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Weather Based Pest Forewarning Model for Major Insect Pests of Rice – An Effective Way for Insect Pest Prediction

Manikandan Narayanasamy^{1*}, J. S. Kennedy² and V. Geethalakshmi¹

¹Department of Agronomy, Agricultural College and Research Institute, Madurai, Tamil Nadu– 625 104, India.

²Department of Agricultural Entomology, TNAU, Coimbatore, Tamil Nadu– 641 003, India.

Authors' contributions

This work was carried out in collaboration between all authors. Authors MN and JSK designed the study, performed the statistical analysis, developed the methodology, and wrote the first draft of the manuscript. Author VG managed the climate pest relationships of the study. All authors read and approved the final manuscript.

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ABSTRACT

Weather parameters viz., Temperature, rainfall, relative humidity, sunshine hours and wind speed are the major weather elements determining the insect pests' occurrence. Weather based forewarning models are widely utilized in the integrated pest management system as a tool which do not cause any harm to the predators and also cuts down environmental pollution. Considering this, an attempt was made to predict the population occurrence of Yellow Stem Borer (YSB), Brown Planthopper (BPH) and Rice Leafhopper (RLF). Generalized Linear Model (GLiM) was developed for YSB, BPH and RLF for predicting the population at a given time. The results of chi square test revealed that, there are many other factors which affect the amount of light trap catches of the insects apart from weather parameter. The predictability of the equation can be increased if the weather factors are combined with the other factors (variety, soil, fertilizer application, etc.,) in developing the model.

*Corresponding author: E-mail: manilakshmi_144@yahoo.com, manik144@gmail.com;

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1. INTRODUCTION

Rice is cultivated over almost all the places on the earth, excluding Antarctica. Rice has a prominent effect on human nourishment and food security all over the world. Over four billion of the world's population has rice as their staple food. In Asia alone, over two billion people receive 60 to 70 per cent of their energy through rice and its value added products [1]. Rice is, thus, running on the front in the battle against undernourishment, hunger and poverty. Insect pests continue to be a constant problem for rice production among many others, in all the rice cultivated areas. Rice is prone to more than 100 invasive species of insects during its crop growth period which markedly reduce the productivity. The key insect pests affecting the yield are *Scirpophoga incertulas*, Yellow Stem Borer (YSB); *Nilaparvata lugens*, Brown Planthopper (BPH); *Cnaphalocrocis medinalis*, Rice Leafhopper (RLF).

Weather parameters viz., Temperature, rainfall, relative humidity, sunshine hours and wind speed are the major weather elements determining the insect pests' occurrence. Weather based pest forewarning models have been formulated to some extent by many researchers [2,3,4,5,6,7, 8]. Abiotic conditions such as minimum temperature, temperature gradient, maximum relative humidity and average relative humidity had a significant positive influence on *C. medinalis* population. In case of minimum relative humidity and sunshine hours a negative influence was observed. In addition, other factors such as maximum temperature, relative humidity gradient, average relative humidity, number of rainy days and rainfall imparted insignificant positive effect on population development [9]. The correlation between weather factors and leafhopper population indicated that the maximum temperature, minimum temperature, rainfall and sunshine hours have a significant negative relationship while morning relative humidity and evening relative humidity exhibited a positive relationship [10].

Weather based forewarning models are widely utilized in the integrated pest management system as a tool which do not cause any harm to the predators and also cuts down environmental pollution by need based application of insecticide spray [8]. However, at present, little is known about the behavior of the insects to

meteorological factors and their temporal variation in the spatial pattern in paddy fields. Hence, an operationally feasible forewarning model for insect pests' prediction is the need of the hour for efficient insect pest management. Considering this, an attempt was made to predict the population occurrence of YSB, BPH and RLF.

2. MATERIALS AND METHODS

2.1 Collection of Historical Pest Surveillance Data

The data on weekly light trap catches of YSB, RLF and BPH of Cauvery delta zone (Aduthurai) were collected from the progress report of Directorate of Rice Research, Hyderabad for a period of 17 years from 1990-2007. Light traps were kept in the rice fields to collect the targeted insect pests in order to know their abundance. Insects trapped during night were counted in the morning were accumulated for total weekly insect numbers. The weekly cumulative abundance of insect pests, weekly averages of rainfall, maximum temperature, minimum temperature, morning relative humidity, evening relative humidity and sunshine hours are computed from the daily data. These data were used for developing a forewarning model for YSB, BPH and RLF.

2.2 Quality Check of Pest Surveillance Data

The weekly data were examined for the quality and availability of the data. The examination revealed that there were extreme values (Table 1) in the data of all the three insects. However, the median of weekly surveillance data were only 70, 68 and 14 for YSB, BPH and RLF, respectively. After data quality check the extreme values were dispersed randomly in the weekly insect surveillance data and did not represent or hint a trend. The extreme values were defined as outliers or noise as it did not follow any trend.

Based on the 95th percentile of the weighted mean weekly surveillance data was truncated in order to curtail noise in the data for all the three insects. The cut off for the number of captures was 900 and 140 for YSB and RLF, respectively (Table 2). Weekly surveillance data that has more number of captures than the 'cut off' figure

was marked as missing. For BPH the cut off was determined to be mean +2SD upward and which happened to be 4200 per week. The data which were more than 4200 was removed from the surveillance data as it was considered as outliers.

As a result of the above statistical procedures, the number of observations removed from the weekly data was 28, 22 and 24 weeks in YSB, BPH and RLF surveillance data. The removed outliers were marked as missing and replaced with mean values from 10 values nearby so not to lose the quantity of data available for the statistical analysis. Thus, after truncation and missing value management the available surveillance data are presented in Table. 3.

2.3 Development of Weather Based Forewarning Model

The data on the number light trap catches of the YSB, BPH and RLF were subjected to different statistical methods like Percentile, Pearson Correlation and Principal Component Analysis in order to make the data ready to develop the model. Generalised Linear Model (GLiM) was developed for YSB, BPH and RLF to predict the population at a given time. Statistical Package for the Social Sciences (SPSS) software was used to employ Principal Component Analysis and Generalized Linear Model. The steps used in

developing weather based model are schematically represented and given in Fig. 1.

2.4 Generalized Linear Model (GLiM)

The Generalized Linear Model is an extension of the General Linear Model to include response variables that follow any probability distribution in the exponential family of distributions. The exponential family includes such useful distributions as the Normal, Binomial, Poisson, Multinomial, Gamma, Negative Binomial, and others. Hypothesis tests applied to the Generalized Linear Model do not require normality of the response variable, nor do they require homogeneity of variances. Hence, Generalized Linear Models can be used when response variables follow distributions other than the Normal distribution, and when variances are not constant. Hence, our insect capture count data would be appropriately analysed as a Poisson random variable within the context of the Generalized Linear Model.

The non-normal data were subject to Generalized Linear Multivariate Model (GLiM) with a number of light trap catches data as the dependent variable and the two principal component score variables (Temperature and relative humidity and Rainfall) as continuous predictor variables. A poisson loglinear regression model was fit for the count data.

Table 1. Basic statistics of weekly surveillance data

| Insect | Available data (No. of weeks) | Number of insects captured | | |
|--------|-------------------------------|----------------------------|---------|--------|
| | | Minimum | Maximum | Median |
| YSB | 562 | 0 | 27900 | 70 |
| BPH | 563 | 0 | 1582610 | 68 |
| RLF | 419 | 0 | 507 | 14 |

Table 2. Percentiles of weekly surveillance data of YSB, BPH and RLF

| Insects | Insect capture percentiles | | | | |
|---------|----------------------------|------|--------|--------|---------|
| | 25 | 50 | 75 | 90 | 95 |
| YSB | 27 | 58 | 142 | 416.6 | 918.25 |
| BPH | 6 | 56.5 | 261.75 | 1336.1 | 4256.75 |
| RLF | 1 | 14 | 43 | 88 | 143.5 |

Table 3. Availability of surveillance data after missing value management

| Insect | Number of weeks available | Minimum | Maximum | Mean number of insects captured |
|--------|---------------------------|---------|---------|---------------------------------|
| YSB | 564 | 0 | 859 | 119.3 |
| BPH | 419 | 0 | 135 | 24.5 |
| RLF | 564 | 0 | 4055 | 248.2 |

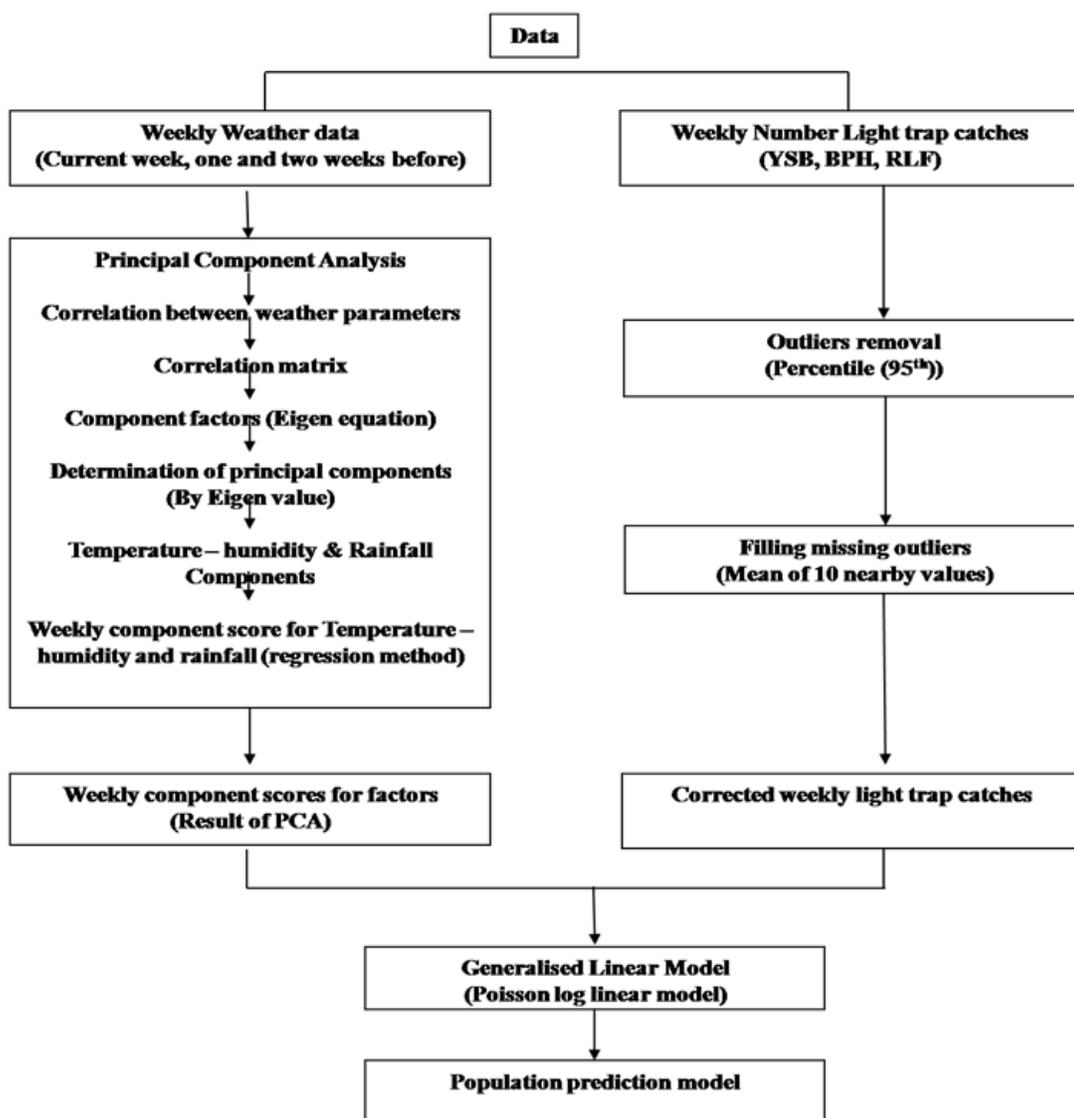


Fig. 1. Schematic diagram for the development of weather based forewarning model

3. RESULTS

3.1 Effect of Weather on Insects

A simple correlation between the weather parameters (maximum, minimum temperature, relative humidity, rainfall and sunshine hours of current week, one and two weeks before) and light trap catches of YSB, BPH and RLF was carried out. The results revealed that the light trap catches of YSB, BPH and RLF were significantly negatively correlated with the maximum and minimum temperature of current, one and two weeks before (Table 4).

At the same time relative humidity of current, one and two weeks before had a significant positive correlation with light trap catches of YSB, BPH and RLF. Rainfall (current, one and two weeks before) also had the positive correlation with the light trap catches of all the pests except YSB, where current week of rainfall had negative relationship. But, the relationship between rainfall and light trap catches were statistically insignificant.

In the case of sunshine hours, it was observed that the sunshine hours of current and one week before had a positive correlation with the light trap catches of YSB, whereas sunshine hours of

two weeks before had a negative correlation with the light trap catches YSB. But the correlation was not significant. In the case of BPH, sunshine hours (current, one and two weeks before) had a negative relationship with the light trap catches. But, except the sunshine hours before two weeks, others are not significant. Sunshine hours of current week had a positive relationship with the light trap catches of RLF, whereas sunshine hours of one and two weeks before had a negative relationship. It was also noted that none of the relationship was significant (Table 4).

3.2 Principal Component Analysis

Principal component analysis was performed to understand the relationships between the weather parameters and with a purpose to reduce the number of variables that need to be regressed with the number of insects captured. Correlation matrix (Table 5) was established from the PCA to understand the relationship between the weather variables. The correlation matrix revealed that there was a strong correlation between weather variables such as temperature (maximum and minimum), relative humidity, rainfall and sunshine hours of current, one and two weeks before the occurrence of the pests.

3.2.1 Selection of weather factors by PCA

PCA grouped the weather variables into two factors based on its effect on the light trap catches of the insect. In the first factor temperature (maximum and minimum), relative humidity were included, whereas in the second factor rainfall was included (Table 6). Sunlight hours of the day was not included in the analysis as it was found to be statistically significantly ($p < 0.001$, $r = -0.69$) correlated with temperature. Though the temperature and relative humidity variables were correlated significantly with the past (1 week and 2 weeks) measurements, they were still included in the model as their effect on the previous stages of the insect could affect the light trap catches of the insects at a particular time. The current, one week and 2 weeks before data of temperature (minimum and maximum), relative humidity and rainfall was included in the model.

3.2.2 Component scores (by regression method)

It is a method for estimating factor score coefficients for the factors developed i.e. Temperature – humidity factor and rainfall factor.

The scores that were produced have a mean of zero and a variance equals to the squared multiple correlations between the estimated factor scores and the true factor values. The developed component scores of the two factors were stored as two variables. A value of 0 in the first component score implies 'average temperature and relative humidity. A negative value denotes less than average temperature and relative humidity and a positive value denote more than average temperature and relative humidity. The same was considered for the second factor 'rainfall'. Thus 12 variables introduced in the Principal Components Analysis were reduced to two consolidated variables representing 'temperature and relative humidity' and 'rainfall' (Table 7). These two variables were used as predictor variables to create a model that would explain the number of weekly insect capture.

Rotation of the extracted matrix was done by Varimax method (An orthogonal rotation method that minimizes the number of variables that have high loadings on each factor). Two factors (eigen value more than 1.0) that were extracted explained 68.0% of the total variance in the weather parameter data (Table 7). The first factor extracted had temperature and relative humidity parameters that were highly correlated between them. The factor could be labeled as 'Temperature - Relative humidity factor'. The second factor had the current and past rainfall variables and could be labeled as 'rainfall factor'.

3.2.3 Correlation between component score factors and light trap catches

Correlations were performed to understand the relationship between the component score factors of temperature-humidity, rainfall and number of light trap catches. The results of the study revealed that the temperature – humidity factor had a significant negative correlation ($r = -0.452$; $p < 0.001$) with the number light trap catches of YSB. On the other hand, the rainfall factor had an insignificant negative relationship ($r = -0.034$; $p = 0.419$) with the number of light trap catches of YSB. The above relationships indicated that, if the temperature – humidity and rainfall factors increased then there will be a decrease in the number of light trap catches. The scatter plot diagram of light trap catches of YSB and temperature – humidity factor, rainfall clearly indicated the trend (Figs. 2 and 3).

In the case of BPH, temperature – humidity factor had a significant negative correlation ($r =$

0.260; $p < 0.01$) with the number of light trap catches, whereas rainfall factor had a significant positive correlation ($r = 0.127$; $p = 0.03$) with the number of light trap catches. The scatter plot diagram of BPH with the temperature - humidity factor, rainfall factor showed that both were having an opposite relationship with the light trap catches (Figs. 4 and 5). Correlation studies in the light trap catches of RLF indicated that it had a significant negative correlation ($r = -0.334$; $p < 0.001$) with temperature - humidity factor, whereas an insignificant positive relationship ($r = 0.064$; $p = 0.195$) with the rainfall factor (Figs. 6 and 7).

3.3 Forewarning Model

The results of the generalized linear model for YSB, BPH and RLF are given in the table (Table 8). The equations which were used to predict the light trap catches of YSB, BPH and RLF were developed from the results of the generalized linear model by using the link function and predictor values of the two factors; temperature and relative humidity factor and rainfall factor.

3.4 Goodness of Fit

Based on the equations developed, insect catches were predicted for all the pests under study for a year which had been observed from light trap catches. The results of the above evaluation indicated that there was a difference in the observed and predicted number of light trap catches for all the insects under study. The chi-square test which was carried out to check the fitness of the model indicated that the test value for all the three insects were higher than the table value. Hence, the hypothesis formed was rejected as the predicted and actual numbers are different.

However, rising and decreasing trend was observed to be coinciding at most of the points. The predicted and observed light trap catches of YSB was observed to be following the same trend from March to September and in November (Fig. 8). The highest number of insect catches was originally observed during the month of January, whereas the highest insect catches were predicted to occur during the month of February. In the case of BPH, it was noted that there was a large difference in the observed and predicted number of light trap catches of insects. The highest number of light trap catches was occurred during December in both observed and

predicted values (Fig. 9). The trend between observed and predicted was same for the light trap catches of RLF from January to March. The highest insect catches were predicted to occur during December whereas, it was originally observed during the month of October (Fig. 10).

4. DISCUSSION

The results of the correlation studies indicated that temperature (maximum and minimum) of all the periods had a significant negative relationship with the number of light trap catches of all the insects, whereas the relative humidity had a significant positive relationship. In the case of sunshine hours it exhibited different relationships with YSB, BPH and RLF. Rainfall (current, one and two weeks before) had the positive correlation with the light trap catches of all the pests except YSB where the current week of rainfall had negative relationship. But, none of the rainfall relationships were statistically significant. Similar results were reported by many scientists from different part of the world [4,9,10,11].

Principal component analysis was carried out to reduce the number of weather parameters which were carried to the model development as a large number of variables would affect the model prediction. The results of the correlation between the temperature - humidity factor had a negative relationship with the light trap catches of all the insects. The rainfall factor had a significant positive relationship with the light trap catches of BPH and RLF and negative relationship with YSB. Many authors have also used PCA to find out the factors which play important roles in the population build up of the yellow stem borer and rice gundhi bug [12]. They reported that rainfall and relative humidity played a significant role in the population build up of the yellow stem borer and in case of the population of rice gundhi bug no meteorological variables were found to be significant. Stem borer damage had a positive significant correlation with maximum, minimum temperature and a negative correlation with relative humidity [13]. From the above studies, we could understand that effect of weather variables on the light trap catches varied with different locations. Hence, it was inferred that effect of weather variables on the insect catches were location specific, as the relationship between weather variables and insect population were not the same at all places.

Table 4. Correlation coefficients of weather parameters and light trap catches of YSB, BPH and RLF

| Weather parameters | Number of YSB captured | | Number of RLF captured | | Number of BPH captured | |
|----------------------------------|------------------------|---------|------------------------|---------|------------------------|---------|
| | Pearson's r | p-value | Pearson's r | p-value | Pearson's r | p-value |
| Maximum Temperature | -0.277 | <0.001 | -0.297 | <0.001 | -0.293 | <0.001 |
| Minimum Temperature | -0.441 | <0.001 | -0.344 | <0.001 | -0.233 | <0.001 |
| Rainfall | -0.054 | 0.200 | 0.057 | 0.246 | 0.041 | 0.328 |
| Humidity | 0.342 | <0.001 | 0.229 | <0.001 | 0.243 | <0.001 |
| Sunshine hours | 0.135 | 0.001 | 0.010 | 0.834 | -0.084 | 0.046 |
| Maximum Temperature past week | -0.346 | <0.001 | -0.326 | <0.001 | -0.297 | <0.001 |
| Minimum Temperature past week | -0.429 | <0.001 | -0.322 | <0.001 | -0.199 | <0.001 |
| Rainfall past week | 0.013 | 0.759 | 0.035 | 0.480 | 0.065 | 0.122 |
| Humidity past week | 0.335 | <0.001 | 0.215 | <0.001 | 0.237 | <0.001 |
| Sunshine hours past week | 0.064 | 0.133 | -0.046 | 0.351 | -0.104 | 0.014 |
| Maximum Temperature 2 weeks back | -0.412 | <0.001 | -0.315 | <0.001 | -0.277 | <0.001 |
| Minimum Temperature 2 weeks back | -0.395 | <0.001 | -0.270 | <0.001 | -0.172 | <0.001 |
| Rainfall 2 weeks back | 0.067 | 0.115 | 0.050 | 0.306 | 0.072 | 0.088 |
| Humidity 2 weeks back | 0.304 | <0.001 | 0.203 | <0.001 | 0.207 | <0.001 |
| Sunshine hours 2 weeks back | -0.038 | 0.376 | -0.069 | 0.161 | -0.113 | <0.001 |

Table 5. Correlation matrix developed from principal component analysis

| Weather | Parameters | Max temp | Max T1 W | Max T 2 W | Min T | Min T 1W | Min T 2 W | RF | RF 1 W | RF 2 W | RH | RH 1 W | RH 2 W | SSH | SSH 1 W | SSH 2 W |
|--------------|------------|----------|----------|-----------|--------|----------|-----------|--------|--------|--------|--------|--------|--------|--------|---------|---------|
| Max T | r value | 1 | 0.877 | 0.799 | 0.688 | 0.599 | 0.493 | -0.387 | -0.346 | -0.306 | -0.658 | -0.61 | -0.54 | 0.464 | 0.387 | 0.348 |
| | p value | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Max T 1 W | r value | 0.877 | 1 | 0.876 | 0.723 | 0.684 | 0.603 | -0.207 | -0.395 | -0.326 | -0.631 | -0.656 | -0.607 | 0.222 | 0.466 | 0.371 |
| | p value | <0.001 | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Max 2 W | r value | 0.799 | 0.876 | 1 | 0.767 | 0.72 | 0.687 | -0.171 | -0.215 | -0.376 | -0.645 | -0.628 | -0.655 | 0.113 | 0.219 | 0.454 |
| | p value | <0.001 | <0.001 | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | 0.007 | <0.001 | <0.001 |
| Min T | r value | 0.688 | 0.723 | 0.767 | 1 | 0.869 | 0.811 | -0.08 | -0.106 | -0.115 | -0.664 | -0.642 | -0.618 | -0.129 | -0.031 | 0.03 |
| | p value | <0.001 | <0.001 | <0.001 | | <0.001 | <0.001 | 0.058 | 0.012 | 0.006 | <0.001 | <0.001 | <0.001 | 0.002 | 0.47 | 0.482 |
| Min T 1 W | r value | 0.599 | 0.684 | 0.72 | 0.869 | 1 | 0.87 | -0.04 | -0.087 | -0.09 | -0.624 | -0.66 | -0.636 | -0.12 | -0.136 | -0.05 |
| | p value | <0.001 | <0.001 | <0.001 | <0.001 | | <0.001 | 0.344 | 0.038 | 0.033 | <0.001 | <0.001 | <0.001 | 0.004 | 0.001 | 0.242 |
| Min T 2 W | r value | 0.493 | 0.603 | 0.687 | 0.811 | 0.87 | 1 | 0.014 | -0.047 | -0.076 | -0.584 | -0.622 | -0.658 | -0.186 | -0.126 | -0.15 |
| | p value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | | 0.734 | 0.27 | 0.07 | <0.001 | <0.001 | <0.001 | <0.001 | 0.003 | <0.001 |
| RF | r value | -0.387 | -0.207 | -0.171 | -0.08 | -0.04 | 0.014 | 1 | 0.142 | 0.153 | 0.276 | 0.15 | 0.149 | -0.416 | -0.236 | -0.159 |
| | p value | <0.001 | <0.001 | <0.001 | 0.058 | 0.344 | 0.734 | | 0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| RF 1 W | r value | -0.346 | -0.395 | -0.215 | -0.106 | -0.087 | -0.047 | 0.142 | 1 | 0.138 | 0.191 | 0.279 | 0.153 | -0.188 | -0.417 | -0.235 |
| | p value | <0.001 | <0.001 | <0.001 | 0.012 | 0.038 | 0.27 | 0.001 | | 0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| RF 2 W | r value | -0.306 | -0.326 | -0.376 | -0.115 | -0.09 | -0.076 | 0.153 | 0.138 | 1 | 0.168 | 0.182 | 0.272 | -0.195 | -0.188 | -0.408 |
| | p value | <0.001 | <0.001 | <0.001 | 0.006 | 0.033 | 0.07 | <0.001 | 0.001 | | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| RH | r value | -0.658 | -0.631 | -0.645 | -0.664 | -0.624 | -0.584 | 0.276 | 0.191 | 0.168 | 1 | 0.799 | 0.718 | -0.113 | -0.093 | -0.109 |
| | p value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | | <0.001 | <0.001 | 0.007 | 0.028 |
| RH 1 W | r value | -0.61 | -0.656 | -0.628 | -0.642 | -0.66 | -0.622 | 0.15 | 0.279 | 0.182 | 0.799 | 1 | 0.797 | -0.044 | -0.112 | -0.082 |
| | p value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | | <0.001 | 0.303 | 0.008 |
| RH 2 W | r value | -0.54 | -0.607 | -0.655 | -0.618 | -0.636 | -0.658 | 0.149 | 0.153 | 0.272 | 0.718 | 0.797 | 1 | 0.004 | -0.041 | -0.1 |
| | p value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | | 0.923 | 0.337 |
| SSH | r value | 0.464 | 0.222 | 0.113 | -0.129 | -0.12 | -0.186 | -0.416 | -0.188 | -0.195 | -0.113 | -0.044 | 0.004 | 1 | 0.411 | 0.306 |
| | p value | <0.001 | <0.001 | 0.007 | 0.002 | 0.004 | <0.001 | <0.001 | <0.001 | <0.001 | 0.007 | 0.303 | 0.923 | | <0.001 | <0.001 |
| SSH 1 W | r value | 0.387 | 0.466 | 0.219 | -0.031 | -0.136 | -0.126 | -0.236 | -0.417 | -0.188 | -0.093 | -0.112 | -0.041 | 0.411 | 1 | 0.408 |
| | p value | <0.001 | <0.001 | <0.001 | 0.47 | 0.001 | 0.003 | <0.001 | <0.001 | <0.001 | 0.028 | 0.008 | 0.337 | <0.001 | | <0.001 |
| SSH 2 W | r value | 0.348 | 0.371 | 0.454 | 0.03 | -0.05 | -0.15 | -0.159 | -0.235 | -0.408 | -0.109 | -0.082 | -0.1 | 0.306 | 0.408 | 1 |
| | p value | <0.001 | <0.001 | <0.001 | 0.482 | 0.242 | <0.001 | <0.001 | <0.001 | <0.001 | 0.01 | 0.054 | 0.019 | <0.001 | <0.001 | |

Table 6. Varimax rotated components extracted by PCA

| Weather parameters | Factor 1 | Factor 2 |
|----------------------------------|----------|----------|
| Minimum Temperature | 0.871 | |
| Minimum Temperature past week | 0.849 | |
| Minimum Temperature 2 weeks back | 0.799 | |
| Maximum Temperature | 0.836 | |
| Maximum Temperature past week | 0.883 | |
| Maximum Temperature 2 weeks back | 0.891 | |
| Relative Humidity | -0.821 | |
| Relative Humidity past week | -0.835 | |
| Relative Humidity 2 weeks back | -0.812 | |
| Rainfall | | 0.603 |
| Rainfall past week | | 0.555 |
| Rainfall 2 weeks back | | 0.501 |

Table 7. Component factors and their eigen value developed from PCA

| Component | Initial eigen values | | | Extracted and rotated sums of squared loadings | | |
|-----------|----------------------|---------------|--------------|--|---------------|--------------|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | 6.77 | 45.14 | 45.14 | 6.25 | 41.67 | 41.67 |
| 2 | 2.73 | 18.17 | 63.31 | 3.25 | 21.64 | 63.31 |
| 3 | 1.12 | 7.46 | 70.77 | | | |
| 4 | 1.00 | 6.69 | 77.46 | | | |
| 5 | 0.78 | 5.21 | 82.68 | | | |
| 6 | 0.59 | 3.94 | 86.62 | | | |
| 7 | 0.55 | 3.68 | 90.30 | | | |
| 8 | 0.48 | 3.23 | 93.53 | | | |
| 9 | 0.29 | 1.91 | 95.45 | | | |
| 10 | 0.19 | 1.23 | 96.68 | | | |
| 11 | 0.17 | 1.12 | 97.81 | | | |
| 12 | 0.12 | 0.82 | 98.63 | | | |
| 13 | 0.11 | 0.70 | 99.33 | | | |
| 14 | 0.06 | 0.38 | 99.71 | | | |
| 15 | 0.04 | 0.29 | 100.00 | | | |

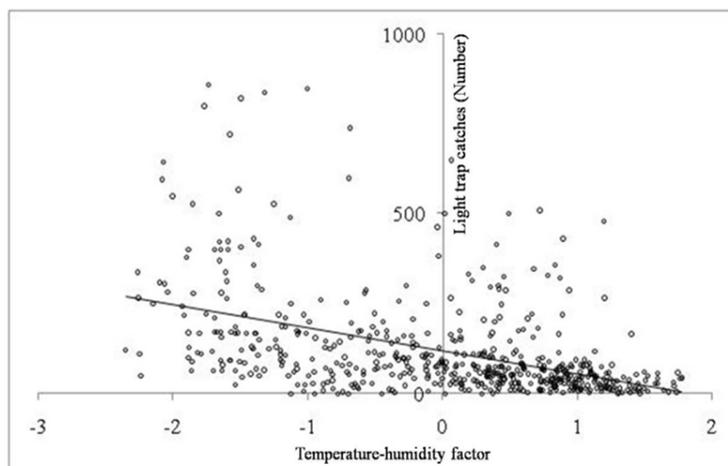


Fig. 2. Weekly number light trap catches of YSB and temperature – humidity factor

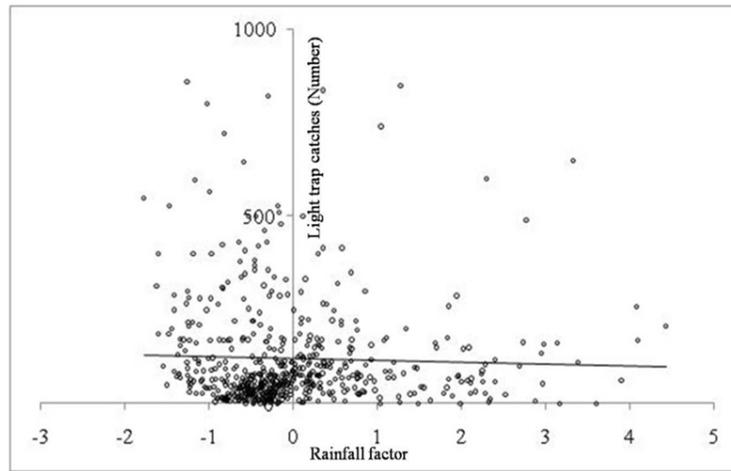


Fig. 3. Weekly light trap catches of YSB and rainfall factor

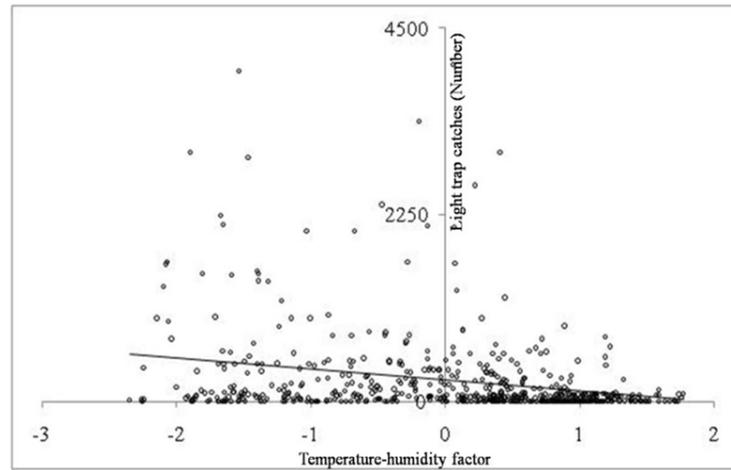


Fig. 4. Weekly light trap catches of BPH and temperature – humidity factor

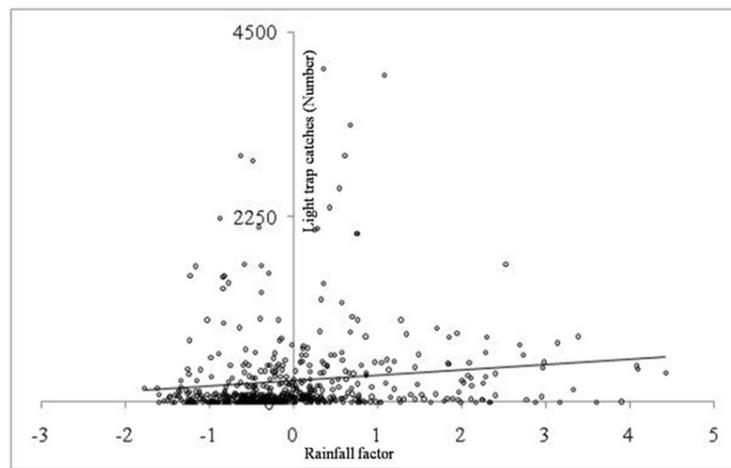


Fig. 5. Weekly light trap catches of BPH and rainfall factor

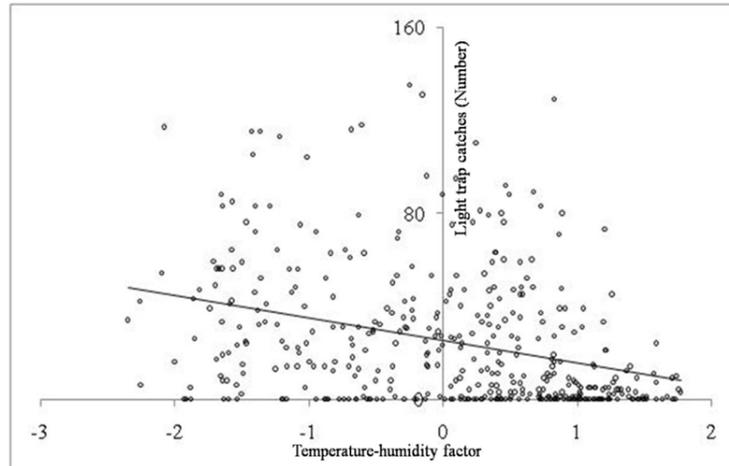


Fig. 6. Weekly light trap catches of RLF and temperature – humidity factor

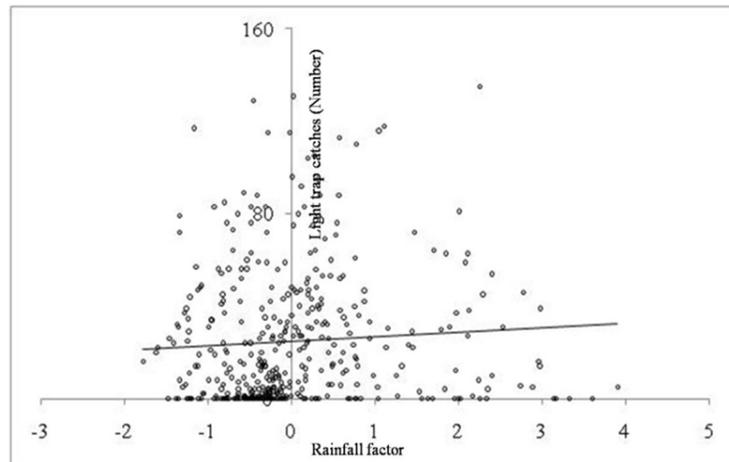


Fig. 7. Weekly light trap catches of RLF and rainfall factor

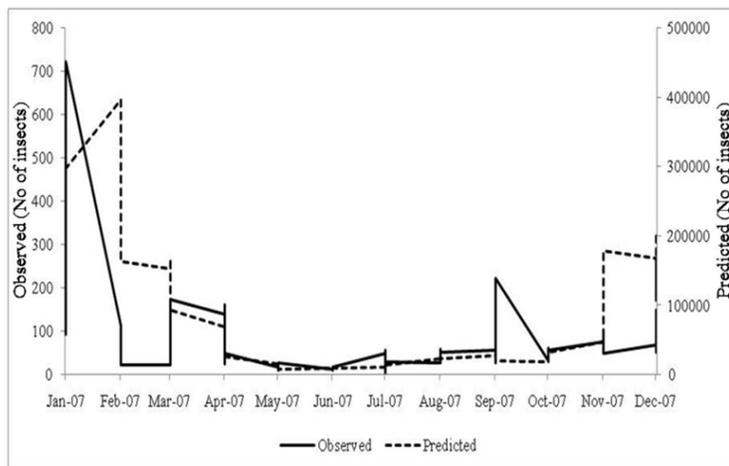


Fig. 8. Observed and predicted light trap catches of YSB

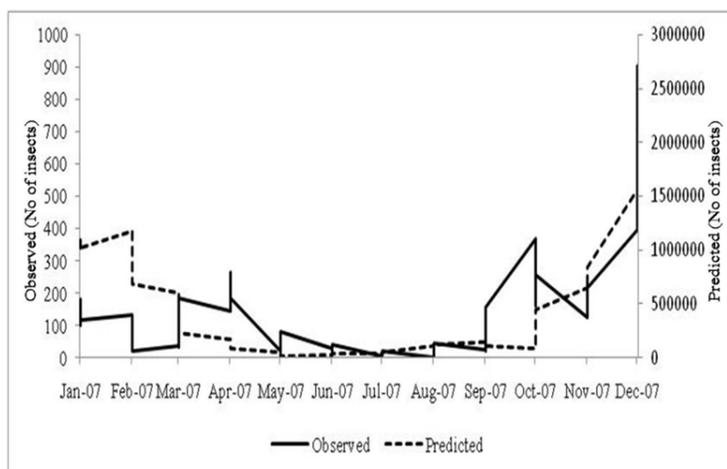


Fig. 9. Observed and predicted light trap catches of BPH

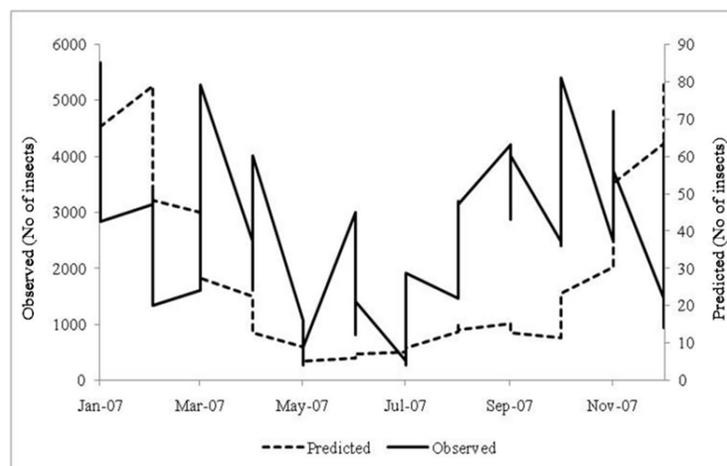


Fig. 10. Observed and predicted light trap catches of RLF

Table 8. Prediction equations for the major pests of rice

| Insect | Model | Equation |
|--------|------------------------------------|---|
| YSB | Log linear poison regression model | $\text{Log } E(y) = -0.525 (\text{Temperature-humidity factor}) + 0.006 (\text{rainfall}) + 4.65.$ (Chi-square – 198.8; $p < 0.01$) |
| BPH | Log linear poison regression model | $\text{Log } E(y) = -0.554 (\text{Temperature-humidity factor}) + 0.235 (\text{rainfall}) + 5.33$ (Chi-square – 44.5; $p < 0.01$) |
| RLF | Log linear poison regression model | $\text{Log } E(y) = -0.37 (\text{Temperature-humidity factor}) + 0.079 (\text{rainfall}) + 3.137$ (Chi-square – 95.9; $p < 0.01$) |

Most of the literature which is devoted to forecasting of insect pest is based on weather, contains only simple forecasting models on the base of the time series methods or linear regression methods. Here we have used the generalized linear model, which generalizes the linear regression. Generalized linear

model was used over other linear models as it returns predictions on the scale of the response and the response variable need not be of normal distribution. The use of the link functions avoids the need for prior transformation of the response for back-transformation of predictions.

The result of the chi square test indicated that, there are many other factors which affect the amount of light trap catches of the insects apart from weather parameter. Statistical models used to predict pest population rely only on approximated weather. The reliability of predictions based on weather is less because there are variables that are either not calculated in prediction or they are ruled out of the prediction. For example, in order to predict pest occurrence, a simulator would need to have all the current factors affecting pest occurrence, such as cultivar, management practices, etc.,. The predictability of the equation can be increased if the weather factors are combined with the other factors (variety, soil, fertilizer application, etc.,) in developing the model.

5. CONCLUSION

The results of the experiment indicated that the trend in the predicted and observed insect numbers are almost same for YSB and BPH. In the case of leaf folder, there was difference of trend between prediction and observation. The predictability of these equations can be further increased if the weather factors are combined with the other factors (variety, soil, fertilizer application, etc.,) in developing the model.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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