Data Mining and Wireless Sensor Network for Agriculture Pest/Disease Predictions

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***Abstract*— Data driven precision agriculture aspects, particularly the pest/disease management, require a dynamic crop-weather data. An experiment was conducted in a semi-arid region to understand the crop-weather-pest/disease relations using wireless sensory and field-level surveillance data on closely related and interdependent pest (Thrips) – disease (Bud Necrosis) dynamics of groundnut crop. Data mining techniques were used to turn the data into useful information/knowledge/relations/trends and correlation of crop-weather-pest/disease continuum. These dynamics obtained from the data mining techniques and trained through mathematical models were validated with corresponding surveillance data. Results obtained from 2009 & 2010 *kharif* seasons (monsoon) and 2009-10 & 2010-11 *rabi* seasons (post monsoon) data could be used to develop a real to near real-time decision support system for pest/disease predictions.**

Keywords- Wireless Sensor Networks; Data Mining; Precision Agriculture; Pest/Disease Management;

I. Introduction

In recent years, there has been a large infection area of crop diseases and insect pest as well as the degree of its seriousness, which caused enormous economic losses to the peasants. Crop losses due to pests and diseases are quite considerable, particularly in the Indian semi-arid conditions [Reddy]. Weather plays an important role in agricultural production. Oilseed crops are more prevalent in the weather based fragile agriculture systems (semi arid regions). Among the oilseed crops groundnut (peanut) crop is prone to attack by numerous pest/disease to a much larger extent than many other crops. Significant crop losses by these diseases have been reported from Australia, India and the USA [15, 4].

Among the pests, Thrips species occur as a complex, starting from vegetative stage till the harvest of the crop. It damages the chlorophyll content of the leaf terminals. Besides causing direct damage to the crop, Thrips are known to cause more indirect damage by attacking as vectors of viral disease viz, groundnut Bud Necrosis Virus (BNV). In India, the disease occurs with the incidence ranging from 0-98% [9, 19]. BNV infection in the young stage will result in death of the plant due to server necrosis.

Forecasting systems are based on assumptions about the pathogen's interactions with the host environment and the disease triangle. The objective is to accurately predict when the three factors - host, environment, and pathogen - all economic losses [7, 10]. Critical threshold of the meteorological elements for the incidence, spread and intensification of pests and disease determined in the laboratory conditions have little relevance to the field condition. Therefore, they have to be determined and monitored under field conditions through simultaneous observation of micrometeorological parameters and the pertinent data on pest and disease [16].

Sensor network technology (wired or wireless) is a potential system suitable for collecting the real time data on different parameters pertaining to weather, crop/soil and environment, which in turn helps in developing open solutions for majority of the agricultural processes. The wireless sensors are cheap enough for wide spread deployment in the form of a mesh network and also it offers robust communication through redundant propagation paths. Wireless Sensor Network (WSN) allow faster deployment and installation of various types of sensors as the network provides self-organizing, self-configuring and self-diagnosing capabilities to the sensor nodes. It is a system comprised of radio frequency transceivers, sensors, microcontrollers and power sources. They are relatively low-cost, consumes low-power, small devices equipped with limited sensing, data processing and wireless communication capabilities, which perfectly suites the precision agriculture where decisions are made at micro-climatic level at right time/place/input [3].

In the present scenario, agricultural data virtually are being harvested along with the crops and are being collected/ stored in databases. As the volume of the data increases, the gap between the amount of the data stored and the amount of the data analyzed increases. Such data can be used in productive decision making if appropriate data mining (DM) techniques are applied. DM allows to extract the most important information from such a vast data and to uncover previously unknown patterns and the hidden relationships within the data that may be relevant to current agricultural problems. With the ever-increasing amount of information about their farms, farmers are not only harvesting in terms of agriculture output but also a large amounts of data. These data should be used for optimization [8].

Numerous advances in science and technology has made it quite essential that farming in the future would adopt techniques that aid better decision making during a crop cycle. Precision farming is an emerging methodology in today's context of agriculture and it definitely holds the key in the future. Researches on utility of macroclimatic data on

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Precision Agriculture has been carried at [12, 18, 29], however, very few research works available with sensory based microclimatic data.

AgriSens were used to test the feasibility of capturing and analyzing data and facilitated global data accessibility from multiple wireless sensor pods to study the efficient irrigation as well disease forecasting for grape vineyard [3]. Prabhakar et al., 2010 discussed through a WSN named COMMON-Sense Net that monitors several environment parameters and is deployed in an Indian semi-arid region for the benefit of small and marginal farmers to provide better diagnosis for better crop management [12]. 'U-Agri' from Centre for Development of Advanced Computing (C-DAC), Hyderabad developed low cost sensor networks which encompass the farm environment and provide macro and micro climate information on groundnut crop for a Decision Support System (groundnut pest Leaf Miner and disease Leaf Spot) [18]. However, U-Agri does not address the hidden correlation of weather-pest/disease-crop and the vector pest (Thrips) and disease (BNV) interaction. It is essential that an efficient methodology should be capable of forecasting the pest & disease dynamics accurately. Thus, there is a need for development of viable and functionally realistic model to correlate pest/disease with weather/ surveillance data.

In this study, micro-level weather data (Temperature, Humildity and Leaf Wetness) obtained through Mote based AgriSens WSN, DM techniques and surveillance data have been used to understand and quantify hidden correlation between crop-pest/disease-weather parameters. Subsequently a cumulative (Thrips & BNV) prediction models have been developed with which one can Decision Support System (DSS) with multi-season data.

In order to study the crop-weather-pest/disease interactions, a test bed for WSN experiments was chosen at Agriculture Research Institute (ARI) of Acharya N G Ranga Agricultural University falling in semi arid tropic. This work is a part of Indo-Japan initiative to develop a real time decision support system called GeoSense [17], integrating Geo-ICT and WSN for Precision Agriculture. In this work an attempt has been made to develop a viable model for groundnut pest/disease dynamics using the state of the art data mining techniques to find out the hidden correlations (crop-pest & disease–meteorological continuum) and there by development of Empirical as well as Multivariate Regression Models. Initial experimental results revealed interesting crop-weather correlations that helped in generating a multivariate regression model for Thrips and an empirical model for BNV disease in association with carrier pest (Thrips).

II. MATERIALS AND MEHTODS

A. *Sensory Data collection*

Sensory data from the field was transmitted through GPRS to the GeoSense server for data storing, analysis and mining. Other related weather data (sunshine hours SH, wind speed WS, rainfall RF and evapotransipiration ET) were obtained from the weather station with in the vicinity of the Agromet Cell of ARI, ANGRAU, Hyderabad. The data collected through GPRS technology was stored in an OpenSource data base (PostgreSQL) for further analysis at Agro-Informatics Lab, CSRE, IIT Bombay, India.

The deployed WSN system consists of the battery-powered nodes equipped with sensors for continuously monitoring agricultural/weather parameters such as temperature, relative humidity, soil temperature and leaf wetness [3]. Figure 1 shows the schematics of agricultural / environment sensors deployed in the field. Each node was able to transmit/receive packets (data) to/from other nodes every 15 minute over a transmission range of 25 meter. Data collected by the sensors were wirelessly transferred in a multi-hop manner to a base station node (*stargate*) connected with embedded gateway for data logging and correlation. In a WSN, when the transmission range of a sensor node is not sufficient, it uses multi-hop communication to reach the destination node or sink node. This data forwarding mechanism continues till it reaches the sink node.

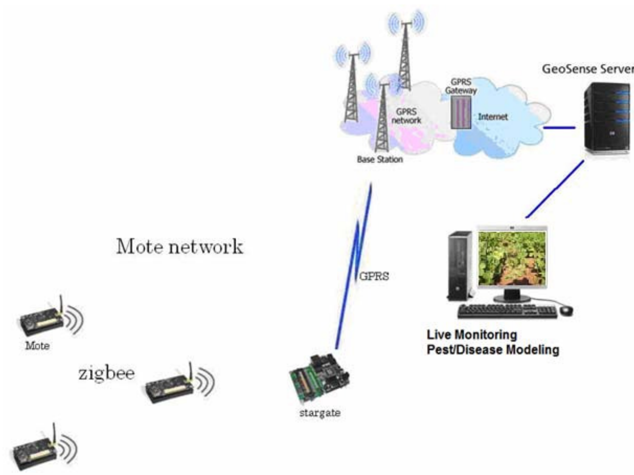

Figure 1 WSN architecture in the experimental site with Agrisens

The base station has a GPRS connectivity through which it routes data to the FTP server (GeoSense server) setup at Agro-Informatics Lab at CSRE, IIT Bombay and collect all the sensory information. The sensory data coming to the server through GPRS is raw and has been converted to usable real time data through appropriate conversion formula for further analysis and mining.

Sensory data was collected during the *kharif* (monsoon) seasons of 2009 & 2010 as well as *rabi* 2009-10 & 2010-11 with multiple sensor nodes (named M_1, M_2, etc.) in groundnut field (Figure 2).

B. *Surveillance Data Collection*

A standard field experiment design was laid out in the test bed. Thrips pest and (BNV) disease population dynamics (surveillance data) were obtained at every week from flowering to reproductive stages (as majority of pest and disease incidences are occurred during these phonological stages) at various locations in the experimental site.

Four different dates of sowing (D_1, D_2, D_3 and D_4) were taken in to consideration. These different dates will determine the impact of pest & disease incidence in order to observe dynamics in pre and post normal week of sowing (in which D_2 & D_3 are normal dates of sowing). Apart from this, to have uniform and unbiased observation, surveillance data has been collected from each plot in randomly selected one square meter area with three replicas (R1, R2 and R3).

Figure 2. AgriSens deployment in the field

C. *Data Mining and Statistical Models*

In the present study, Data Mining (DM) techniques were used to understand Thrips / BNV dynamics and correlations with sensory and weather station based meteorological and other surveillance parameters in Groundnut crop. Gaussian Naïve Bayes DM algorithm was used for classification, Rapid Association Rule Mining algorithm for association and correlation analysis (Figure 3).

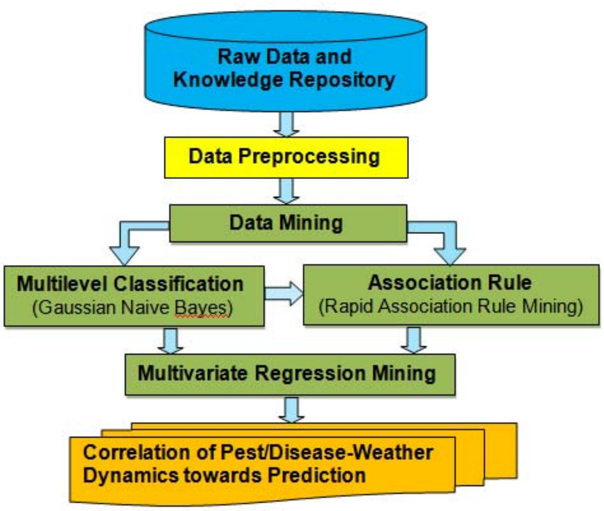

Figure 3. DM Processing Flow for Pest/Disease Dynamics

Raw sensory data obtained from the experimental field is not uniform in its collection. Owing to the climatic conditions or non-function of field sensors or due to network errors, there have been a few breaks in collecting continuous sensory data that may lead to biased outcomes while developing the model. Expectation–Maximization (EM) algorithm was used to deal with missing data. Relative data from nearest sensor node was used to fill the missing data with EM algorithm. The data set is provided in daily and weekly means wherever is required. Quality data is accomplished by performing satisfactory data pre-processing (data selection, data reduction and elimination of null values or other noise values). Though the real-time data were collected at 15 minute interval, all such data were not used for the current experiment. For example, the temperature has been used by computing maximum and minimum temperature of respective day. Relative Humidity has been taken as RH1 and RH2 having recorded data at morning 7:30 am and afternoon 3:00 pm (which is a standard practice in Indian agriculture [4]). Leaf Wetness (LW) data has been used in the scale of 1 to 10 as Leaf Wetness Index. And the Leaf Wetness Index value above 5 has been taken as leaf is wet and hence computed for wetness period [3].

As Groundnut crop was infested with multiple pests and diseases, multi level classification modules were developed in the model, which classifies crop pests & diseases based on the severity. Gaussian Naive Bayes classification [6, 11] was used in the experiment.

Bayesian network principle was used to model uncertainty by combining experimental knowledge and observational evidences. Gaussian Naive Bayes (NB) classifier, which is a term in Bayesian statistics dealing with a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence, was used to assume the presence (or absence) of a particular feature of a class unrelated to the presence (or absence) of any other feature [11].

Rapid association rule mining has been used in association with Classification techniques to find out correlation of multiple weather parameters with respect to Thrips and BNV. This phenomenon is to identify signature patterns as well to discover their presence/dependency [1, 5] with other related pest and/or weather parameters. This algorithm helps in discovering effects of pest/disease over the other pest/disease with respect to weather parameters. For example, how the Thrips incidence occurred due to presence/absence of BNV or vice versa. The outcomes are in the form of correlation indexes scaling from -1 to 1.

Regression Mining is a data mining (machine learning) technique used for developing multivariate equation for the training dataset. Following are the multivariate regression equations developed by using XLminer (a data mining tool).

Thrips-

$$Y_{TH} = -4.84 + 1.23 * Tmax - 0.78 * Tmin - 0.11 * RH_1 + 0.25 * RH_2 - 5.38 * RF - 2.05 * SH - 0.59 * WS - 0.28 * ET + 1.56E\text{-}02 * AC \quad (1)$$

Where, Tmax is the Maximum Temperature, Tmin is the Minimum Temperature, RH_1 and RH_2 are the Relative Humidity in morning and afternoon, RF is Rainfall, RD is Rainy days, SH is Sunshine Hours, WS is Wind Speed, ET is Evapotranspiration and AC is the age of crop.

An empirical model [20] has been adapted and modified by taking Temperature, Humidity and Leaf wetness factors. Later, in association with the carrier pest Thrips, the infection index of BNV was calculated:

$$I = f(W, T, RH_1, RH_2) = a\,(1- \exp\{-[b\,(W- c)]^{d}\}) \quad (4)$$

Where, W = Cumulative Wetness duration (obtained from Leaf Wetness Sensor), T= Temperature, b = characterize the intrinsic rate of increase (0 to 1) of Incidence with respect to *W*, d = the rate of acceleration, c = characterizes the lag period (0 to ∞) before the response of I to *W* begins, I = Infection index for BNV. RH_1 & RH_2 = Relative Humidity at 7:30 am and 2:30 pm. respectively, a = scale of response to W and varies with temperature and RH_2

$$a = f(T, RH_2) = \frac{e'\{\exp[f(T-g)/RH_2 + 1]}{\{1+\exp[f(T-g)]\}} \quad (5)$$

where, g = Optimum Temperature for GBN.
f = a parameter which is the intrinsic rate of change of Temperature with respect to optimal temperature (0 to 1)

$$e' = e\frac{[RH_1 - RH_2]/[T_{\max} - T_{opt}]}{RH_2} \quad (6)$$

in which *e* characterizes the scale of the response to *T* and RH. The BNV virus attack infection in association with pest Thrips can be modeled as
I' = f(RH, Leaf Wetness, Crop Age, Thrips)

$$I' = \frac{dI}{dI_{th}} + I + \frac{dI_{th}}{dW_{nd}} + AGDD \quad (7)$$

Where, I' = Infection Index, I = GBN Incidence, I_{th} = Thrips Incidence, W_{nd} = Wind Speed and AGDD is the accumulated Growing Degree Days.

Complex Polynomial Cumulative model [2] was adapted and remodified for pest/disease forecasting by including various aspects viz. maximum pest population/disease severity, time of first appearance, time of maximum pest population/disease severity as well as Life Cycle, Season, Weather Parameter, Stages, Incidence at flowering stage, Growing Degree Days, Previous Year Record, Correlation with Other Pest/Disease, Previous Season Crop:

$$Y = a_0 + \sum_{i=1}^{p} \sum_{j=0}^{1} a_{ij} Z_{ij} + \sum_{i\neq 1}^{p} \sum_{j=0}^{1} b_{ii'j} Z_{ii'j} + e \quad (8)$$

Where $Z_{ij} = \sum_{w=n1}^{n2} r_{iw}^{j} X_{iw}$ and $Z_{ii'j} = \sum_{w=n1}^{n2} r_{ii'w}^{j} X_{iw} X_{i'w}$

Z_i's and Z_{ij}'s are the independent variables which are functions of the basic weather variables like maximum temperature, relative humidity, leaf wetness, etc. 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 variable in w^{th} week, $r_{ii'w}$ = Correlation coefficient between Y and product of X_i and $X_{ii'}$ in w^{th} week, n1= initial incidence, n2 = fist Peak population week.

Pest/Disease life cycle plays an important role for their prediction. For example, the first BNV incidence in a particular date of sowing and then cumulative affect with respect to Thrips population increase or decrease has carried out by taking the life cycle of Thrips vector. Though the Thrips population increase rapidly, its impact (on BNV incidence) will be seen two weeks later i.e after going through three stages i.e. larva (picking the BNV virus), then pupa (an inactive stage around one week) and then transmit to the plant. Hence, the high BNV infection value could be the cumulative result of the virus acquired two week prior to the present infection level. Moreover, if BNV infection has occurred in the initial stage of the plant then the plant will die if proper care has not been taken. However, if the infestation is in the later half then the plant survives but with low yields.

III. Results and Discussions

Disease/pest-crop-weather interactions were carried out with four seasons data starting from 2009 *kharif* (monsoon) to 2010-11 *rabi* (post monsoon) season. Correlation of Thrips and BNV, with the help of weather and surveillance data (including crop age), were discovered and quantified using DM techniques in the test bed.

The correlation values (both positive & negative) of predictor (e.g. T_{max}, RH_1, ET, etc.) versus target (e.g. Thrips, BNV infection index) were obtained from various datasets (sensory, weather-station and surveillance) during flowering to harvesting stages (Figure 4 and Figure 5) for all the four seasons. A correlation Index matrix was obtained from Association Rule mining (with Weka tool using Apriory algorithm).

It was found that Relative Humidity has strong positive correlation and AC has strong negative correlation with BNV. Correlation indexing greater than 0.5 in the scale (-1 to 1) has been considered as strong +ve, where as -0.5 and more for strong negative correlation. In case of thrips, ET, and AC found to be strongly correlated. Apart from this, it was also found that there is a strong correlation with pest Thrips and disease BNV with an index value 0.75 and more.

With correlation studies revealing the crop-weather-pest/ disease relationship/ interactions, there is a possibility of developing an early warning models (Cumulative and non-cumulative) on pest/disease infestations. Prediction computations have been carried out and presented in graphical format for *kharif* 2010 (Figure 6 for Thrips and Figure 7 for BNV) and *rabi* 2010-11 (Figure 8 and 9 for Thrips and BNV respectively) in case of plot D2 date of sowing. These computations have been carried out for near to equal to the peak period only as rest of the prediction has a less pest/disease management significance if the crop is already infected during these peak stages.

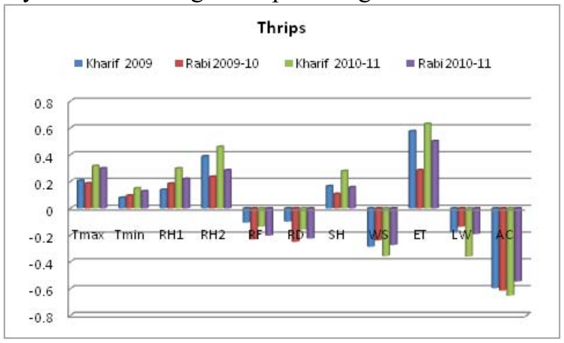

Figure 4. Correlation Index Values for Thrips with weather and crop age

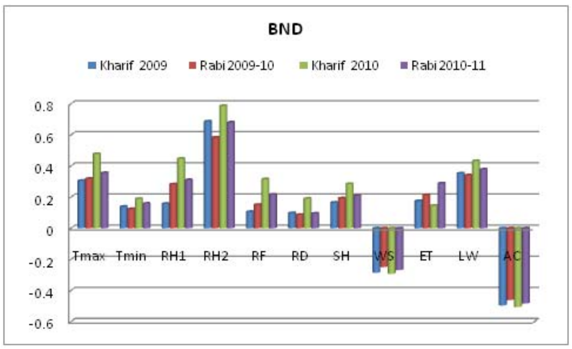

Figure 5. Correlation Index Values for BNV with weather and crop age

It has been observed in all the cases that one week (1wk) prediction is very closer to the regression/empirical model (MVR), where as the cumulative (CWK) method is probably a preferable prediction strategy as it is closer to the ground level data. It has been observed that the impact of carrier pest Thrips on BNV was more prone after two weeks as the virus acquired in first week from the plant and multiply in the vector in 2nd week. Then the transition happen consequently when it come in contact with the plant. For example, 17.75% BNV incidence on 17/8/2010 comes up with 49.34% on 8/9/2010.

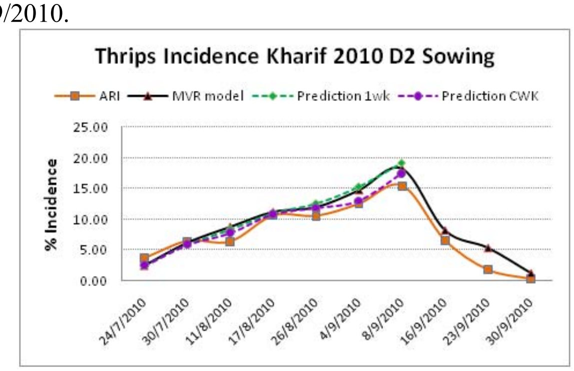

Figure 6. Thrips Incidence Prediction for *kharif* 2010

These pest/disease interactions indicate that if Thrips pest are controlled on 17/8/2010, there is a possibility to counter BNV disease and it yield loss (for D2 sowing date). Overall, the CWK value has been observed to be in the range of 2 to 5% increased value with respect to ground level data. However, in case of 1wk prediction approach it has been found 5 to 10% increase in prediction value as compared to ground level data. Thus, the CWK model found to be more accurate prediction method.

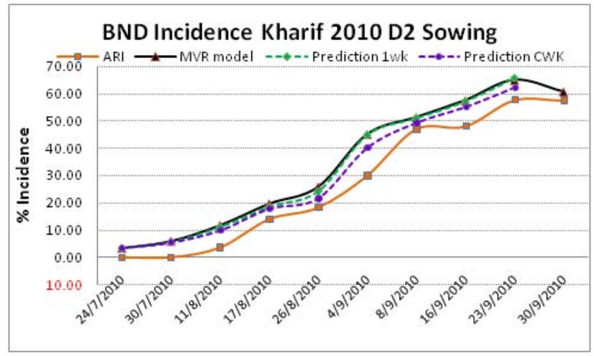

Figure 7. BNV Incidence Prediction for *kharif* 2010

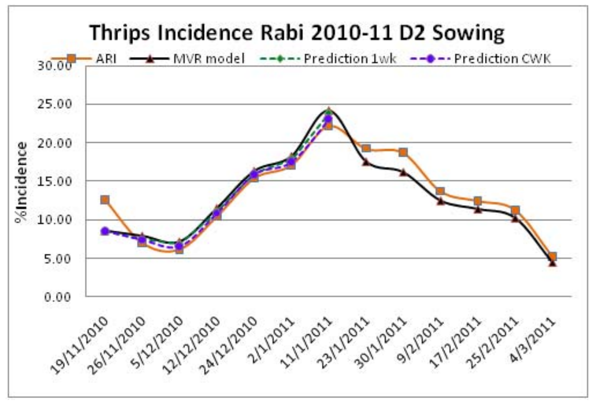

Figure 8. Thrips Incidence Prediction for *rabi* 2010-11

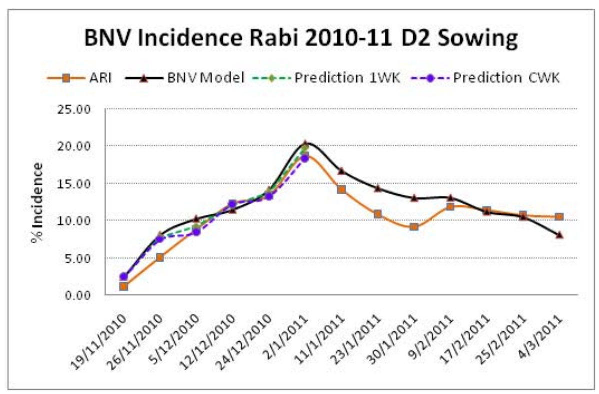

Figure 9. Thrips Incidence Prediction for *rabi* 2010-11

Figure 10. Thrips pest (in microscope) and its Incidence in the test bed

Similar trends were observed during 2010-11 *rabi* season also, and care should be taken after appearance of first peak incidence of Thrips. Figure 10 and 11 depicts the field photos of Thrips and BNV incidences respectively.

Figure 11. Different stages of BNV Incidence in the test bed

CONCLUSION

An attempt has been made to understand the hidden relationships between most prevailed disease (BNV) / pest (Thrips) and weather parameter of Groundnut crop. WSN was established in the test bed to obtain real-time weather parameters (Temperature, Humidity and Leaf wetness) at micro-climatic level and a few related weather parameters were taken from the nearby weather station. The crop-weather-pest/disease dynamics and hidden relations were obtained and quantified using DM techniques. The statistical approach together with regression mining based correlations helped in developing multivariate regression model that have been used to develop an empirical prediction model (non-cumulative) to issue the forecast for population buildup, initiation & severity of pest /disease. Apart from this, a cumulative prediction model has been developed (which found to be more accurate than the non-cumulative one) and tested using two season's data. This will help to take strategic decisions so as to save the crop from pest/disease affects and improve the crop yields.

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