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Development of fore-warning model for brown plant hopper in rice using satellite and meteorological data

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ABSTRACT

Brown planthopper (BPH),(Nilaparvata lugens (Stål.) Hemiptera: Delphacidae), is one of the notorious insect-pestsresponsible for large-scale devastation in rice crop. Scientists monitoring and modeling agriculture insect-pest patterns generally use informationfrom in-situ meteorological stations which are sparsely distributed in a region and therefore,leads to a gap in the observation dataset. The present study involved developing brown planthopper fore-warning model for peak population, utilizing ground based weather parameters and remote sensing derived vegetation indices (NDVI, EVI, LSWI) and land surface temperature. Weather indices based regression model involved computation of two indices *viz.*, accumulated and distribution index. Predictor variables were first lag-correlated with the peak brown planthopper population for eight years (2002-2004 & 2007-2011). Significant variables were then selected with the help of stepwise regression technique. Results showed that 38th week is the best time for prediction of peak population of brown planthopper in rice, supported by high coefficient of determination (0.98) and less MSE (0.054) where relative humidity (morning and evening) and Land Surface Wetness Index (LSWI) are responsible for build-up or decline of BPH population to peak level.

***Keywords*:** Prediction modeling, brown planthopper, weather indices based model, insect-pestand weather

Among several insect-pests of rice, brown planthopper (BPH), (*Nilaparvata lugens* (Stål.) Hemipterans: Delphacidae), is responsible for large-scale devastation in rice crop and results in economic crop losses which can be as high as 60 per cent. It has been a cause of great concern since green revolution, has led to outbreaks and crop failure throughout the country for example, in North India, in 2008. Understanding of pest-weather relationship is of paramount importance for effective pest suppression. Besides, knowledge of the seasonal abundance and pest build up trend is essential to ensure timely preparedness to tackle impending pest problems and prevent crop losses (Das *et al*., 2008).

Role of remote sensing derived weather parameters in the insect-pest modeling

Scientists monitoring and modelling agriculture insect-pest patterns generally use information from *in-situ* meteorological stations which are sparsely distributed in a region and therefore, leads to a gap in the observation dataset (Bao*et al.*, 2011). Weather parameters when retrieved from satellite data having fine spatial and temporal resolution has an advantage of recording spatial variability of weather parameters, and this can be advantageous in terms of predicting insect-pest population with respect to its temperature and other development thresholds. Brown plant hopper population fluctuates according to dynamic conditions of biotic and abiotic factors such as temperature, rainfall and relative humidity (Heong *et al*., 2007). Studies have already been conducted for developing afore-warning model of brown plant hopper for different regions using information from the ground weather station and few studies have been conducted incorporating remote sensing for prediction of an insect-pest population. However, involving both ground based weather station data and satellite data for developing afore-warning model for brown plant hopper is quite new. The present study was an attempt of developing brown plant hopper fore-warning model for predicting outbreak of the pest in advance, utilizing ground based weather parameters and remote sensing derived vegetation indices (NDVI, EVI, LSWI) and land surface temperature (day, night and day and night difference).

MATERIALS AND METHODS

Study area and data required

Remote sensing derived parameters and meteorological data, entomological data were used for developing a fore-warning model for Ludhiana region of Ludhiana district.Materials used for the research work included remote sensing data where NASA Terra MODerate-resolution Imaging Spectroradiometer (MODIS) product was utilized for deriving land surface temperature. MODIS MOD11 A2 is the eight-day composite land surface temperature data of 1-Km day and night (10:30 AM/PM) LST product.The MOD 11A2 eight-day data are an average of clear-sky values. Eight-day composite values have the advantage over daily LST data as eight-day LST data minimizes the loss of data due to clouds to a larger extent. Besides this, MODIS derived surface reflectance (MOD09 A1) Terra product for deriving vegetation indices viz. NDVI, EVI, land surface wetness index. Ten years' (2002-2004 & 2007-2013) historical weather parameters data from Ludhiana was also procured. Entomology data including BPH population survey data (pest intensity and counts) for the past eight (2002-2004 & 2007-2011) years, for Ludhiana region was utilized for developing a fore-warning model of BPH with respect to weather data. Brown planthopper population was monitored using light trap at 75.80277 longitudes and 30.90083 latitude region, weekly. For validation, 2012 & 2013 years' BPH and weather data were used**.** Source of entomology data of Brown planthopper: ICAR, New Delhi.

Brown planthopper fore-warning model

Before developing a fore-warning model, MODIS MOD11 A1 satellite data from which land surface temperature was retrieved, was pre-processed to convert from Kelvin to Celsius. To calculate vegetation indices and LST at rice fields in Ludhiana region, rice mask map was extracted by first creating NDVI of all images and then by classifying further using land use map of the district as the major cropping pattern of the region is wheat-rice.

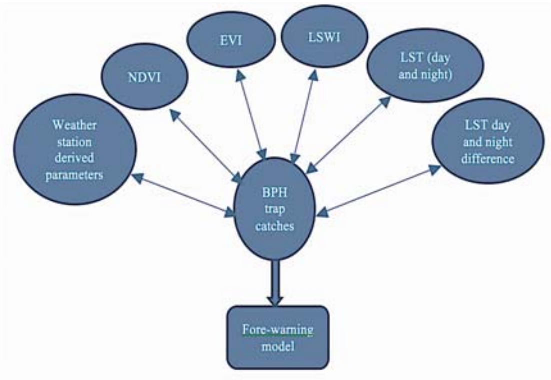

Fig.1. Input for prediction modeling of *Nilaparvata lugens*

After generation of rice mask, vegetation indices and LST were computed of those regions of Ludhiana region where rice crop was grown using 'extract by the mask' and 'zonal statistic option' in ArcGIS, and weighted mean was computed for all 8-day composite images from 2002 to 2004 & 2007 to 2011 yearsduring rice season. The vegetation indices (NDVI, LSWI, and EVI) and land surface temperature (day, night and day-night difference) were computed from MODIS MOD09A1 surface reflectance data and MODIS MOD09A2 data (2002-2004 & 2007-2011) respectively, after re-projection and scaling. Land surface wetness index (LSWI) is sensitive to the total amount of vegetation liquid and also for soil backgroundand gives the status of moisture in and around rice canopy while Normalized difference vegetation index (NDVI)is a linear combination of NIR and RED bands, suggested by Tucker (1979) was used to estimate vegetation cover. Enhanced vegetation index (EVI**)** is an optimized vegetation index intended to improve the vegetation signal with enhanced sensitivity in high biomass regions and improved vegetation monitoring due to the reduction in atmospheric influences. The extent of weather influence on crop pest depends not only on the intensity of weather variables but also on the distribution behavior of weather parameters over the particular crop season. Therefore, in the present investigation, Weather Indices (WI) based regression model was utilized for developing the fore-warning model where, for each predictor variable, two indices were developed, one as total of values of predictor variables in different weeks and the other oneas weighted total, weights being correlation coefficients between variable to forecast and weather variable in respective weeks. The first index gives the total amount of predictor variable received by the crop over the season while the second one takes care of the distribution of the predictor variable with reference to its significance in different weeks in relation to the variable to forecast (Agrawal, Mehta, Kumar, and Bhar, 2004). Ground weather station derived parameters included maximum temperature, minimum temperature, relative humidity (morning and evening), and rainfall. Thus, ground weather station derived parameters along with vegetation indices from satellite data, were stepwise regressed for selecting significant predictor variables to be included in the fore-warning model using SAS software.

RESULTS AND DISCUSSION

Analysis forthe development of a fore-warning model of brown planthopper

The independent variables of eight years were lag correlated (up to five weeks) to the peak population of BPH population. Firstly, the lag-correlated independent variables were stepwise regressed with respect to brown planthopper peak incidence for a specific week without any interaction among the predictor variables. This approach has been used earlier by workers especially, in computing yield of field crops. However, the models developed had a very high value of RMSE coupled with large differences in the observed and predicted values which rendered them as failures as they were misleading and deterring the main purpose of the model i.e. prediction. Kumar *et al.* (2016) reported that for insect-pest development, instead of an individual variable, the cumulative effect of two or more variables and their distribution is more important and more related to the pest incidence than individual weather variables. Therefore, models were developed involvingan interaction of different predictor variables with respect to brown planthopper population was computed for different weeks.

The predictor variables were stepwise regressed in relation to peak brown planthopper population incidence using SAS software. As peak brown planthopper population in all the years occurred between September 4th week and October 3rd week, so, observations only up to October 2nd week were considered for model development. Among various models developed, the final fore-warning model was selected based on the highest coefficient of determination and other statistic measures.

The final fore-warning model of brown planthopper

Table 1 shows the result of stepwise regression for 38th-week model, which showed the highest coefficient of determination, least mean square error. All variables in the model were found to be significant, Z341, which indicates the interaction of morning and evening relative humidity with respect to peak BPH population in eight years, contributed the maximum to the model at 73.74 per cent and significant at 0.0030. Also, Z41 (evening relative humidity) contributed 13.62 per cent variability to the model, significant at 0.0005. Z451 which showed the interaction of evening relative humidity and land surface wetness index contributed 11.58 per cent to the model. Thus, 38th-week model is significant ($F = 154.18$, $p < 0.0001$) indicating that the model accounts for a significant portion of variation in the data ($R2 = 0.98$) and thus, was found to be the best fit model for the prediction of peak BPH population.

Table 1 Result of final fore-warning model for brown planthopper (38th SMW)

Summary of Stepwise Selection						
Y (log BPH) = 8.34 + 0.005 Z341 – 1.372 Z451 – 0.265 Z41						
Step	Variable Entered	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Z341	0.7374	0.7374	1.69E11	19.66	0.0030
2	Z451	0.1158	0.8531	9.45E10	4.73	0.0726
3	Z41	0.1362	0.9893	6.881E9	63.66	0.0005

Hence, relative humidity and land surface wetness index were found to be important factors in the present investigation in influencing the progression and peak BPH population. Studies on diseases like fungal and bacterial also show relation of plant disease epidemiology and leaf surface wetness (Huber and Gillespie, 1992). The present investigation concurs with previous findings in a way that relative humidity is an important factor to influence the population levels of brown planthopper (Yadav *et al.*, 2010). It was observed while investigation that land surface wetness index affects peak brown planthopper population and was more than 0.30 on an average for all years for few weeks before, and during peak population of the insect while relative humidity fluctuated between 70 to 90 per cent during September and thereafter, having influence on the hoppers' population.

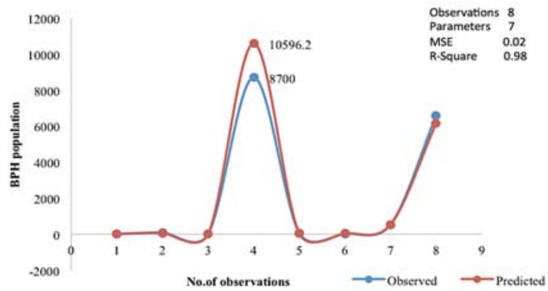

Fig. 2 Observed and predicted graph in different years for brown planthopper

Figure 2 shows observed and predicted pattern for peak brown planthopper population. Forecast values followthe observed pattern very closely, also depicted by a very high coefficient of determination of 0.98 and mean square error, 0.02.

Table 2 Observed and forecast in years based on weather indices based regression model

Model	Year	Observed	Forecast	% deviation of forecast
38th (Standard Meteoro-logical Week)	2002	31.29	24.75	26.42
	2003	96.43	73.00	32.10
	2004	6.14	8.00	23.25
	2007	8700.00	10596.20	17.90
	2008	70.00	49.92	40.22
	2009	30.00	50.57	40.68
	2010	539.00	538.50	0.09
	2011	6571.00	6151.36	6.82

Table 3 shows the per cent deviation of forecast values from observed in different years. The observed values varied from 6.14 to 6571 while predicted values ranged between 8 and 10596. There was a close association between observed and predicted values for peak brown planthopper population count in the 38th standard meteorological week model. The lowest peak population was observed in 2004, the value being 6.14 average counts per light trap per week and the predicted value for this year was 8.00 per light traps. There was a surge in the peak BPH population from 2010. The peak BPH population showed minimum deviation in forecasting in 2010, where both observed (539) and forecasted (538.50) population were quite close. As observed from the table, maximum deviation in the forecast values was observed in 2009 (40.68%) while minimum deviation was found in 2010 (0.09%).

Validation of the fore-warning model

Validation of the final fore-warning model for BPH was done for 2012 and 2013, for the same location by incorporating the relationship derived from the fore-warning model, of the significant parameters and peak BPH population. Fore-warning model was validated with peak BPH light trap catch for 2012-2013 (Fig. 3). As compared to observed population, both in 2012 and 2013, predicted peak BPH population was overestimated by the model. The observed peak population was found to be 3.0 in 2012 whereas the forecasted was 3.72. There was very large scale infestation of BPH in 2013 in Ludhiana as the peak population reached 17685 BPH/light trap, for this predicted peak BPH population was 22357.

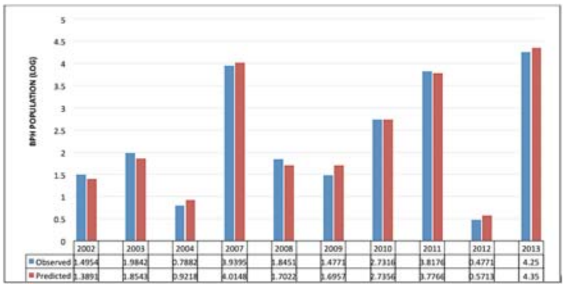

Fig. 3 Validation of the fore-warning model

Table 3 MAPE and RMSE of validation of the fore-warning model

MAPE	MPE	RMSE (%)	R^2
11.51	7.01	7.37	0.98

In some years, there was an overestimation of peak BPH population *viz.*, 2004, 2007, 2009, 2012, and 2013 while in others, under-estimation (2002, 2003, 2008, and 2011) though very less difference was there and R^2 was 0.98 (Table 3). As reported in annual report ofIARI, (IARI, 2014) in 2013, high humidity conditions created due to early onset of rains in June month, favoured fast multiplication of BPH resulting in outbreak of the pest. More vegetation to feed on, favorable conditions of humidity and moderate temperature resulted in the outbreak of BPH in Ludhiana district in 2013. This was validated from the fore-warning model. Validation showed very less value of mean absolute percentage error (MAPE), being 11.51 and mean percentage error of 7.01. Observed RMSE from validation was 7.37 per cent.

CONCLUSION

Weather parameters greatly influence the growth, development and thus, progression or decline of the insect-pest population. This study involved utilizingobservations from both, ground- based weather station and remote sensing, for developing the prediction model of outbreak of brown planthopper in rice. Remote sensing derived LSWI along with an interaction of evening relative humidity had negative relationship with the peak BPH population while evening and morning relative humidity significantly affects the peak BPH population and its outbreak, as was seen in 2013.38th week is the best time for prediction of peak population of brown planthopper in rice by which the outbreak of this pest could be known in advance, so that timely control measures can be taken up to curtail the problem. The present study concurs with earlier studiesthat the interaction of parameters gives better results in the prediction of an insect-pest population. The study of developing afore-warning model using both ground-based weather station and remote sensing data was relatively new in India. Therefore, basic model was developed. More advanced modeling techniques involving machine learning tools can be explored for early warning prediction. Another parameter, growing degree days for particular insect-pest, computed from the satellite data can be incorporated in the model which requires detailed investigation.

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Pre-harvest crop modelling of *kharif* rice using weather parameters in Valsad district of south Gujarat

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ABSTRACT

Rice is the most important staple food in India, which play crucial role in daily requisite of diet. In the Gujarat state, rice occupies about 7-8 per cent of the gross cropped area and accounts for about 14 per cent of the total food grain production. In the present study statistical forecasting models were employed to provide forecast before harvest of crop for taking timely decisions. In this paper Multiple Linear Regression (MLR) technique was utilized for estimating average rice production in Valsad district of South Gujarat. The weather indices were developed utilizing week number as weight by weekly weather parameters for the year 1975 to 2010 and for the cross-validation of the developed forecast models were tested by utilizing data from 2010 to 2014. It is observed that value of Adj. R^2 varied from 55.8 to 61.6 in different models. Based on the findings in the present study, it was observed that model-5 found to be better than all other models for pre harvest forecasting of rice crop yield.

Keywords: Weather indices, MLR techniques, Forecast

Indian economy is mainly based on agriculture and rice is the most important staple food in India as well as Asia. More than 90 per cent of the world's rice is grown and consumed in Asia, where 60 per cent of the world's population lives. India ranks second with 154.6 million tonnes of paddy (FAO, 2015). In the Gujarat state, rice occupies about 7 - 8 per cent of the gross cropped area of the state and accounts for around 14 per cent of the total food grain production. About 90 per cent of area under rice is confined to South and middle Gujarat.

The productivity of the crop was highly influenced by weather parameters. Thus, development of forecasting models based on weather parameter for rice crop is very important role and developed pre-harvest forecast models were utilized in making policy decision regarding export and import, food procurement and distribution, price policies and exercising several administrative measures for storage and marketing of agricultural commodities. Thus, the use of statistical models in forecasting food production and prices for agriculture hold great significance. Although no statistical model can help in forecasting the values exactly but by knowing even approximate values can help in formulating future plans.

MATERIALS AND METHODS

The investigation was carried out in Navsari Agricultural University, Navsari. The study utilized secondary yearly yield data (*Kharif* season) and weekly weather data for 39 years (1975-2014) which were collected from the Directorate of Economics and Statistics, Government of Gujarat, Gandhinagar and Indian Meteorological Department (IMD), Pune respectively. Five weather parameters were included in investigation *viz.* maximum temperature (X_1), minimum temperature (X_2), relative humidity (X_3), wind speed (X_4) and rain fall (X_5). However, weekly weather data related to *kharif* crop season starting from one month before sowing up to one month before harvest of crop (22nd to 37th Standard meteorological week (SMW)) was utilized for development of statistical model. The data of last one month of crop season was excluded keeping in view that forecast crop yield at least one month before harvest. The association between yearly crop yield and different weekly weather parameters were studied by Karl-Person correlation coefficient approach.

Multiple Linear Regressions (MLR) are widely suitable for short or intermediate term forecasting. In present study, MLR was used for developing forecasting models using predictors as appropriate un-weighted and weighted weather indices (Agrawal *et al*., 1980; Jain *et al.,* 1980; Agrawal *et al.,* 1986; Garde *et al.,* 2012; Rajegowda *et al.,* 2014; Singh *et al.,* 2014; Dhekale *et al.,* 2014; and Singh and Sharma, 2017). Weather indices were developed by using week number as weight.

Development of weather indices

1. $$Z_{ij} = \sum_{w=1}^{m}\sum_{j=0}^{1} w^j X_{iw}$$

2. $$Z_{ikj} = \sum_{w=1}^{m}\sum_{j=0}^{1} w^j X_{iw} X_{kw}$$

3. $$Q_{ij} = \frac{\sum_{w=1}^{n}\sum_{j=0}^{1} w^j X_{iw}}{\sum_{w=1}^{n}\sum_{j=0}^{1} w^j}$$

4. $$Q_{ikj} = \frac{\sum_{w=1}^{n}\sum_{j=0}^{1} w^j X_{iw} X_{kw}}{\sum_{w=1}^{n}\sum_{j=0}^{1} w^j}$$

Where, Z_{ij} is the developed weather indices of i^{th} weather parameter for j^{th} weight. Z_{ikj} is the developed weather indices of product of i^{th} and k^{th} weather parameter for j^{th} weight. Q_{ij} is un-weighted (for j=0) and weighted (for j=1) weather indices for i^{th} weather parameter Q_{ikj} is the un-weighted (for j=0) and weighted (for j=1) weather indices for interaction between i^{th} and k^{th} weather parameters. X_{iw} is the value of the i^{th} weather parameter in w^{th} week. m is week of forecast. k=i= 1,2,...,p, j=0,1. and w=1,2,...,m.

Development of models

1. ***Model-1***

This model was developed by using original variables and interaction between original variables. The developed model was

$$Y = A_0 + \sum_{i=1}^{p} a_i X_i + \sum_{i \neq k=1}^{p} a_{ik} X_i X_k + cT + e$$

Where, Y is the observed rice yield. A_0 is the general mean. X_i and X_k are the weather parameters. p is number of weather parameters used. T is the trend parameter and c is the regression coefficients of trend parameter, e is the error term.

2. ***Model-2***

This model was developed by using first and second developed weather indices, only weighted variables were used to develop the model. The developed model was

$$Y = A_0 + \sum_{i=1}^{p} a_{i1} Z_{i1} + \sum_{i \neq k=1}^{p} a_{ik1} Z_{ik1} + cT + e$$

Where, Y is the observed rice yield. A_0 is the general mean. Z_{ij} and Z_{ikj} are the weather indices.

a_{ij} and a_{ikj} are the regression coefficients of Z_{ij} and Z_{ikj} weather indices. p is number of weather parameters used. T is the trend parameter and c is the regression coefficients of trend parameter. e is the error term.

3. ***Model-3***

This model was developed by using third and fourth developed weather indices, only weighted variables were used to develop the model. The developed model was

$$Y = A_0 + \sum_{i=1}^{p} a_{i1} Q_{i1} + \sum_{i \neq k=1}^{p} a_{ik1} Q_{ik1} + cT + e$$

Where, Y is the observed rice yield. A_0 is the general mean. Q_{ij} and Q_{ikj} are the weather indices.

a_{ij} and $a_{ii'j}$ are the regression coefficients of Q_{ij} and Q_{ikj} weather indices. p is number of weather parameters used. T is the trend parameter and c is the regression coefficients of trend parameter. e is the error term.

4. ***Model-4***

This model was developed by using first and second developed weather indices, both un-weighted and weighted variables were used to develop the model. The developed model was

$$Y = A_0 + \sum_{i=1}^{p} \sum_{j=0}^{1} a_{ij} Z_{ij} + \sum_{i \neq k=1}^{p} \sum_{j=0}^{1} a_{ikj} Z_{ikj} + cT + e$$

Where, Y is the observed rice yield. A_0 is the general mean. Z_{ij} and Z_{ikj} are the weather indices.

a_{ij} and a_{ikj} are the regression coefficients of Z_{ij} and Z_{ikj} weather indices. p is number of weather parameters used. T is the trend parameter and c is the regression coefficients of trend parameter. e is the error term.

5. ***Model-5***

This model was developed by using third and fourth developed weather indices, both un-weighted and weighted variables were used to develop the model. The developed model was

$$Y = A_0 + \sum_{i=1}^{p} \sum_{j=0}^{1} a_{ij} Q_{ij} + \sum_{i \neq k=1}^{p} \sum_{j=0}^{1} a_{ikj} Q_{ikj} + cT + e$$

Where, Y is the observed rice yield. A_0 is the general mean. Q_{ij} and Q_{ikj} are the weather indices.

a_{ij} and a_{ikj} are the regression coefficients of Q_{ij} and Q_{ikj} weather indices. p is number of weather parameters used. T is the trend parameter and c is the regression coefficients of trend parameter. e is the error term.

Comparison and Validation of Models

The models were compared on the basis of Forecast error:

$$\text{Forecast Error} = \left\lfloor \frac{O_i - E_i}{O_i} \right\rfloor \times 100$$

Where, O_i the E_i are the observed and forecasted values of crop yield, respectively.

The models were compared on the basis of adjusted coefficient of determination R^2_{adj} as follows:

$$R^2_{adj} = 1 - \frac{SS_{res} / (n-p)}{SS_t / (n-1)}$$

Where, $ss_{res}/(n-p)$ is the residual mean square $ss_t/(n-1)$ is the total mean sum of square.

From the fitted models, rice yield were forecasted for the years 2011-12 to 2014-15 and were compared on the basis of Root Mean Square Error (RMSE).

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^{n} (O_i - E_i)^2 \right]^{1/2}$$

Table 1 Yield Forecasting Models

Model Name	Week No.	Model	Adj. R^2
Model-1	36	$Y = 3644.0 + 19.64T + 0.042Z_{250} - 0.009Z_{350} - 5.24Z_{10}$	55.8
Model-2	32	$Y = -2011.50 + 36.56T + 0.005Z_{451} + 3.53Z_{21} - 0.06Z_{121}$	60.5
Model-3	32	$Y = -2011.45 + 36.57T + 0.317Q_{451} + 233.23Q_{21} - 3.60Q_{121}$	60.5
Model-4	32	$Y = 975.05 + 35.22T + 0.004Z_{451} + 11.02Z_{20} - 1.46Z_{11}$	**61.6**
Model-5	32	$Y = 975.05 + 35.22T + 0.29Q_{451} + 121.25Q_{20} - 96.54Q_{11}$	**61.6**

Table 2 Comparison between yield forecasting models

Model	SMW	Year	Forecast Yield	Actual Yield	Forecast error (%)	RMSE	Adj. R^2
Model-1	36	2010	2058	2634	21.87	644.10	55.8
		2011	1965	2575	23.70		
		2012	1915	2364	18.97		
		2013	2003	2431	17.60		
		2014	1896	2292	17.26		
Model-2	32	2010	1987	2634	24.56	659.10	60.5
		2011	1949	2575	24.28		
		2012	1836	2364	22.32		
		2013	2032	2431	16.42		
		2014	2055	2292	10.34		
Model-3	32	2010	2255	2634	14.39	352.27	60.5
		2011	2216	2575	13.96		
		2012	2100	2364	11.16		
		2013	2258	2431	7.10		
		2014	2297	2292	-0.23		
Model-4	32	2010	2227	2634	15.44	394.80	**61.6**
		2011	2175	2575	15.53		
		2012	2058	2364	12.93		
		2013	2213	2431	8.96		
		2014	2257	2292	1.52		
Model-5	32	2010	2239	2634	15.00	**381.45**	**61.6**
		2011	2185	2575	15.14		
		2012	2063	2364	12.72		
		2013	2235	2431	8.04		
		2014	2281	2292	0.49		

Where, O_i and the E_i are the observed and forecasted values of crop yield, respectively and n is the number of years for which forecasting will be done. Selection of model was made based on highest Adjusted R^2 value and lowest RMSE and forecast error value among the method.

RESULT AND DISCUSSION

The best model was identified on the basis of adjusted coefficient of determination, (Adj. R^2). The forecasting models were developed at different time periods *i.e.* 32th week onwards at weekly interval which shown in Table 1. The values of adj. R^2 were varied from 55.8 per cent in model-1 to 61.6 per cent for model-4 and model-5 which indicates model-4 and model-5 are best among all other models. This 61.6 per cent variation accounted by weather indices T, Z_{451}, Z_{20} and Z_{11} for model-4 and T, Q_{451}, Q_{20} and Q_{11} for model-5. Thus, the model using un-weighted and weighted indices was found to be appropriate in 32th SMW (ten weeks before harvest of crop).

Comparison of models was made by using values of root mean squared error (RMSE) and forecast error (Fig. 5). The validation of the models was done only for those showed meaningful results (for all models). The comparison of results given in Table 2 showed that for forecasting rice yield, model-

3 was better with lower RMSE value of 352.27 as compared to all other models. But Adj. R^2 was less compared model-4 and model-5 with RMSE value of 394.80 and 381.45 which slight difference with mode-3. Both model-4 and model-5 yields same Adj. R^2 but model-5 has lower RMSE and forecast error (0.49 to 15.14) value compared to model-4 hence model-5 was suitable for Valsad district of South Gujarat.

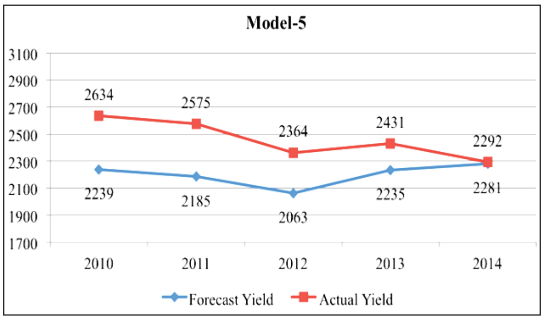

Fig1: Comparison of expected and actual rice yield using model-5

CONCLUSION

Using the forecast model, pre-harvest estimates of rice crop yield for Valsad district could be computed successfully before ten weeks of actual harvest *i.e.* during panicle initiation stage of the crop period. The weather variables involved in models were interaction between wind speed and rainfall, minimum temperature and maximum temperature.

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