले से देने में इसका अधिक उपयोग किया जाता है। उपयोग में लिया जाने वाला एक दूसरा उपकरण रिग्रेशन मॉडल है जो दो या दो से अधिक विचारों (Variables) के बीच संबंधों को दर्शाता है इससे एक विचार का पूर्वानुमान दूसरे विचारों से दिया जा सकता है। हानिकारक कीटों और बिमारियों का समय और मौसम परिवर्तनों (ठीक उसी प्रकार अथवा कुछ परिवर्तित रूपों में) के साथ प्रभावों का अध्ययन करने के लिए रैखिक तथा अरैखिक रिग्रेशन मॉडलों का अधिक प्रयोग किया जाता है। कंप्यूटर के आगमन के साथ ही अधिक जटिल तकनीकों जैसे : सिम्यूलेशन मॉडलिंग और मशीन से सीखने वाली विचारधारा जैसे कि डिसीजन ट्री इंडक्शन एल्गोरिथ्म्स, जेनेटिक एल्गोरिथ्म्स, न्यूरल नेटवर्क, सेटस आदि का विकास हुआ है। कृषि पर मौसम के प्रभाव सहित विभिन्न कारकों को दर्शाने के लिए पूरे विश्व में अनेक सिम्यूलेशन मॉडल विकसित किए गए हैं। इनसे अच्छा पूर्वानुमान दिया जा सकता है परन्तु इसके लिए अपेक्षित मात्रा में डेटा बेस की आवश्यकता है जो संभवतः अभी उपलब्ध नहीं है। अभी हाल में मशीन से जानकारी प्राप्त करने की अवधारणा ने हमारा ध्यान आकर्षित किया है जो परम्परागत मॉडल आधारित विधियों विरोधी है। मशीन से सीखने की अवधारणा स्वतः अनुकूलन की विधि पर आधारित है परन्तु इस मॉडल की समस्याओं के बारे में कुछ पूर्ववर्ती परिकल्पनाओं के बारे में अभी अध्ययन किया जाना है। इस तकनीक में उराहरणों से अधिक सीखा जाता है और डेटा के बीच क्रियाशील जटिल संबंधों को जाना जाता है हालांकि इनके बीच के संबंधों की जानकारी अज्ञात है अथवा उसका वर्णन करना कठिन है अनुभव के द्वारा सीखने पर आधारित यह मॉडल अनेक व्यवहारिक समस्याओं के लिए बहुत उपयोगी है जिसके लिए पर्याप्त डेटा उपलब्ध हैं। सुदूर संवेदी डेटा उस क्षेत्र में लगाई गई फसल के लिए उपयोगी सूचनाएं प्रदान कर सकता है तथा यहाँ की परिस्थितियों के बारे में जानकारी प्रदान कर सकता है बहु बर्णक्रमीय, सिनॉप्टिक तथा आवृत्तिमूलक विस्तार के कारण लिए गए आँकड़ों के उपयोग से धरातल के ऊपर इसके कुछ विशेष फायदे हैं। इसमें हानिकारक कीटों तथा बिमारियों से प्रभावित फसलों के क्षेत्रों का सटीक आकलन के साथ साथ संभावित नुकसान का आकलन करने का प्रयास किया गया है ताकि किसानों को उसका मुआवजा दिया जा सके इस शोध पत्र में फसल सुरक्षा सेवाओं के लिए एक इंटीग्रेटेड डिसीजन सपोर्ट सिस्टम (IDSS) के बारे में भी बताया गया है।

ABSTRACT. Models are means to capture, condense and organize knowledge. These are expressions, which represent relationship between various components of a system. A well-tested weather-based model can be an effective scientific tool for forewarning insect-pests and diseases in advance so that timely plant protection measures could be taken up. Various types of techniques have been developed for the purpose. The simplest technique forms the class of thumb rules, which are based on experience. Though these do not have much scientific background but are extensively used to provide quick forewarning of the menace. Another tool in practice is regression model that represents relationship

between two or more variables so that one variable can be predicted from the other (s). Linear and non-linear regression models have been widely used in studying relationship of insect-pests and diseases with time and weather variables (as such or in some transformed forms). With the advent of computers more sophisticated techniques such as simulation modelling and machine learning approach such as decision tree induction algorithms, genetic algorithms, neural networks, rough sets, etc. have been explored. A number of simulation models have been developed all over the world for quantifying effects of various factors including weather on agriculture. These may provide a good forecast but require detailed data base, which may not be available. Machine learning approach has recently received some attention. As opposed to traditional model-based methods, machine learning approach is self adaptive methods in that there are a few a priori assumptions about the models for problem(s) under study. This technique learns more from examples and captures subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. This modelling approach with ability to learn from experience is very useful for many practical problems provided enough data are available. Remotely sensed data can provide useful information relating to area under the crop and also the condition thereof. It has certain advantages over land use statistics due to multi-spectral, synoptic and repetitive coverage. An attempt has been made for accurate estimation of area affected by insect-pests and diseases in crops along with accurate assessment of damage due to the same are possible for providing compensation to farmers. In this study, an Integrated Decision Support System (IDSS) for Crop Protection Services is also discussed.

Key words – Epidemiology, Epizootology, IDSS.

1. Introduction

Epidemiology deals with dynamics of plant pathogen infecting host population. Bitter memories of Irish famine and potato late blight motivated plant pathologists to probe into reasons behind the same. They looked at biology of the pathogen, its life cycle, host-pathogen systems, etc. Eradication of barberry plants (Mehta, 1933) marked the beginning of phytoepidemiological awareness for plant disease management. ‘Dutch rules’ by van Everdingen (1926) for potato late blight prediction is relevant even today as recent systems consider the same meteorological parameters indicated therein. Gradually, meteorologists (Schroeder, 1960; Bourke, 1970), aerobiologists (Hirst, 1952; Gregory, 1968), mathematicians (Vanderplank, 1963), other phytopathologists *viz.*, Waggoner and Horsfall (1969) joined the bandwagon; Waggoner and Horsfall (1969) simulated plant disease epidemic on computer while Vanderplank (1963) viewed practical epidemiology and forecasting of plant diseases as a multi-disciplinary science. Post-Mehta era, the world saw how Nagarajan and Singh (1990) discovered that wheat rust epidemics over Indian subcontinent are influenced by western disturbance of air and depression that passes over the Nilgiri hills. Spores of wheat stem rust travel from South India to Central and North of the country. Monitoring of ambient conditions with western disturbance by weather satellite over north-west India between November and April could be used as index to find if it will be a year for brown rust, yellow rust or no rust (Nagarajan and Singh, 1990). Mankind has always been eager to know the unknown of the future to enable plan suitably for the same. With generation of knowledge, the disease triangle and tetrahedron were considered involving the interaction among host and pathogen in a given environment over time. Plant pest forecasting is a management system used to predict the occurrence or change in severity of plant diseases and insect-pests. At the field scale, these systems

are used by growers to make economic decisions about pest management. The environment is usually the factor that controls whether pest develops or not, the vulnerability of the host, presence of the pathogen or insect-pest in a particular season through their effects on processes such as over-seasoning or ability of the pest to cause damage. In these cases a pest forecasting system attempts to define when the environment will be conducive to development of the menace.

1.1. *Why study epidemiology/epizootology and forecasting of plant pest (including disease)?*

A wide gap exists between the potential yield and that realized at the farmers’ field. Among the factors contributing towards this yield gap are the biotic stresses that affect the crops. Severity of infestation of the insect-pests and diseases differs between seasons, regions and individual crops within a region. In the absence of stable, desirable and diverse sources of resistance to the biotic menaces, pesticides remain the only effective means to manage them. Knowledge about the timing of start of infestation of these pests and their gradual progress in advance could enable plan necessary pesticide schedule for the season, region on the particular crop against the specific menace expected. This could be enabled by development of region, crop and pest-specific prediction models to forewarn these menaces. Since these biotic menaces are weather-dependent, weather-based prediction models could be developed to enable manage these pests.

1.2. *Where to use forecast models?*

Forecast model devising consumes a lot of resources *viz.*, manpower, time, etc. Hence, it is important that such resources are provided only to an important crop. The candidate pest (both insect-pest and disease) should be sporadic and its occurrence, severity, progression should be influenced by weather factors and hence should vary

accordingly, should cause economically significant yield losses over large area and availability of timely and quality forecast could enable mitigate the risks due to the occurrence of the same by application of effective economic prophylactic measure. Forecast models provide an alternative to calendar spray schedule to bring need-based precision, *e.g.*, instead of sprays at 7-14-day intervals to spray at precise time just when and where the pest is likely to appear or has just initiated to enable cut input costs. Thus, precision pest management may bring down number of chemical pesticide sprays to provide economic and environmental benefits. Finally, the system of forecast should enable take economically acceptable action as an integral part of IPM package while growers should be capable and flexible enough to take due advantage of a pest forewarning. Forecasting model is a set of formulae, rule or algorithm patterned after the biology of the specific pathogen or insect-pest keeping in view the host and standard crop management practices. The stages of modelling start with development [assumptions and selection of key environmental and host variables (resistance to disease, gene-for-gene theory of Flor, 1942, etc.) apart from considering farmers' socio-economic situation (constraints, perceptions)], devising equations based on laboratory and field studies to predict risk of occurrence of disease and / or development of inoculum, validation (testing assumptions over agro-climatic zones and years; revise and refine based on results or needs of different locations) and implementation (grower trials and issue of advisories in public interest, transferred to private domain *viz.*, consultant, industry, etc. for improved crop management). Thus, to devise forecast model, thorough study of temporal and spatial changes in development of epidemics is important apart from reliable sampling procedure, wherein assessment of initial source status [inoculums of pathogen by spore traps and use of serological, molecular tools or egg of insect-pest or adults in insect-trap] could make the job easy. Forecasting plant disease epidemics or insect-pest epizootics is intellectually stimulating. Mostly, having maximum possible information about pest is useful before venturing to predict its development. Sometimes, one or two factors affecting pest development predominate so much that knowledge about them is sufficient to formulate a reasonably accurate forecast. Thus, forecasts could be based on initial inoculum, meteorological parameters and their combinations. Thus, the criteria for making prediction should be based on sound investigation in laboratory and field. If information on favourable weather conditions is known, subjective weights based on this information can be used for constructing weather indices. In absence of such information, correlation coefficients between targeted forecast and respective weather variable/product of weather variables can be used (Agrawal *et al.*, 2004).

2. Methodology for regional forecasting for crop protection advisories

The crux of crop protection advisory services to farmers depends on real-time availability of quality regional short-to-medium range weather forecasts and tested epidemiological models. In order to enable forecast for likely occurrence of any pest to be effective, the risk-related information must be made available to the targeted farmer at least 7-10 days ahead of actual occurrence of the menace so that the client is able to arrange for required economic action (*viz.*, spray of pesticide, etc.) to mitigate the impact of the pest. Thus, the farmers need to be advised on the mitigation strategies for likely impacts of weather parameters on pest infestation. Earlier most of the work focused on effects of a single meteorological variable on the host, pathogen, or the interaction of the two under controlled conditions. Use of 'Dutch rules', thumb rules or even empirical models have been used to forecast plant diseases *viz.*, potato late blight forecast presently in vogue (<http://web.pau.edu/potato/>). There are several disease forecasting networks across the globe *viz.*, maize (EPICORN – for Southern corn leaf blight), tomatoes and potatoes (EPIDEM, TOMCAST, BLITECAST – for early and late blights), apple (Maryblight, EPIVEN – for fireblight and scab), etc.

2.1. Models based on weather indices

The extent of weather influence on crop pests depends not only on the magnitude but also on the distribution pattern of weather variables over the crop season which, as such, calls for the necessity of dividing the whole crop season into fine intervals. This will increase number of variables in the model and in turn a large number of model parameters will have to be evaluated from the data. This will require a long series of data for precise estimation of parameters, which may not be available in practice. Thus, a technique based on relatively smaller number of manageable variables and at the same time taking care of entire weather distribution, weather indices were obtained, which were used as predictors for model development. In this type of model weekly weather data were utilized. For each weather variable two indices have been developed, one as simple total of values of weather parameter in different weeks and the other one as weighted total, weights being correlation coefficients between variable to forecast and weather variable in respective weeks. The first index will be representing the total amount of weather parameter received by the crop during the period under consideration while the other one will take care of distribution of weather parameter with special reference to its importance in different weeks in relation to the variable to forecast. On similar lines, composite indices were computed with

products of weather variables (taken two at a time) for joint effects. The general form of the model was

$$Y = a_0 + \sum_{i=1}^p \sum_{j=0}^1 a_{ij} Z_{ij} + \sum_{i \neq j}^p \sum_{j=0}^1 b_{iij} Z_{iij} + e$$

where

$$Z_{ij} = \sum_{w=n_1}^{n_2} r^{j iw} X_{iw}$$

$$Z_{iij} = \sum_{w=n_1}^{n_2} r^{j i'w} X_{iw} X_{i'w}$$

Y variable to forecast

X_{iw} value of i^{th} weather variable in w^{th} week

r_{iw} correlation coefficient between Y and i^{th} weather parameter in w^{th} week

r_{iij} correlation coefficient between Y and product of X_i and $X_{i'}$ in w^{th} week

p number of weather variables considered

n_1 initial week for which weather data were included in the model

n_2 final week for which weather data were included in the model

ε error term

In some cases previous disease incidence / pest population (or their indices) and /or previous year's last population has also been included in the model. Stepwise regression technique was used for selecting important variables to be included in the model. The performance evaluation measure considered is Mean Absolute Percentage Error (MAPE) :

$$\text{MAPE} = \frac{1}{m} \sum_{i=1}^m \left| \frac{Y_i - F_i}{Y_i} \right| \times 100$$

where, Y_i and F_i are the observed and forecast values respectively and m is the number of observations for which forecasts were worked out. In general, the models fitted well for all the available data with all the coefficients of determination highly significant and forecasts comparing well with the observed values. These weather-based location-specific forewarning models have

been developed for major diseases (Alternaria blight, white rust, powdery mildew) and aphid of oilseed *Brassica* in India (Desai *et al.*, 2004; Chattopadhyay *et al.*, 2005a&b; 2011; Laxmi and Kumar, 2011a). These have been validated with success over 2005-08 at Bharatpur (Rajasthan) for occurrence of Alternaria blight, white rust and aphid on Indian mustard crop, even with issue of agro-advisories for public use. Based on these models a *Weather based Rapeseed Mustard Aphid forewarning system* (<http://www.drmr.res.in/aphidforecast/index.php>) was developed.

2.2. Machine learning techniques

Fuzzy regression analysis can be applied to many real-life problems, in which strict assumptions of classical regression analysis cannot be satisfied. In regression analysis, the errors between a regression model and observed data are generally assumed as error that is a random variable having a normal distribution, constant variance, and a zero mean. In fuzzy regression analysis, the same unfitted errors are viewed as the fuzziness. Fuzzy regression can be quite useful in estimating the relationship among variables where the availability data are imprecise and fuzzy. It gives a fuzzy functional relationship between dependent and independent variables where vagueness is present in some form. There are three situations where the fuzzy analysis can be viewed *viz.* Crisp parameters and fuzzy data, Fuzzy parameters and crisp data and Fuzzy parameters and fuzzy data. Fuzzy regression method is based on minimizing fuzziness as an optimal criterion, which can be achieved by linear programming procedures (Kumar *et al.*, 2014). Machine learning techniques offer many methodologies like decision tree induction algorithms, genetic algorithms, neural networks, rough sets, fuzzy sets as well as many hybridized strategies for the classification and prediction (Komorowski *et al.*, 1999; Witten and Frank, 1999; Pujari, 2000; Han and Kamber, 2001; Jain *et al.*, 2009). Decision tree induction represents a simple and powerful method of classification that generates a tree and a set of rules representing the model of different classes from a given dataset. Decision Tree (DT) is a flow chart like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test and each leaf node represents the class. The top most node in a tree is the root node. For decision tree ID3 algorithm and its successor C4.5 algorithm by Quinlan (1993) are widely used. One of the strengths of decision trees compared to other methods of induction is the ease with which they can be used for numeric as well as nonnumeric domains. Another advantage of decision tree is that it can be easily mapped to rules. Artificial Neural Networks (ANNs) is another attractive tool under machine learning techniques for forecasting and classification purposes. ANNs are data-driven self-adaptive methods wherein

there are a few a priori assumptions about the models for problems under study. These learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe. After learning from the available data, ANNs can often correctly infer the unseen part of a population even if data contains noisy information. As forecasting is performed *via* prediction of future behaviour (unseen part) from examples of past behaviour, it is an ideal application area for ANNs, at least in principle (De wolf *et al.*, 2000; Jain *et al.*, 2009; Laxmi and Kumar, 2011a; Laxmi and Kumar, 2011b). However, the technique requires a large data base.

2.3. Model for qualitative data - Logistic model

$$P(Y=1) = \frac{1}{1 + e^{-L}} + \varepsilon$$

The pest population/damage below the threshold value can be taken as non-epidemic status whereas above the threshold value as epidemic status of a pest (including disease). Accordingly, the quantitative data on character under study (*Y*) has been converted into two categories *i.e.*, dichotomous form: *Y* = 0 for non-epidemic and 1 for epidemic status. To forecast epidemic status of crop, logistic regression model was developed. The pest epidemic-status (*Y*) was considered as dependent variable and weather indices as explanatory variables. The model used was :

L being a linear function of weather-indices defined below:

$$L = a_0 + \sum_{i=1}^p \sum_{j=0}^1 a_{ij} Z_{ij} + \sum_{i \neq i}^p \sum_{j=0}^1 b_{ii'j} Z_{ii'j} + \varepsilon$$

where,

$$Z_{ij} = \sum_{w=n_1}^{n_2} r_{iw}^j X_{iw}$$

$$Z_{ii'j} = \sum_{w=n_1}^{n_2} r_{ii'w}^j X_{iw} X_{i'w}$$

The symbols are already defined earlier.

Forecast / Prediction were obtained using following rule:

P > 0.5 possibility of pest epidemic

P ≤ 0.5 possibility of non-occurrence of pest-epidemic

For qualitative data or mere availability of epidemic status, logistic regression models could be developed for forewarning occurrence of pests by classifying the data into two or three categories [occurrence and non-occurrence as 1/0 (2 categories) or low, medium and high severity as 0, 1, 2 (three categories) etc.] of disease (Agrawal *et al.*, 2014).

2.4. Use of remote sensing in forecasting of crop pests

We have discussed the success of regional or location-specific networks or models in vogue to forecast occurrence of different plant diseases. These are all based on observations recorded at surface level for disease and meteorological factors. Data recorded at surface meteorological observatories remain valid to a maximum range of 75 km radius. In order to cover all agro-ecological zones of India (3287240 sq km), we would require weather data recording at least at ~1200 observatories (presently ~1000 meteorological observatories are functional in India with some linked through satellite communication, not uniformly distributed) apart from multi-year observations on disease epidemics in those many locations. Most (70%) of the land-holding size of farmers average 0.39 ha (some even 20 m × 20 m) and only 1% crop growers hold > 10 ha (mean: 17.3 ha). Patchiness of pest incidence could pose problems in its proper assessment. Thus, such exercise could be highly time-consuming and labour-intensive for the seventh largest country with difficult terrain, 66% gross cropped area under food crops, lacking in number of skilled manpower and shrinking resources. Remote sensing overcomes such limitations with ability to access all parts of the country and can often achieve a high spatial resolution (5 m × 5 m by multi-spectral LISS IV at 25-day intervals), thus leading to an accurate estimation of area affected. Further, in case of possible failures in forecasts, accurate assessment of damage due to pest is possible for providing compensation to farmers. Of course, remote sensing does involve standardization of techniques based on ground-truths and hence could be cross-checked with actual ground situation.

2.5. Coping with climate change and sustain accuracy of forecast

In view of changing climate, the devised and to-be-born models need to be oriented to dynamic mode. The models already developed are based on some meteorological and pest observations recorded in the past and they are based on previous pest-weather correlation.

However, with change in climate, the concerned relationship is also bound to change apart from behaviour of the hosts, newer varieties, cropping practices, etc. (Chakraborty *et al.*, 2008). A dynamic model incorporates the recorded data of each crop season for a particular pest to suitably revise itself and thus remains stable, relevant enough to continue providing accurate forecast. Farmers' decisions are of vital importance for good yields of crops. Forecasted weather products and area-wide weather networks are becoming more prevalent. Now, the challenge is to bring continuous improvement in productivity, profitability, stability and sustainability of major farming systems, wherein scientific management of crop pests holds a pivotal role (Swaminathan, 1995). Crop loss models, representing a dynamic interaction between pest and host, are essential for forecasting losses due to the same. Accurate information concerning possible yield losses due to occurrence of a pest is needed by growers or plant protection specialists to decide on cost-effective control measures. With an increasing concern for cleaner environment and discouragement for chemical pesticide use, there is need to approach pest management through knowledge on dynamics of plant diseases as an art of living with them (Zadoks, 1985). Thus, future research and education in crop protection does need to include this aspect of pest management, for which fund requirement would certainly be lesser than many ambitious ones.

3. Discussion

The first multi-spectral airborne study for identification of plant disease using remote sensing in India was conducted jointly by ICAR and ISRO that demonstrated identification of coconut wilt using aerial false colour photography (Dakshinamurti *et al.*, 1971). At present, satellite remote sensing (ISRO) data are also being used in generating and improving weather forecasts, providing crop estimate in terms of net sown area and yield, issued in operational mode for the last few years with reasonable accuracy for rice, wheat, mustard, potato, etc. thanks to ICAR-ISRO (SAC) collaboration under MoA (DAC)-funded project FASAL (Forecasting Agricultural output using Space, Agrometeorological and Land-based observations). Mustard production has been forecasted at national level under FASAL using multi-date temporal AWiFS (Advanced Wide Field Sensor on IRS-P6; 56 m × 56 m) and RADAR (Radio Detection And Ranging) data. Two forecasts were made during the season at different crop growth stages. Encouraged by these successes, India Meteorological Department (GoI) envisages implementation of FASAL initially at 46 centres, which is likely to be extended to 130 stations in due course (IMD, 2011). Success of remote sensing for forecasting crop pests depends on high-resolution (1-5 m) multispectral / hyperspectral or microwave observations from satellite platform. Research efforts have been put to

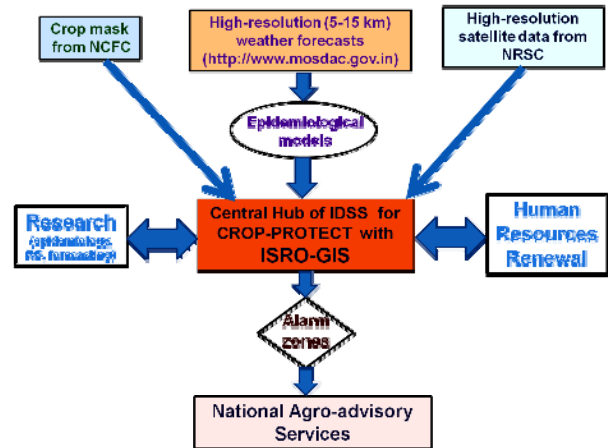


Fig. 1. Proposed architecture of IDSS for crop protection services

apply or refine ground-based models using satellite-based spatial weather and high-resolution remote sensing (RS) observations for mustard aphid infestation (Bhattacharya *et al.*, 2007a; Dutta *et al.*, 2008). Use of remote sensing (RS) and Geographic Information System (GIS) could be explored for analysis of satellite-based agro-met data products, mapping geographical distribution of pests and delineating the hotspot zones. Super-imposition with causative abiotic and biotic factors on visual pest maps can be useful for pest forecasting. Since, damaged plants increase reflectance particularly in chlorophyll absorption band (0.5-0.7 μm) and water absorption bands (1.45-1.95 μm), forecasting crop pests is possible by remote sensing. Though information on this aspect is scanty, pest severity assessment and yield loss estimation using changed reflectance pattern of affected plants can be attempted. Remote sensing (greenness vegetation index derived from LANDSAT MSS digital data, four bands) has been successfully used to distinguish the healthy wheat in India from diseased wheat in Pakistan. Favourable weather from January to April and a sudden rise in temperature during cropping season are the main causes for yellow rust disease. Routine monitoring at surface for weather and by remote sensing could help predict epidemic well before first appearance of the disease on the crop, giving a positive edge to make accurate decision related to disease management (Krishna *et al.*, 2014). Similarly, preparation of mustard crop mask, mapping of spatial distribution of aphid (population density) growing zones and prediction of its growth, dates of severe pest infestation (peak population) at each grid level in the Bharatpur region of Rajasthan state (Bhattacharya *et al.*, 2007a; Dutta *et al.*, 2008) was possible. It has also been possible to detect *Sclerotinia* rot-affected mustard using remote-sensing technology (Dutta *et al.*, 2006; Bhattacharya *et al.*, 2007b). In fact, development of three-stage tracking system of candidate

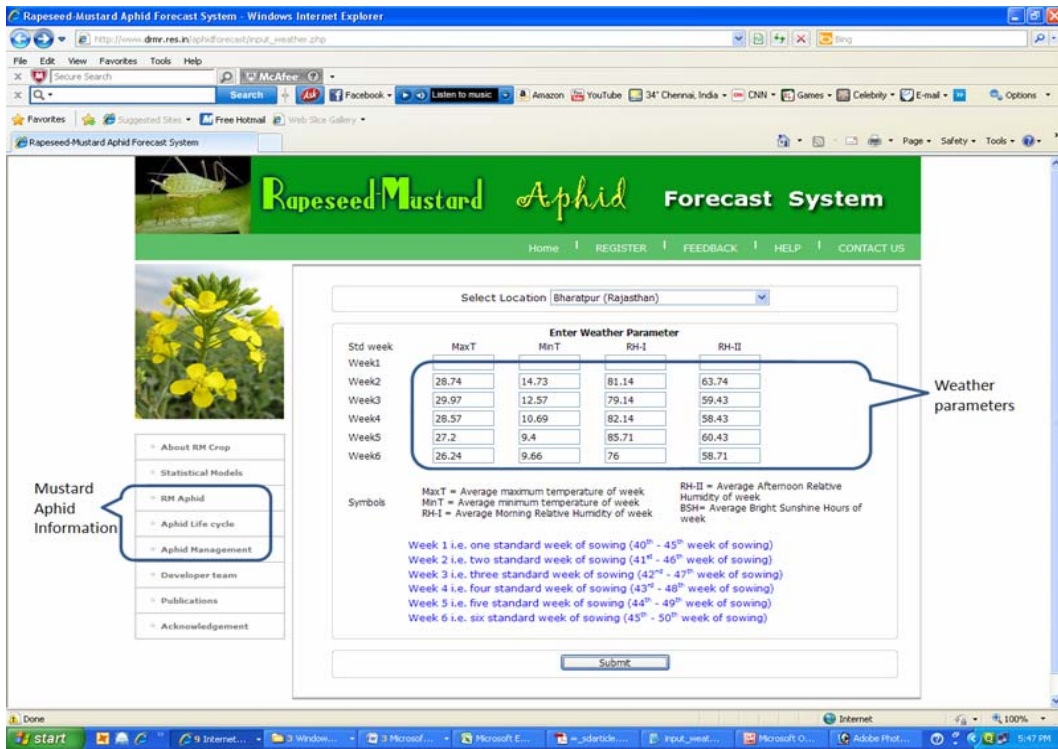


Fig. 2. Browse aphid information & submit of weather parameter

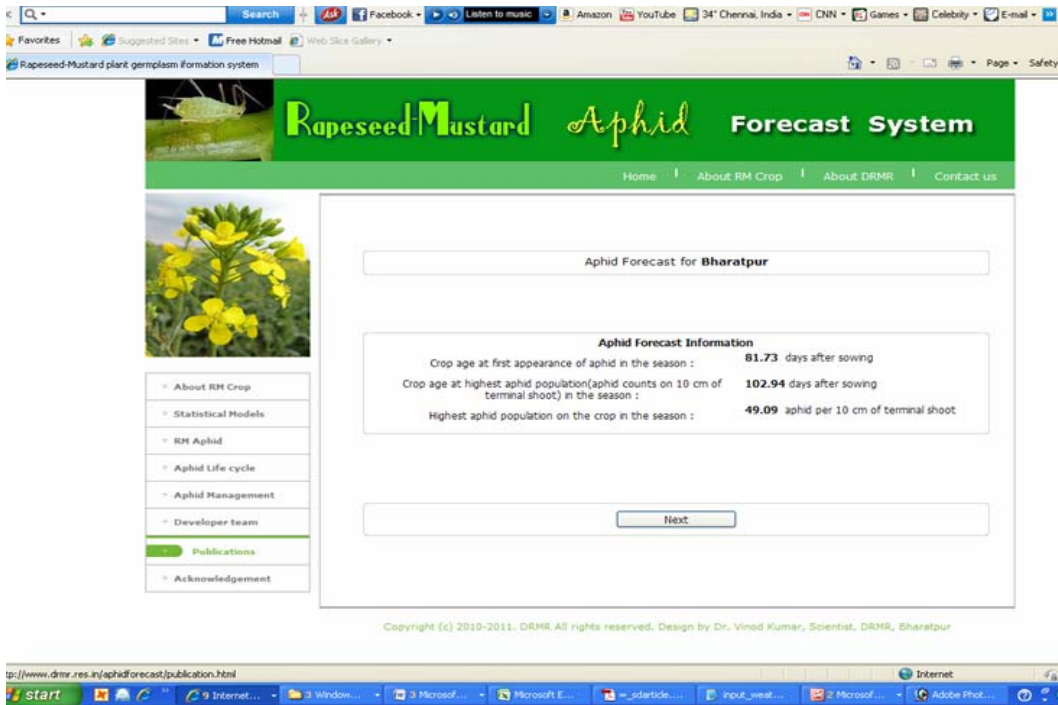


Fig. 3. System forecast output results

pests would be ideal for onset, persistence and diagnosing damaged and healthy crop patches using meteorology,

high-resolution remote sensing as demonstrated for multi-spectral and hyperspectral mustard rot

disease (Bhattacharya and Chattopadhyay, 2013). These successful experiences could certainly be effective boosters for any future endeavour.

But the potential benefits of short-to-medium range weather forecast from numerical weather prediction (NWP) models or future climate projections have been least harnessed in India for regional crop protection services. Recent momentum to assimilate more updated satellite-based spatio-temporal atmospheric and land surface products from Indian geostationary satellites (Kalpana-1, INSAT 3A) for high resolution (5-15 km) weather forecasts from advanced NWP model such as WRF (Weather Research and Forecasters) is encouraging. Such regular high-resolution forecast products are available for the registered users (<http://www.mosdac.gov.in>). The National Crop Forecasting Centre (NCFC) has been functioning at IARI, New Delhi under the behest of MoA (DAC). Therefore, an Integrated Decision Support System (IDSS) for Crop Protection Services (Fig. 1) can be imagined with its evolution in a phased manner, which could have the following three components: (A) Operational focus (with periodic production of alarm zones encompassing 127 agro-climatic zones through well-tested models, forecast weather, high-resolution remote sensing data and operational crop map in the GIS framework), (B) Research priorities [(i) Development of forecast models for major pests with large-scale applicability, validation in farmers' fields and model refinements, (ii) Evaluation and improvement in quality of well-validated satellite-based products, improved data assimilation approaches, (iii) field-to-satellite-based remote sensing with high-resolution observations to differentiate among crops, among phenological stages within crop growth period, biotic stresses from abiotic stresses (moisture and nutrients), normal health and (iv) development of models for minor pests in view of climate change scenario], (C) Human Resources renewal [(i) creation of experts on handling of spatial data, who could be brave enough to think differently, bold enough to believe that as a team they could bring a positive change in the present practices of pest management and talented enough to do it, (ii) familiarization of policy makers with more of digital products for interpretation and (iii) regular feedback mechanism from farmers through VRC (Village Resources Centre) network using satellite communication].

Use of computer-based decision support system for local-scale

Forecasted information needs to be simple and user-friendly. Interpretation and use of these devised prediction

models is difficult for persons not having proper statistical knowledge. Further, keeping in view the need to help the plant researchers, extension personnel and farmers in forecasting of pests and timely application of control measures, computer and web-based systems are developed. The software uses statistical models to predict pest occurrence well in advance of its actual arrival on the crop. The architecture of software could be multi-layered viz., Client Side Interface Layer [CSIL; using Hyper Text Markup Language (HTML) and JavaScript with forms for accepting information from the user and validating those forms], Server Side Application Layer (SSAL) and Database Layer (DBL; by using MS-SQL Server database for storing users' information (*i.e.*, login name, login password). On-line decision support systems to forecast different pests are in use across the globe viz., tan spot, septoria leaf blotch, leaf rust and Fusarium head blight /scab diseases of wheat (<http://www.ags.ndsu.edu/ndsuaug/features/small-grain-disease-forecasting/>), canola light leaf spot (*Pyrenopeziza brassicae* on <http://www.rothamsted.bbsrc.ac.uk/Research/Centres/Content.php?Section=Leafspot&Page=l1sforecast>) and Phoma stem canker (*Leptosphaeria maculans*, *L. biglobosa* on <http://www.rothamsted.bbsrc.ac.uk/Research/Centres/Content.php?Section=Leafspot&Page=phomaforecast>). With support from ICAR, we too have designed and implemented web-based forecast software (www.drmr.res.in/aphidforecast/index.php) for prediction of mustard aphid (*Lipaphis erysimi*) on oilseed *Brassicacae* for different locations (Bharatpur, Morena, Hisar, Ludhiana, Pantnagar, Berhampur) in India. This software, developed by deploying ubiquitous unbeatable open sources LAMP technology, uses weather parameters as independent variables to predict crop age at time of first appearance of aphid on crop, peak number of aphid and crop age at peak population as dependent variables, well ahead of actual occurrence of the event. Online evaluation of the system is in process and initial user-response has been very positive due to effective forecast and the easy user interface. Parallel to this, we have also developed a computerized image-based Rapeseed-Mustard Disease Identification and Management (RMDI&M) expert Software to identify and manage oilseed *Brassica* diseases, which provides necessary support for the mustard grower. The system can be used on any machine having internet connectivity.

This internet-based system to forecast rapeseed-mustard aphid occurrence, has been implemented by embedding most effective location-specific statistical models for aphid forecast. This web-based tool for mustard growers on the status of aphid infestation in crops for different locations can decide the schedule of insecticide application. The user has to input weather parameter by selecting location closest to their crop

planting area and the system provides a forecast of aphid incidence along with recommendations for insecticide application. The forecast regarding occurrence of aphid (*Lipaphis erysimi*) on oilseeds *Brassica* crops in season can be available to farmers with sufficient lag period for taking necessary action. This tool enables avoid unwarranted sprays of insecticide to prevent avoidable expenditure of the farmer and also safeguards the environment from undue chemical pesticide load. Weather indices based regression models are used in the backend for the online aphid forewarning systems (Kumar *et al.* 2012). The software is a user-friendly one. Users just have to feed the recorded weather variables prevailing in their areas, *viz.*, weekly averages of temperature (maximum), temperature (minimum), relative humidity (morning), relative humidity (afternoon), and hours of bright sunshine for any set of six consecutive weeks from 40th to 50th week of crop season starting at week of sowing in the 'submit' form of the server (Fig. 2). After submission of weather parameters, the software forecasts: (i) crop age at which mustard aphid first appears on the crop, (ii) peak number of aphid (aphid population) expected on the crop in the season and (iii) crop age at peak number of aphid just by submitting the data (Fig. 3). These models used in the software are advantageous over earlier ones (Kar and Chakravarty, 2000; Chakravarty and Gautam, 2002) as these take in to account several weather parameters and not just the temperature. Further, these models cover the major locations of the oilseed *Brassica* growing regions of India that face onslaught of the aphid menace.

4. Conclusion

The main challenges of crop protection advisory service within the overall gamut of value-added agro-advisory service are the availability of high-quality weather forecasts capable of predicting anomalies at shorter time scales, real-time spatio-temporal data on crop phenology and hydro-thermal regimes such as soil moisture, land surface temperature to predict onset and evaluate the persistence. Discrimination between abiotic and biotic stresses is a highly complex issue, which needs thorough research. However, detection and quantification of damage or yield loss need the use of hyperspectral data. In addition, most of the state-of-the-art models are solely based on weather elements devoid of any biological or surface characteristics. Therefore, with the availability of new datasets from space-based observations these models would also require improvement and fine-tuning. With the changing global climate there is a possibility of appearance of new category of pests instead of traditionally recurrent ones. Therefore, the root cause needs to be investigated through host-pest interaction using crop-climate data.

References

- Agrawal, R., Mehta, S. C., Bhar, L. M. and Kumar, A., 2004, "Development of weather-based forewarning system for crop pests and diseases", Report, MM-III-17, NATP, IASRI, ICAR.
- Agrawal R., Kumar, Amrender and Singh, S. K., 2014, "Forecasting podfly in late pigeonpea", *Indian Journal of Agricultural Sciences*, **84**, 214-17.
- Bhattacharya, B. K., Dutta, S., Dadhwal, V. K., Parihara, J. S., Chattopadhyay, C., Agrawal, R., Kumar, V., Khan, S. A., Roy, S. and Shekhar, C., 2007a, "Predicting aphid (*Lipaphis erysimi*) growth in oilseed *Brassica* using near surface meteorological data from NOAA TOVS – a case study", *International J. Remote Sensing*, **28**, 3759-3773.
- Bhattacharya, B. K., Chattopadhyay, C., Dutta, S., Meena, R. L., Roy, S., Parihar, J. S. and Patel, N. K., 2007b, "Detection of Sclerotinia rot incidence in Indian mustard from polar orbiting satellite platform", In : Proceedings, 12th International Rapeseed Congress, Vol. IV (Plant Protection), Wuhan, China, 26-30 Mar 2007 (Eds. Fu Tingdong, Guan Chunyun), Science Press USA Inc., 79-83.
- Bhattacharya, B. K. and Chattopadhyay, C., 2013, "A multi-stage tracking for mustard rot disease combining surface meteorology and satellite remote sensing", *Computers and Electronics in Agriculture*, **90**, 35-44.
- Bourke, P. M. A., 1970, "Use of weather information in the prediction of plant disease epiphytotic", *Ann. Rev. Phytopathol.*, **8**, 345-369.
- Chakravarty, N. V. K. and Gautam, R. D., 2002, "Forewarning Mustard Aphid", Division of Agril. Physics, IARI, New Delhi, p63.
- Chakraborty, S., Luck, J., Holloway, G., Freeman, A., Norton, R., Garrett, K. A., Percy, K., Hopkins, A., Davis, C. and Karnosky, D. F., 2008, "Impacts of global change on diseases of agricultural crops and forest trees", *CAB Reviews: Perspectives in Agriculture, Veterinary Sciences, Nutrition and Natural Resources*, **3**, 1-15.
- Chattopadhyay, C., Agrawal, R., Kumar, A., Bhar, L. M., Meena, P. D., Meena, R. L., Khan, S. A., Chattopadhyay, A. K., Awasthi, R. P., Singh, S. N., Chakravarty, N. V. K., Kumar, A., Singh, R. B. and Bhunia, C. K., 2005a, "Epidemiology and forecasting of Alternaria blight of oilseed *Brassica* in India - A case study", *Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz*, **112**, 351-365.
- Chattopadhyay, C., Agrawal, R., Kumar, A., Singh, Y. P., Roy, S. K., Khan, S. A., Bhar, L. M., Chakravarty, N. V. K., Srivastava, A., Patel, B. S., Srivastava, B., Singh, C. P. and Mehta, S. C., 2005b, "Forecasting of *Lipaphis erysimi* on oilseed Brassicas in India - A case study", *Crop Protection*, **24**, 1042-1053.
- Chattopadhyay, C., Agrawal, R., Kumar, A., Meena, R. L., Faujdar, K., Chakravarty, N. V. K., Kumar, A., Goyal, P., Meena, P. D. and Shekhar, C., 2011, "Epidemiology and development of forecasting models for White rust of *Brassica juncea* in India", *Archives of Phytopathology and Plant Protection*, **44**, 751-763.
- Dakshinamurti, C., Krishnamurthy, B., Summanwar, A. S., Shanta, P. and Pisharoty, P. R., 1971, "Remote sensing for coconut wilt", In: *Proc. 6th Intl. Symposium on Remote Sensing of Environment*. Environmental Res. Inst., Michigan, Ann Arbor, USA, 25-29.

- De Wolf, E. D. and Franci, L. J., 2000, "Neural network classification of tan spot and Stagonospora blotch infection periods in a wheat field environment", *Phytopathology*, **90**, 108-113.
- Desai, A. G., Chattopadhyay, C., Agrawal, R., Kumar, A., Meena, R. L., Meena, P. D., Sharma, K. C., Rao, M. S., Prasad, Y. G. and Ramakrishna, Y. S., 2004, "Brassica juncea powdery mildew epidemiology and weather-based forecasting models for India – a case study", *Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz*, **111**, 429-438.
- Dutta, S., Bhattacharya, B. K., Rajak, D. R., Chattopadhyay, C., Dadhwal, V. K., Patel, N. K., Parihar, J. S. and Verma, R. S., 2008, "Modelling regional level spatial distribution of aphid (*Lipaphis erysimi*) growth in Indian mustard using satellite-based remote sensing data", *International J. Pest Management*, **54**, 51-62.
- Dutta, S., Bhattacharya, B. K., Rajak, D. R., Chattopadhyay, C., Patel, N. K. and Parihar, J. S., 2006, "Disease detection in mustard crop using EO-1 hyperion satellite data", *J. Indian Soc. Remote Sensing (Photonirvachak)*, **34**, 325-329.
- Flor, H. H., 1942, "Inheritance of pathogenicity in *Melampsora lini*.", *Phytopathology*, **32**, 653-669.
- Gregory, P. H., 1968, "Interpreting plant disease dispersal gradients", *Ann. Rev. Phytopathol.*, **6**, 189-212.
- Han, J. and Kamber, M., 2001, "Data Mining Concepts and Techniques", Morgan Kaufmann Publisher.
- Hirst, J. M., 1952, "An automatic volumetric spore trap", *Annals Appl. Biol.*, **39**, 257-265.
- IMD (India Meteorological Department), 2011, "Future projections in AAS", Retrieved from http://www.imd.gov.in/services/agri_new/Activities.htm on 15 October, 2011 at 12:42 hrs IST.
- Jain, R., Minz, S. and Ramasubramanian, V., 2009, "Machine learning for forewarning crop diseases", *J. Indian Soc. Agril. Stat.*, **63**, 97-107.
- Kar, G. and Chakravarty, N. V. K., 2000, "Pod area index, crop growth rate and intercepted photosynthetically active radiation as influenced by sowing dates in cultivars of Brassica", *Indian. J. Pl. Physiol.*, **5**, 248-252.
- Komorowski, J., Pawlak, Z., Polkowi, L. and Skowron, A., 1999, "Rough Sets : A Tutorial", In: *Rough Fuzzy Hybridization*, Pal S.K. and Skowron, A.(eds.), Springer, 3-99.
- Krishna, G., Sahoo, R. N., Pargal, S., Gupta, V. K., Sinha, P., Bhagat, S., Saharan, M. S., Singh, R. and Chattopadhyay, C., 2014, "Assessing wheat yellow rust disease through hyperspectral remote sensing", *The Intl. Archives of the Photogrammetry, Remote Sensing and Spatial Information Science*, Vol. XL-8, ISPRS tech. Commission, VIII Symposium, 09-12 December 2014, Hyderabad, India, 1413-1416 (doi:10.5194/isprsarchives-XL-8-1413-2014).
- Kumar A., Srinivas P. S., Mishra A. K. and Chandrasekhran, H., 2014, "Fuzzy regression interval models for forewarning onion thrips", *IEEE - International Conference on Computing for Sustainable Global Development (INDIACom)*, 197-201.
- Kumar, V., Kumar, A. and Chattopadhyay, C., 2012, "Design and implementation of web-based aphid (*Lipaphis erysimi*) forecast system for oilseed Brassicas", *The Indian Journal of Agricultural Sciences*, **82**, 608-614.
- Laxmi, R. R. and Kumar, A., 2011a, "Forecasting of powdery mildew in mustard (*Brassica juncea*) crop using artificial neural networks approach", *Indian J. Agric. Sci.*, **81**, 855-860.
- Laxmi, R. R. and Kumar, A., 2011b, "Weather based forecasting model for crops yield using neural network approaches", *Statistics and Applications*, 9 (1&2 New Series), 55-69.
- Mehta, K. C., 1933, "Rusts of wheat and barley in India - A study of their annual recurrence, life- histories and physiologic forms", *Indian J. Agric. Sci.*, **3**, 939-962.
- Mishra, A. K., Prakash, O. M. and Ramasubramanian, V., 2004, "Forewarning powdery mildew caused by *Oidium mangiferae* in mango (*Mangifera indica*) using logistic regression models", *Indian Journal of Agricultural Sciences*, **74**, 2, 84-87.
- Nagarajan, S. and Singh, D. V., 1990, "Long-distance dispersion of rust pathogens", *Ann. Rev. Phytopathol.*, **28**, 139-153.
- Pujari, A. K., 2000, "Data Mining Techniques", Universities Press, Hyderabad, India.
- Quinlan, J. R., 1993, "C4.5: Programs for Machine Learning", Morgan Kaufman, San Mateo, CA, USA.
- Schröder, H., 1960, "Dispersal by air and water – the flight and landing", In: *Plant Pathology – An Advanced Treatise*, Vol. 3 (Eds. J. G. Horsfall and A. E. Dimond), 169-227.
- Swaminathan, M. S., 1995, "Foreword", In: *Dynamics of Plant Diseases* (S. Nagarajan and K. Muralidharan), Allied Publ. Ltd., New Delhi, pV.
- Van Everdingen, E., 1926, "Het verband de wears gesterheid ende aardappelzeiekte (*Phytophthora infestans*)", *Tijdschr. Plantennziekten.*, **32**, 129-140.
- Vanderplank, J. E., 1963, "Plant Disease – Epidemics and Control", Acad. Press, NY, p349.
- Waggoner, P. E. and Horsfall, J. G., 1969, "Epidem – A simulator of plant disease written for a computer", In: *Bull. Conn. Agric. Expt. Stn. No. 698*, Connecticut, USA, p80.
- Witten, I. H. and Frank, E., 1999, "Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations", Morgan Kaufmann Publishers.
- Zadoks, J. C., 1985, "On the conceptual basis of crop loss assessment: the threshold theory", *Ann. Rev. Phytopathol.*, **23**, 455-473.