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Research Paper

Combining satellite and meteorological insights for yellow stem borer risk prediction in rice cultivation

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ABSTRACT

Yellow stem borer (YSB) is a major pest responsible for substantial rice yield losses which can be significantly reduced through accurate forecasting, enabling timely interventions. This study aimed to develop a forewarning model for YSB using weather parameters and remotely sensed vegetation indices based on 19 years (2000–2018) of data from Raipur, Chhattisgarh. Weather variables and satellite derived vegetation indices were used as predictors, with pest population as the response variable. The model developed for the 39th Standard Meteorological Week (SMW) indicated that lag-time period of four week i.e., advance prediction of peak YSB population by 35th SMW achieved with high coefficient of determination ($R^2 = 0.77$), low root mean square error (RMSE = 0.34) and low mean absolute percentage error (MAPE = 15%). Key predictors included the interaction of land surface wetness index and enhanced vegetation index, evening relative humidity and maximum temperature. A risk zoning map generated using the model indicated that most of Raipur falls under a low pest risk zone. Overall, this study highlights the potential of integrating satellite-based variables into pest forewarning systems, providing a foundation for more accurate agromet-advisory services in India.

Keywords: Yellow stem borer, Forewarning model, Weather indices-based model, Remote sensing, NDVI, EVI, LSWI

Globally, more than 10,000 insect species causes substantial losses in food grains and affects overall food security. It is estimated that annual crop losses due to insect pests are approximately 13.6% at the global level (Benedict, 2003) and 23.3% in India (Dhaliwal *et al.*, 2006). Among the various insect pests infesting rice crops, the yellow stem borer (*Scirpophaga incertulas* (Walker); Lepidoptera) is particularly responsible for substantial devastation, ultimately leading to considerable economic losses for farmers. This monophagous insect's larvae bore into rice stems, feeding on internal tissues, stems, and panicles, resulting in "dead heart" symptoms during the vegetative stage and "white heads" during the reproductive stage, where the panicles fail to produce grains (Kumar *et al.*, 2016). Meteorological conditions play a pivotal role in the outbreak and development of insect pests across different fields. Regular monitoring of pest incidence is valuable not only for understanding insect activity in relation to varying weather conditions but also for analyzing the population dynamics of pests over time. Gaining insights into population dynamics is crucial for planning and implementing timely pest control measures

(Rajalakshmi *et al.*, 2017; Pandi *et al.*, 2020; Giri *et al.*, 2022).

Accurate forecasting of pest population development and dynamics is essential for effective pest management, which in turn helps minimize crop yield losses. Traditionally, the monitoring and modelling of agricultural insect pests have relied on data from in-situ meteorological stations, often resulting in gaps in spatial coverage (Bao *et al.*, 2011; Rajalakshmi *et al.*, 2017; Rana *et al.*, 2017). In contrast, satellite-derived weather parameters, with their finer spatial and temporal resolution, provide a valuable advantage in capturing the spatial variability of weather conditions. This capability is particularly useful for predicting pest populations based on a combination of weather data, ground observations, and satellite-derived datasets (Rana *et al.*, 2017; Skawsang *et al.*, 2019). For instance, Rana *et al.*, (2017) developed early-warning models for brown planthopper outbreaks using ground-based weather station data. However, relatively few studies have incorporated remote sensing for insect pest prediction. Remote sensing (RS) derived spectral indices i.e. normalized difference

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Table 1: Description of Satellite and weather related data used in present study

Satellite	Sensor/ data source	Resolution		Period	Use in the study
		Spatial	Temporal		
Observatory Weather	IMD	Point	weekly	June-Nov. for 2000-2018	Weather Indices
Resourcesat-2	AWiFS	56 m	5 days	8 Sep, 24 Sep & 18 Oct (2013) 5 Sep, 25 Sep & 16 Oct (2017)	Crop classification
MODIS (MOD09A1.061)	Terra/ MODIS	250 m	1 day (8- day composite)	June to Nov. for 2000-2018	Vegetation indices (NDVI, EVI & LSWI)
Gridded Climate (ERA5)	ECMWF	9.0 Km	Daily	June to Nov. 35-38 SMW for 2000-2018	Pest risk Zoning

vegetation index (NDVI), enhanced vegetation index (EVI), land surface wetness index etc. depict the crop vigour, crop growth and leaf/ canopy wetness at spatial scale. The high scale value of these indices explicitly define the certain trigger condition for insect-pest infestation at larger area in spatio-temporal scale. Thus, integration of satellite-derived parameters in forewarning model possibly illustrate the more realistic details of insect-pest prediction in spatial scale. Considering the importance of weather variables, in-situ observations, and satellite-derived data, the present study aims to develop a forewarning model for yellow stem borer (YSB) outbreaks by integrating remote sensing-derived vegetation indices with ground-based weather parameters.

MATERIAL AND METHOD

Study area and data required

In this study, the meteorological & entomological datasets of Raipur district, Chhattisgarh were obtained from the M.Sc. (Ag.) thesis of Dubey (2019) to develop the forewarning models for yellow stem borer (YSB) of rice crop. The data included YSB light trap catches for *Kharif* season, weather variables (maximum & minimum air temperature, morning and evening relative humidity) for the period of 2000-2018. Satellite derived parameters such as NDVI, EVI and LSWI from 2000-2018 were generated from the NASA Terra MODIS eight-day surface reflectance product (MOD09; modis.gsfc.nasa.gov/data/dataproduct/mod09.php). All datasets were organised on a Standard meteorological week (SMW) basis for both model development and validation. A preliminary correlation analysis was conducted to identify variables exhibiting a meaningful relationship with YSB population. Based on this analysis, five predictor variables—EVI, LSWI, maximum temperature, morning relative humidity, and evening relative humidity were selected for further modelling. In addition, ERA-5 reanalysis datasets (provided by Copernicus Climate Change Service), including maximum temperature, relative humidity (morning and evening), were used to develop a spatial distribution map of pest risk zonation across the study area. The detailed description of satellite and weather data is illustrated in Table 1.

Development of RS derived forewarning model

In this approach, two indices were developed for each weather and RS derived variable, following the methodology described by Agrawal *et al.*, (2007) and Desai *et al.*, (2004). Remote sensing-derived variables, along with weather variables, were integrated into the model development as both weighted and

unweighted inputs, enabling the forewarning model to operate at a spatial scale. The first index represented a weighted total of the predictor variable itself, without accounting of interactions. The weights applied were the correlation coefficients between the target variable (i.e., the variable to be forecasted) and the individual weather and RS derived variables for each respective week. The second index was designed to capture the combined effects of weather and RS derived variables. This was achieved by calculating the weighted sum of the products of paired weather and RS derived variables. The weights, in this case, were the correlation coefficients between the forecasted variable and the product of two weather and RS derived variables during each respective week. The mathematical formulation of the model is as follows (Agrawal *et al.*, 2007; Desai *et al.*, 2004; Ghosh *et al.*, 2014; Hendrick and Scholl 1943):

$$= A_0 + \sum_{i=1}^p \sum_{j=0}^1 a_{ij} z_{ij} + \sum_{i \neq j=1}^p \sum_{j=0}^1 a_{iij} z_{iij} + e$$

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

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

Where, Y = variable to forecast; A_0 = Intercept or constant term; / = Regression coefficients; i = value of i^{th} / i^{th} weather variable in w^{th} week; r_{iw}/r_{iirw} = correlation coefficient between Y with i^{th} predictor variable/ product of i^{th} and i^{th} predictor variable in w^{th} week; p = number of predictor variables; n_1 & n_2 = initial & final week for which weather data was included in the model (i.e., 34th to 38th SMW) and e = error term. Predictor variables used for are maximum temperature (T_{max}), morning relative humidity (RH-I), evening relative humidity (RH-II), Satellite derived indices i.e., EVI and LSWI.

The stepwise regression technique was employed to identify and select the most significant variables for inclusion in the model. Forewarning models for YSB were developed using different lag periods, ranging from two to five weeks prior to the forecast week. The forecasting performance of the models was evaluated using the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The selected best-performing model was validated using independent data from the years 2015 to 2018. Additionally, a comparative analysis was conducted between two sets of models: one integrating both satellite-derived indices and ground-based meteorological predictor variables and another using only ground-based meteorological variables. The performance of both models was assessed based on the aforementioned evaluation criteria.

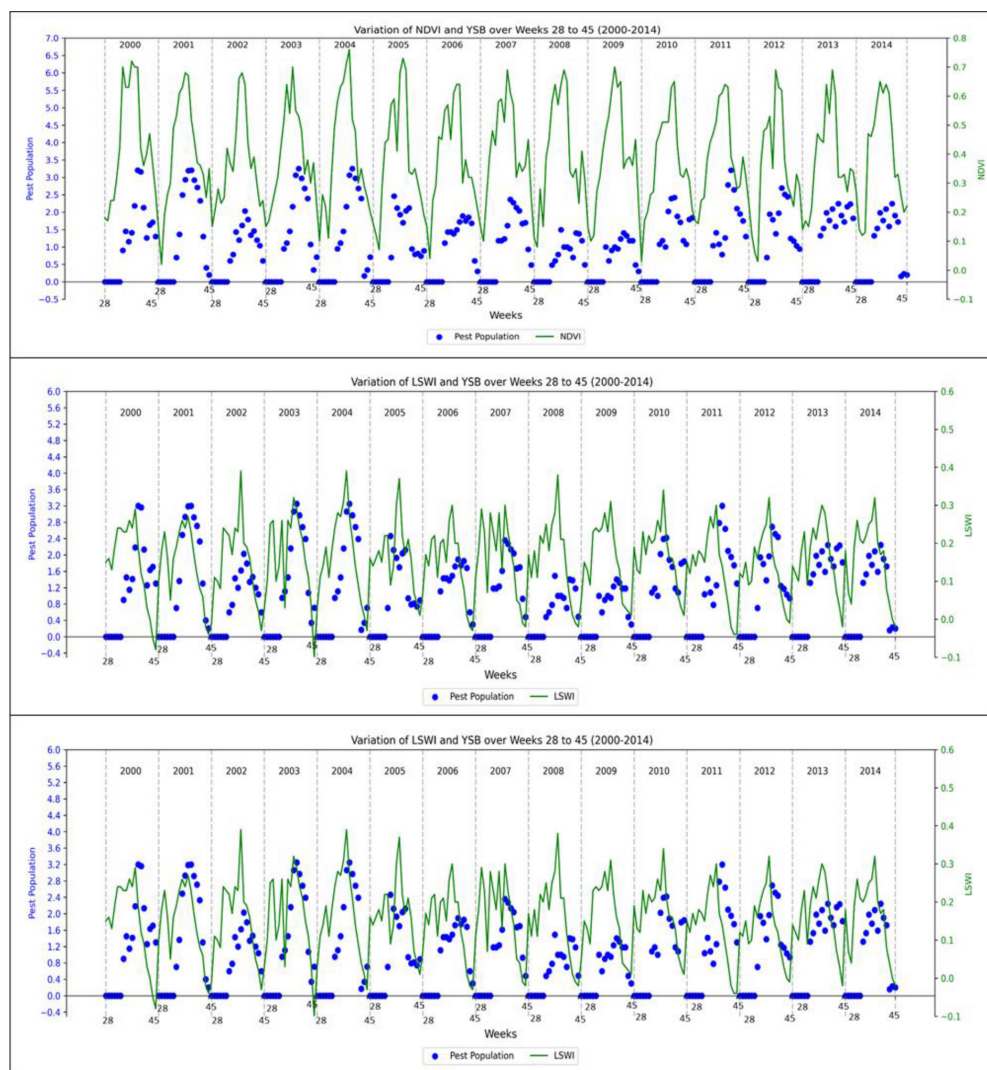


Fig. 1: Variation of NDVI, EVI and LSWI with YSB Incidence over weeks 28 to 45 (2000-2014)

Pest risk zoning for Raipur, Chhattisgarh

Pest risk zoning is a valuable tool for managing insect pests over large areas, as it helps identify hotspots of pest concentration and predict potential outbreak zones. This, in turn, provides critical insights for implementing targeted and timely pest management strategies. To develop the pest risk zone map, significant predictor variables were identified from the forewarning models. For generating spatial variables relevant to pest risk assessment in the Raipur region, satellite-derived meteorological datasets from ERA-5 (including maximum temperature and morning and evening relative humidity) were obtained through Google Earth Engine. These datasets, corresponding to weeks 35 to 38 for the years 2000 to 2014, were used to develop the spatial distribution map for pest risk zonation.

RESULTS AND DISCUSSIONS

Variation of spectral indices and YSB population

To examine the relationship between different spectral indices and YSB population, a trend analysis was conducted by plotting YSB population data against corresponding values

of various spectral indices. Fig. 1 illustrates the trend between vegetation indices (NDVI, EVI and LSWI) and pest population. As shown in the figure, there is a noticeable increase in YSB population following a rise in NDVI values. This observation suggests that higher NDVI values, which indicate healthier and denser vegetation, may provide favorable conditions and increased food availability for YSB, thereby promoting a spike in its population. However, significant changes in NDVI are typically observed only during periods of high pest incidence or outbreaks, when severe damage such as “dead heart” or “white ear head” symptoms become apparent in the crop canopy.

Like NDVI, EVI is used to assess vegetation greenness; however, EVI offers improved correction for atmospheric influences and canopy background noise, making it particularly effective in areas with dense vegetation. Throughout the study period, EVI values ranged from 0.12 to 0.51, with peaks observed between the 33rd and 37th Standard Meteorological Weeks (SMW), corresponding to August and September—the peak vegetative phase of the rice crop, as illustrated in Fig. 1. The EVI trend closely mirrored that of NDVI in relation to the YSB population, showing a clear increase in pest population following a rise in EVI values.

Table 2: Models for forewarning of yellow stem borer

Model	Model equation	R ²	RMSE	MAPE
Model A (2 lagged weeks)	$Y_{(LOG)} = 2.04 + 0.06 * Z_{341} - 0.001 * Z_{41}$	0.12	0.67	33%
Model B (3 lagged weeks)	$Y_{(LOG)} = 0.39 + 30.56 * Z_{121}$	0.15	0.66	32%
Model C (4 lagged weeks)	$Y_{(LOG)} = 8.12 + 0.52 * Z_{51} + 78.91 * Z_{121} - 0.003 * Z_{131}$	0.77	0.34	15%
Model D (5 lagged weeks)	$Y_{(LOG)} = 11.85 + 0.42 Z_{251}^* + 0.28 * Z_{41} - 0.003 * Z_{341}$	0.67	0.41	17%

(Z_{341} = Weighted interactions of minimum temperature and morning humidity, Z_{41} = Weighted morning humidity, Z_{121} = Weighted interaction of EVI and LSWI, Z_{51} = Weighted evening humidity, Z_{131} = Weighted interaction of EVI and maximum temperature, Z_{251} = Weighted interactions of LSWI and evening humidity)

Table 3: Comparison of models

Sr. No.	Model	Model Equation	R ²	RMSE	MAPE
1.	Model including both meteorological & satellite derived indices	$(Y_{(LOG)} = 8.12 + 0.52 Z_{51} + 78.91 Z_{121} - 0.003 Z_{131})$	0.77	0.34	15%
2.	Model excluding satellite derived indices	$(Y_{(LOG)} = -5.19 + 0.46 Z_{51} + 0.38 Z_{41})$	0.60	0.45	20%

(Z_{121} = Weighted interaction of EVI and LSWI, Z_{51} = Weighted evening humidity, Z_{131} = Weighted interaction of EVI and maximum temperature, Z_{31} = Weighted maximum temperature)

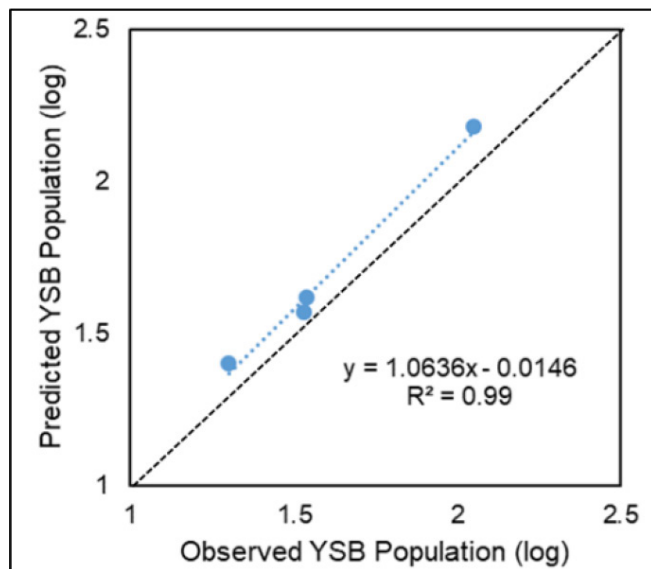
**Fig. 2:** Validation of the forewarning model

Fig. 1 illustrates the trend of the Land Surface Water Index (LSWI), which is highly sensitive to variations in vegetation canopy water content. During the transplanting stage, LSWI values ranged from 0.03 to 0.18. As the crop progressed into the vegetative growth phase, LSWI values steadily increased, peaking at 0.39 by the 38th Standard Meteorological Week (SMW). The data presented in Fig. 1 indicate a clear association between higher LSWI values and increased YSB infestation. This relationship suggests that periods of elevated canopy water content, as captured by LSWI, often coincide with a rise in YSB population, potentially due to favourable microclimatic conditions that support pest development and survival.

Models for yellow stem borer

The forewarning models developed using different lag periods are presented in Table 2, along with their respective R², RMSE, and MAPE values. Among these, the model with a four-week lag was identified as the most effective for predicting YSB

population, based on its highest R² and lowest RMSE and MAPE values. The final model equation was constructed using stepwise regression analysis, incorporating both weighted and unweighted weather variables to optimize predictive performance. Table 2 presents the various forewarning models developed for YSB, among which Model C, the four-week lagged model, was identified as the optimal model for predicting YSB population. This model achieved the highest coefficient of determination (R² = 0.77) and the lowest Mean Absolute Percentage Error (MAPE = 15%). All variables included in the selected model were statistically significant. Notably, the variable Z121, representing the interaction between EVI and LSWI in relation to peak YSB populations over a 15-year period, had a strong positive influence on pest population. This is evident from its coefficient of 78.91 and high statistical significance (p = 0.001). Additionally, Z51 (relative humidity) and Z131 (interaction between maximum temperature and EVI) were identified as key contributing factors, with significance levels of p = 0.0002 and p = 0.02, respectively. The overall model was highly significant (p < 0.01; p = 0.0006).

These findings are in consistent with earlier research that highlights the pivotal role of maximum temperature, morning humidity, and evening humidity in influencing YSB population dynamics (Bao *et al.*, 2011). Furthermore, the study reinforces previous conclusions that LSWI and relative humidity (both morning and evening) are crucial in the build-up or decline of brown plant hopper (BPH) populations to their peak levels (Rana *et al.*, 2017).

Validation of the model

The final forewarning model for YSB was validated using data from 2015 to 2018 for the same location, applying the relationship derived from the model. The validation results are illustrated in Fig. 2. When comparing the predicted YSB population with the observed values for the validation period, it was found that the model overestimated the pest population in the years 2015, 2016, and 2018, while it underestimated the population in 2017. Despite these variations, the overall trends were closely aligned, demonstrating the model's capability to reasonably forecast YSB outbreaks.

Comparison of the models

A comparison was conducted between two four-week lagged models: one that incorporated both satellite-derived spectral indices and ground-based meteorological predictor variables and another that utilized only ground-based meteorological data. This comparison aimed to highlight the added value of integrating remote sensing parameters in predicting YSB population dynamics. As shown in Table 3, the inclusion of satellite-derived indices significantly improved model performance. The R^2 value increased from 0.60 to 0.77, and the MAPE decreased from 20% to 15%, indicating enhanced predictive accuracy. These findings align with previous research by Skawsang *et al.*, (2019), which demonstrated that integrating EVI time series with ground-based meteorological variables notably improved pest forecasting models for brown planthopper (BPH) in rice, with an increase in adjusted R^2 from 0.356 to 0.585 ($p < 0.01$).

Pest risk zone mapping

Pest risk zoning for YSB in the Raipur district was conducted by spatially generating the model's predictor variables using ERA-5 datasets. These variables were then incorporated into the best-performing model equation (the four-week lagged model) within a GIS environment to produce the pest risk zone map. The resulting map was reclassified into three pest risk categories based on predicted YSB population levels: low (<500), medium (500–1500), and high (>1500) pest risk zones, depicted in Fig. 3. The reclassification was done based on the classification criteria used by Rana (2017). The pest risk map predicted the peak YSB population across the district and revealed that most of the Raipur district falls within the low-risk category, while the southern part of the district exhibited moderate to high pest risk zones.

Pest risk prediction plays a crucial role in enhancing crop productivity by providing vital information on potential pest outbreaks and enabling early detection of pest surges. This timely insight allows for the strategic application of control measures—such as bio-pesticides and insecticides at the most effective times. It also helps reduce unnecessary pesticide usage, as treatments can be applied only under high-risk conditions, thus minimizing environmental impact. By preventing severe pest infestations, such predictive approaches help safeguard crop health, ultimately leading to increased yields and improved income for farmers. In the long term, data-driven pest management fosters resilience and promotes sustainability by encouraging the adoption of Integrated Pest Management (IPM) practices and maintaining ecological balance.

CONCLUSION

Weather play a critical role in influencing the growth and development of insect pest populations. Maximum temperature, relative humidity, and vegetation indices such as EVI and LSWI were identified as significant factors influencing the YSB pest population and were crucial in the model development. The forewarning model, with a four-week lag, was developed using relative humidity (Z51) and the interaction between EVI and LSWI (Z121) through stepwise regression analysis. This model significantly predicted the YSB population, demonstrating that the combined effect of vegetation

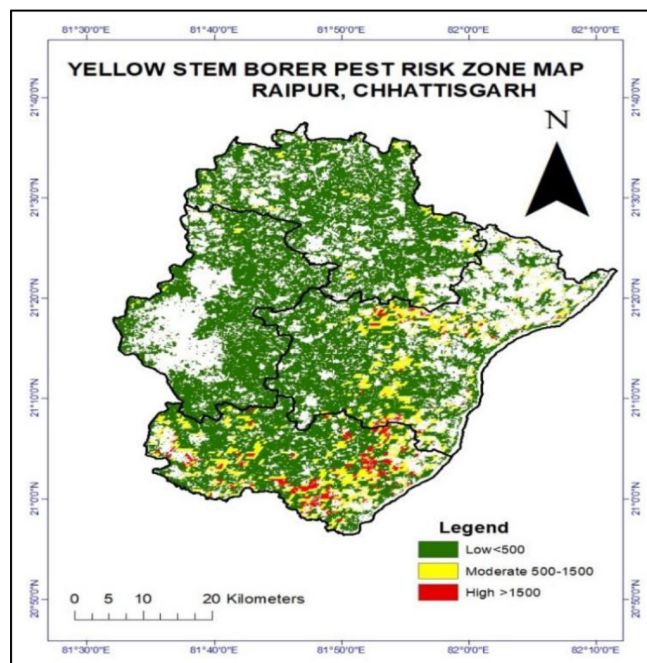


Fig. 3: Pest risk zones from low to high YSB population for different regions of Raipur district

health and surface wetness notably increases the YSB population. Integrating satellite-derived data (spectral indices) with ground-based meteorological information improved the overall accuracy of the model. Specifically, it increased the R^2 from 0.60 to 0.77, reduced the RMSE from 0.45 to 0.34, and decreased the MAPE from 20% to 15%. By incorporating satellite data, weather data, and ground/ancillary data, the model effectively captured the seasonal dynamics of crop vigour, pest growth, and prevailing meteorological conditions. Thus, the forewarning model provides both spatial and temporal insights, enabling risk prediction under both normal and favourable conditions for pest dynamics. This model-based risk prediction is highly valuable for improving productivity by supporting timely pest management decisions and strengthening the foundation for more accurate agromet-advisory services in India.

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REFERENCES

- Agrawal, R. and Mehta, S. C. (2007). Weather Based Forecasting of Crop Yields, Pests and Diseases - IASRI Models. *J. Ind. Soc. Agril. Statist.*, 61(2): 255-263.
- Bao, Y.W., Yu, M.X. and Wu, W. (2011). Design and implementation of database for a web GIS-based rice diseases and pests system. *Proc. Environ. Sci.*, 10: 535-540.
- Benedict, J.H. (2003). Strategies for controlling insect, mite and nematode pests. In: Plants, Genes and Crop Biotechnology (Eds. Chrispeels, M.J. and D.E. Sadava). pp. 414-442, Jones and Bartlett Publishers. USA.
- Desai, A. G., Chattopadhyay, C., Agrawal, Ranjana, Kumar, A., Meena, R. L., Meena, P. D., Sharma, K. C., Rao, M. Srinivasa, Prasad, Y. G. and Ramakrishna, Y. S. (2004). Brassica juncea powdery mildew epidemiology and weather-based forecasting models for India - A case study. *J. Plant Dis. Prot.*, 111, 5: 429-438.
- Dhaliwal, L.K., Hundal, S.S., Aneja, A. and Chahal, S.K. (2006). Incidence of rice stem borer in relation to meteorological parameters under different planting methods. *J. Res. Punjab Agric. Univ.*, 43 (3): 182-84.
- Dubey, P. (2019). Formulation of prediction model for major rice insect pests and its validation through light trap catches (Master's thesis, Indira Gandhi Krishi Vishwavidyalaya, Raipur, Chhattisgarh).
- Ghosh, K., Balasubramanian, R., Bandopadhyay, S., Chattopadhyay, N., Singh, K. K. and Rathore, L.S. (2014). Development of crop yield forecast models under FASAL: A case study of kharif rice in West Bengal. *J. Agrometeorol.*, 16(1): 1-8. <https://doi.org/10.54386/jam.v16i1.1479>
- Giri, G.S., Raju, S.V.S., Mohapatra, S.D. and Mohapatra, M. (2022). Effect of elevated carbon dioxide on biology and morphometric parameters of yellow stem borer, *Scirpophaga incertulas* infesting rice (*Oryza sativa*). *J. Agrometeorol.*, 22(1): 77-82. <https://doi.org/10.54386/jam.v22i1.1778>
- Hendrick, W.A. and Scholl. J.C. (1943). Technique in measuring joint relationship the joint effects of temperature and precipitation on crop yield. *North Carolina Agric. Exp. Sta. Tech. Bull.*, 74.
- Kumar, A., Misra, T., Batra, K., Sharma, R., Mishra, A. K., Vennila, S., Tanwar, R. K., Singh, N., Wahi, P., Rajendran, R., Sidde Gowda, D. K., Sarao, P. S., Jalgaonkar, V. N., Roy, S. K. and Chattopadhyay, C. (2016). Web enabled and weather based forewarning of yellow stem borer [*Scirpophaga incertulas* (Walker)] and leaf folder [*Cnaphalocris medinalis* (Guenee)] for different rice growing locations of India. *Mausam*, 67 (4): 861-868.
- Pandi, Guru-Pirasanna G., Annamalai M., Basana Gowda, N.K. Patil, Prasanthi Golive, Totan Adak, P.C. Rath, and Mayabini Jena. (2020). Effect of weather parameters on rice yellow stem borer *Scirpophaga incertulas* (walker) population dynamics under shallow low land ecology. *J. Agrometeorol.*, 22(1): 89-91. <https://doi.org/10.54386/jam.v22i1.134>
- Rajalakshmi, D., Balasubramanian, R. and Ahmed, M. (2017). Development of forewarning model for rice yellow stem borer over West Bengal. *J. Agrometeorol.*, 19 (special issue- AGMET 2016): 265-269.
- Rana, V. (2017). Pest risk mapping and forewarning model of brown plant hopper using weather station and remote sensing derived parameters (Master's thesis, Andhra University, Visakhapatnam, Andhra Pradesh).
- Rana, V., Patel N. R., Chattopadhyay C. and Kumar A. (2017). Development of forewarning model for brown plant hopper in rice using satellite and meteorological data. *J. Agrometeorol.*, 19 (Special Issue - AGMET 2016), 192-195.
- Skawsang, S., Nagai, M., Tripathi, N.K. and Soni, P. (2019). Predicting Rice Pest Population Occurrence with Satellite-Derived Crop Phenology, Ground Meteorological Observation, and Machine Learning: A Case Study for the Central Plain of Thailand. *Appl. Sci.*, 9 (22), 4846.