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Influence of weather parameters on the population dynamics of major rice insect pests and natural enemies: A multiple regression analysis of light-trap catches

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Abstract
Rice insect populations are strongly influenced by weather conditions, but the magnitude and direction of these relationships vary among pest species. The present study assessed the influence of selected weather parameters *viz*., maximum and minimum temperature, rainfall, morning relative and evening relative humidity and sunshine hours, on the population dynamics of major rice insect pests and natural enemies i.e. yellow stem borer (YSB), gall midge (GM), leaf folder (LF), green leafhopper (GLH), brown planthopper (BPH), white-backed planthopper (WBPH), mirid bugs and coccinellids by using weekly light-trap catches recorded during 2012–2014 at the Regional Agricultural Research Station, Maruteru, Andhra Pradesh, India. A total of 157 weekly observations were analyzed, of which 155 complete observations were used for multiple linear regression. Significant overall regression models were obtained for YSB females, YSB males, leaf folder, GLH, BPH and WBPH. The explanatory power of the significant models was relatively low to moderate, with R^2 values ranging from 0.081 for GLH to 0.237 for WBPH. Evening relative humidity showed a significant negative association with both female and male YSB catches. Rainfall had a significant positive effect on leaf-folder abundance, while morning relative humidity and sunshine hours were positively associated with BPH. For WBPH, maximum temperature showed a significant negative association, whereas rainfall and sunshine hours had significant positive effects. Multicollinearity among weather variables was moderate, with the highest VIF recorded for maximum temperature (4.72). Residual diagnostics indicated temporal dependence in the weekly observations, particularly for the WBPH model. Overall, the study demonstrated that weather conditions contribute to the population dynamics of several rice insect pests, but current-week weather variables alone explain only a limited proportion of their variation. Incorporating crop phenology, pest abundance, natural-enemy activity and other ecological factors may improve the understanding and prediction of rice pest dynamics.

Keywords: Rice insect pests, Light trap, Weather parameters, Multiple regression, Pest forecasting

Introduction

Rice (*Oryza sativa* L.) is cultivated under diverse agroecosystems in which insect communities are regulated by interactions among the crop, weather, natural enemies and crop management. Although many arthropods occur in rice, yellow stem borer, gall midge, leaf folder, green leafhopper, brown planthopper and white-backed planthopper are among the pests that can periodically become important. Planthoppers are of particular concern because outbreaks can cause direct feeding injury and, in some species, facilitate virus transmission; their population build-up is also closely linked to crop management and ecosystem processes. Heong *et al.* (2009) [1] emphasized the importance of conserving biological control and avoiding management practices that destabilize rice arthropod communities.

Weather is also an important environmental driver of insect population dynamics because temperature affects development rate, survival and generation time, whereas humidity, rainfall and solar radiation can influence adult activity, dispersal and host-plant suitability. These relationships are generally species and location specific. In rice, weather-based regression has been used successfully to relate light-trap catches to meteorological variables. Prasannakumar *et al*. (2015) related yellow stem borer light-trap peaks, weather parameters and identified minimum temperature, rainfall and morning relative humidity as important predictors in their final model. Jasrotia *et al.* (2019) [2] demonstrated significant associations between weather variables and YSB and leaf folder incidence.

Light traps provide repeated observations of adult insect activity and are useful for monitoring seasonal emergence and population trends. Long term studies have demonstrated relationships between light trap catches of rice pests and climatic factors. Rai *et al.* (2002) [3] reported a measurable 22% contribution of

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morning relative humidity to green leafhopper light trap catches. While, Udayababu *et al.* (2021) [4] examined multiyear light trap catches of rice insect pests in relation to abiotic factors in Andhra Pradesh. Light trap-based weather relationships are therefore useful for regional surveillance, although trap catches represent adult activity as well as population density. Hence the present investigation was taken up by using three years light trap catches data with the objectives (i) quantify the combined effect of six meteorological variables on weekly light-trap catches of major rice insect pests and selected natural enemies; (ii) develop species-specific multiple regression equations; (iii) identify significant weather predictors and their direction of association; and (iv) assess model explanatory power and statistical diagnostics relevant to the use of these equations in pest surveillance and forecasting.

Materials and methods

Study area, data source and variables

The present investigation used weekly light-trap observations recorded for three years (2012–2014) at the Regional Agricultural Research Station, Maruteru, West Godavari district, Andhra Pradesh, India. The experimental site is situated in the Godavari delta region between 16°38′ N latitude and 81°44′ E longitude, at an altitude of approximately 5 m above mean sea level. The region has a tropical humid climate characterized by hot summers, a southwest monsoon (June–September) and a northeast monsoon (October–December). Rice is the predominant crop cultivated throughout the year under irrigated conditions.

Adult populations of major rice insect pests and beneficial insects were monitored continuously using a standard Chinsurah light trap installed at the experimental farm. The trap was operated from dusk to dawn (approximately 18:00–06:00 h) following the standard procedures adopted by the All India Coordinated Research Project on Rice. Insects attracted to the trap were collected each morning, sorted, identified and counted. Daily catches were pooled to obtain weekly observations corresponding to each Standard Meteorological Week (SMW). Corresponding weekly meteorological observations were obtained from the Agrometeorological Observatory at the Regional Agricultural Research Station, Maruteru. The insect variables comprised yellow stem borer (YSB; female and male catches), gall midge, leaf folder, green leafhopper (GLH), brown planthopper (BPH), white-backed planthopper (WBPH), green mirid bugs and coccinellids. Weather variables were maximum temperature (°C), minimum temperature (°C), rainfall (mm), sunshine duration (h day^{-1}), morning relative humidity (%) and evening relative humidity (%).

Statistical analysis

Separate ordinary least-squares multiple linear regression models were fitted for each insect group. Multiple regression was used as an initial explanatory framework because it estimates the partial contribution of several meteorological predictors while controlling for the remaining variables (Montgomery *et al.*, 2012) [5]. The general model was $Y = a + b_1Tmax + b_2Tmin + b_3Rainfall + b_4RHm + b_5RHe + b_6SSH + e$. Regression coefficients were interpreted as the expected change in weekly trap catch associated with a one-unit increase in a predictor, with all other predictors held constant. Model fit was assessed using R^2, adjusted R^2, the overall *F*-test and RMSE. Individual predictors were evaluated using t-tests, and standardized regression coefficients (β) were calculated to facilitate comparison among predictors measured on different scales.

Additional statistical diagnostics

Pearson correlation analysis was used to examine associations among insect variables and weather variables. Variance inflation factors (VIF) were calculated to assess multicollinearity and were treated as diagnostic measures rather than automatic variable-deletion criteria (O'Brien, 2007) [6]. Residual-versus-fitted plots were examined for systematic patterns and heteroscedasticity. Durbin–Watson statistics were calculated to assess first-order residual serial correlation (Durbin *et al.*, 1950) [7].

Results

Descriptive and contemporaneous multiple regression model-level results

The performance of the contemporaneous multiple regression models varied among the insect pests and natural enemies. Significant overall models were obtained for YSB female, YSB male, leaf folder, green leafhopper, brown planthopper and white-backed planthopper ($P < 0.05$). Among these, WBPH exhibited the highest explanatory power ($R^2 = 0.237$; adjusted $R^2 = 0.206$; $F = 7.641$; $P < 0.001$), followed by YSB female ($R^2 = 0.208$) and YSB male ($R^2 = 0.196$). The models for gall midge, mirid bugs and coccinellids were not significant at the 5% level. Overall, R^2 values ranged from 0.041 to 0.237, indicating that contemporaneous weather variables alone explained a limited proportion of the variation in weekly light-trap catches. The Durbin–Watson statistics ranged from 0.622 to 1.094 across the regression models, with all values below the reference value of 2.0, indicating positive first-order serial correlation in the residuals. The strongest indication of temporal dependence was observed for BPH (DW = 0.622), followed by YSB male (0.758) and mirid bugs (0.844). Because the dataset comprised successive weekly light-trap observations, the observed residual autocorrelation suggests that current insect abundance was partly related to preceding observations and that the contemporaneous weather-only models did not fully account for temporal dependence. This finding supports the incorporation of lagged pest abundance and lagged weather variables in subsequent model development (Table 1).

Correlation between rice insect populations and weather parameters

The correlation analysis (Fig. 1) showed that rice insect populations and weather variables were related to different degrees during 2012–2014. Among the insects, YSB-F and YSB-M showed the strongest positive correlation ($r = 0.89$), indicating that their weekly catches followed a similar pattern. GLH and WBPH ($r = 0.60$) and BPH and mirid bugs ($r = 0.52$) also showed strong positive relationships. Moderate positive correlations were observed between LF and mirid bugs ($r = 0.45$), WBPH and mirid bugs ($r = 0.45$), and YSB-F and coccinellids ($r = 0.45$).

Among the weather variables, maximum and minimum temperature were positively correlated ($r = 0.64$). Morning and evening relative humidity also showed a positive relationship ($r = 0.43$). In contrast, both morning and evening relative humidity were negatively related to maximum temperature. Sunshine hours were negatively correlated with rainfall ($r = -0.42$) and evening relative humidity ($r = -0.53$).

Regarding insect–weather relationships, YSB-F and YSB-M were negatively related to evening relative humidity, but positively related to sunshine hours. WBPH was positively associated with rainfall ($r = 0.42$) and negatively associated with maximum temperature ($r = -0.23$). Leaf folder also showed a positive relationship with rainfall ($r = 0.30$). Overall, the results indicate that different rice insects responded differently to weather conditions, while some insect populations also showed similar seasonal patterns.

Explanatory power of weather variables for rice insect abundance

The explanatory power of weather variables differed among the insect groups (Fig. 2). WBPH showed the highest R^2 value (0.237), followed by YSB-female (0.208), YSB-male (0.196), LF (0.119), BPH (0.101), GLH (0.081), coccinellids (0.080), mirid bugs (0.078) and gall midge (0.041). Thus, the weather variables explained more variation in WBPH and YSB, while their effect was relatively low for gall midge, mirid bugs and coccinellids.

The low R^2 values for several insects indicate that current-week weather alone could not explain most of the changes in insect abundance. Other factors such as previous pest population, crop growth

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stage, crop management, migration and natural-enemy interactions may also influence insect populations. Overall, the results indicate that current weather conditions provide some useful information, but they are not sufficient to predict rice insect abundance on their own.

Relative contribution of individual weather variables to rice insect abundance

Figure 3 shows the effect of individual weather variables on insect abundance after accounting for the effects of the other weather variables.

Yellow stem borer (YSB): Evening relative humidity had a significant negative relationship with both YSB-female (β = −0.42) and YSB-male (β = −0.39). Sunshine showed a positive but non-significant relationship (β = 0.15). Thus, evening relative humidity was the most important weather variable for YSB in the model.

Gall midge (GM): The relationships with weather variables were weak (β = −0.13 to 0.18), and none were significant. This agrees with its low R^2 (0.041).

Leaf folder (LF): Rainfall had the strongest and significant positive relationship with LF abundance (β = 0.30). Minimum temperature and evening relative humidity showed weaker, non-significant relationships.

Green leafhopper (GLH): Maximum temperature showed a negative relationship (β = −0.20), while sunshine (β = 0.20) and evening relative humidity (β = 0.17) showed positive relationships. However, none were significant.

Brown planthopper (BPH): Morning relative humidity (β = 0.20) and sunshine (β = 0.21) showed significant positive relationships with BPH abundance. Although maximum temperature also had a positive coefficient (β = 0.26), it was not significant.

White-backed planthopper (WBPH): Rainfall had the strongest positive relationship (β = 0.42), while maximum temperature showed a significant negative relationship (β = −0.32). Sunshine also showed a significant positive relationship (β = 0.24).

Mirid bugs and coccinellids: Mirid bugs showed positive relationships with morning and evening relative humidity and sunshine, while coccinellids showed positive relationships with minimum temperature and sunshine. However, these relationships were not statistically significant. Overall, rainfall, relative humidity and sunshine were important weather variables for some insect groups, whereas their effects differed among species.

Regression analysis of weather variables and rice insect abundance

Regression analysis and the regression equations presented in Table 2 showed that rice insect species responded differently to the weather variables. At the 5% significance level, evening relative humidity was negatively associated with female and male yellow stem borer abundance, whereas rainfall showed a significant positive association with leaf-folder abundance. Brown planthopper abundance was positively associated with morning relative humidity and sunshine hours. White-backed planthopper showed a significant negative association with maximum temperature and significant positive associations with rainfall and sunshine hours, with rainfall exhibiting the strongest standardized effect (β = 0.421). No individual weather variable significantly affected gall midge, green leafhopper, mirid bugs or coccinellids. These results indicate that the influence of weather parameters was species-specific and that the direction and magnitude of individual predictor effects varied considerably among insect species.

Multicollinearity assessment of weather variables

Variance Inflation Factor (VIF) was used to assess multicollinearity among the weather variables included in the multiple regression models and presented in the table 3. VIF values ranged from 1.33 to 4.72. The highest VIF was recorded for maximum temperature (4.72), followed by minimum temperature (3.97), while rainfall showed the lowest VIF (1.33). The VIF values indicated moderate collinearity between the temperature variables but no severe multicollinearity among the weather predictors.

Observed and fitted values of rice insect pests

Figure 4 compares the observed weekly light-trap catches with the values estimated by the significant contemporaneous weather-based regression models. The dashed 1:1 line represents perfect agreement between observed and fitted values.

Yellow stem borer (female): The model was significant (R^2 = 0.208; $P < 0.001$). Fitted values followed the observed trend, but considerable scatter indicated that much variation was not explained by current weather conditions.

Yellow stem borer (male): The model was also highly significant (R^2 = 0.196; $P < 0.001$). However, fitted values showed less variation than the observed catches, indicating limited prediction of population peaks.

Leaf folder: The model was significant but explained relatively little variation (R^2 = 0.119; P = 0.004). Several high observed catches were not well represented by the fitted values.

Green leafhopper: The model was just significant (R^2 = 0.081; P = 0.048), but the wide scatter showed that current weather variables explained only a small part of the variation.

Brown planthopper: The model was significant (R^2 = 0.101; P = 0.014), but it underestimated several high observed catches, showing limited ability to describe population peaks.

White-backed planthopper: This model showed the highest explanatory power (R^2 = 0.237; $P < 0.001$). Nevertheless, considerable scatter remained, particularly at higher pest abundance.

The observed-versus-fitted plots show that a statistically significant model does not necessarily provide accurate prediction. Even the best model, for WBPH, explained only 23.7% of the variation in weekly catches. The large differences between observed and fitted values suggest that current-week weather alone cannot fully explain fluctuations in rice insect populations. Other factors, such as crop stage, pest biology, migration, natural enemies and previous week pest abundance, may also contribute to population changes. These results support the need for lagged weather variables and previous pest abundance to improve the explanation and prediction of rice insect population dynamics.

Residual diagnostics of the WBPH regression model

The residual plot (Fig 5) showed a non-random pattern, indicating that the model did not fully explain the variation in WBPH abundance. Residuals were mostly positive at lower fitted values and became more negative at higher fitted values. Considerable scatter and some extreme residuals were also observed. The model explained 23.7% of the variation (R^2 = 0.237; adjusted R^2 = 0.206), with an RMSE of 913.22. The Durbin–Watson value of 1.02 indicated positive autocorrelation among successive weekly observations. The results indicate that the WBPH model has useful explanatory value but limited predictive ability. The non-random residual pattern and autocorrelation suggest that current week weather variables alone are not sufficient to describe WBPH fluctuations. Previous pest abundance, lagged weather conditions, crop stage and other time-dependent factors may improve the model and its forecasting ability.

Discussion

The present study showed that the response of rice insects to weather conditions was species-specific, and the effects of individual weather variables were generally modest.

Yellow stem borer: Both female and male yellow stem borer (YSB) models were highly significant, with evening relative humidity showing a significant negative association with trap catches. This agrees with Jasrotia *et al.* (2019) [2], who reported negative relationships of YSB infestation with morning and evening relative humidity and rainfall. Murali Baskaran *et al.* (2019) [8] also observed greater YSB activity under higher temperature, lower relative humidity and low rainfall conditions. These findings indicate that atmospheric humidity may influence YSB activity, although the relationship can vary with season and location.

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Gall midge: The gall-midge model was not significant (R^2 = 0.041), suggesting that current-week weather variables alone were insufficient to explain its population fluctuations. Gall midge populations may be influenced by crop stage and delayed weather effects. Recent work in Andhra Pradesh has shown that combining count time-series models with weather variables and machine-learning approaches can improve gall-midge prediction, supporting the importance of temporal effects in modelling this pest (Kumari *et al*., 2025) [9]

Leaf folder: The leaf folder model was significant, with rainfall showing a positive effect, but the model explained only 11.9% of the variation. Jasrotia *et al.* (2019) [2] reported positive relationships between leaf folder incidence and maximum and minimum temperature, indicating that the important weather factors may differ between locations.

Green leafhopper: The GLH model was also significant but weak (R^2 = 0.081), suggesting that factors other than current weather, such as crop stage, host condition and biological interactions, may contribute substantially to population changes. Rai *et al.* (2002) [3] reported a positive association between morning relative humidity and green leafhopper light-trap catches, He also reported that pest appearance depends upon the availability of choice food along with the climatic factors.

Brown planthopper: BPH showed a significant overall relationship with weather, with morning relative humidity and sunshine hours having positive partial effects. Similar associations between BPH and weather variables have been reported in rice-growing regions, although the important variables differ among seasons and locations. Studies from the Godavari Delta also demonstrated relationships between BPH populations, light-trap catches and weather variables, while more recent work has highlighted the importance of lagged weather variables in BPH prediction (Krishnaiah *et al*., 2006) [10].

White-backed planthopper: WBPH showed the highest explanatory power (R^2 = 0.237) among the pests studied. Maximum temperature had a negative effect, whereas rainfall and sunshine hours had positive effects. However, relationships between WBPH and weather are not consistent across seasons. Anand Kumar *et al.* (2021) [11], working at Maruteru, reported a significant negative relationship with current-week morning relative humidity during *kharif* 2016, while no significant relationship was observed during *rabi* 2016–17. This supports the need for location- and season-specific weather models for WBPH.

Natural enemies: Mirid bugs and coccinellids did not show significant overall relationships with the weather variables. Their abundance may depend not only on direct weather effects but also on prey availability, crop stage and habitat conditions. In the Godavari Delta, mirid bugs have been reported to occur in close association with planthopper populations, highlighting the importance of considering pest–natural-enemy interactions when explaining predator abundance (Krishnaiah *et al*., 2007) [12].

Overall, the results demonstrate that weather influences rice insect populations, but its effect is species-specific and explains only part of the observed variation. The relatively low R^2 values suggest that crop phenology, previous pest abundance, migration, natural enemies and other environmental factors should be incorporated into future models. The findings also support the use of lagged weather variables and pest abundance for improving pest forecasting and weather-based integrated pest management.

Conclusion

The present study demonstrated that weather parameters significantly influenced the population dynamics of several major rice insect pests, although the strength of the relationship varied among species. Yellow stem borer (female and male), leaf folder, green leafhopper, brown planthopper and white-backed planthopper showed significant overall relationships with the selected weather variables, whereas gall midge, mirid bugs and coccinellids did not show significant relationships.

Among the weather variables, evening relative humidity was negatively associated with both female and male yellow stem borer, while rainfall positively influenced leaf-folder abundance. Brown planthopper showed positive associations with morning relative humidity and sunshine hours. In WBPH, maximum temperature had a negative association, whereas rainfall and sunshine hours showed positive associations. However, the relatively low R^2 values (0.041–0.237) indicated that current week weather conditions alone explained only a limited proportion of the variation in insect abundance.

Residual diagnostics, particularly for WBPH, also indicated temporal dependence and some deviation from the assumptions of simple linear regression. Therefore, the regression models should be considered mainly as descriptive tools for understanding weather–pest relationships rather than as stand-alone forecasting models.

Overall, the findings highlight the species-specific nature of weather effects on rice insect populations. Incorporating crop phenology, previous pest abundance, natural-enemy activity and other ecological factors, together with longer-term observations, would help improve the reliability of weather-based pest forecasting and support more effective integrated pest management in rice.

Acknowledgments

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Conflict of interest

The authors declare that they have no competing interests related to this study

Table 1. Performance and diagnostic statistics of weather-based multiple regression models for rice insect pests and natural enemies

Response	n	R^2	Adjusted R^2	F	P	RMSE	Durbin–Watson
YSB female	155	0.208	0.176	6.495	4.219e-06	222.17	0.879
YSB male	155	0.196	0.163	5.998	1.23e-05	61.72	0.758
GM	155	0.041	0.003	1.065	0.3862	324.71	0.927
LF	155	0.119	0.083	3.337	0.00412	95.04	1.040
GLH	155	0.081	0.044	2.180	0.04803	1071.25	1.065
BPH	155	0.101	0.065	2.777	0.01377	5854.25	0.622
WBPH	155	0.237	0.206	7.641	3.693e-07	913.22	1.021
Mirids	155	0.078	0.041	2.085	0.05829	3178.48	0.844
Cocci	155	0.080	0.043	2.150	0.05111	119.80	1.094

YSB = Yellow stem borer; GM = gall midge; LF = leaf folder; GLH = green leafhopper; BPH = brown planthopper; WBPH = white-backed planthopper; RMSE = root mean square error; DW = Durbin–Watson statistic.

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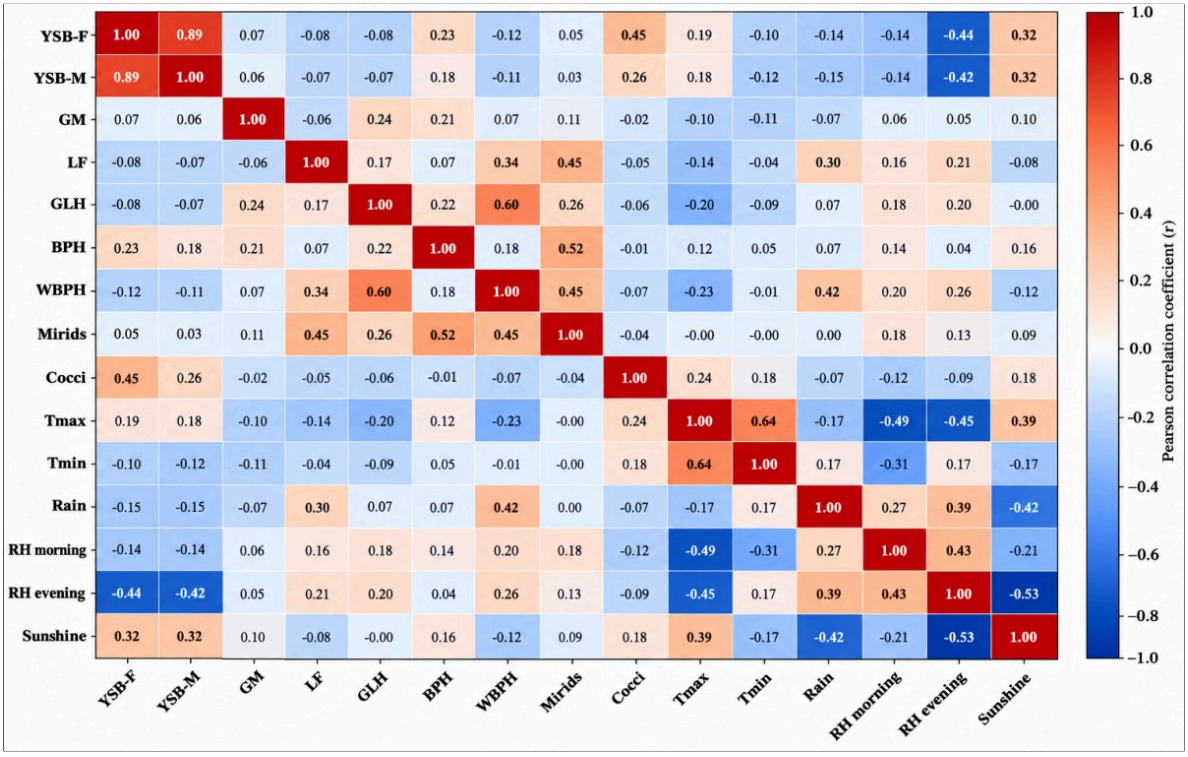


Figure 1. Pearson correlation matrix of major rice insect pests, natural enemies and weather variables during 2012–2014.

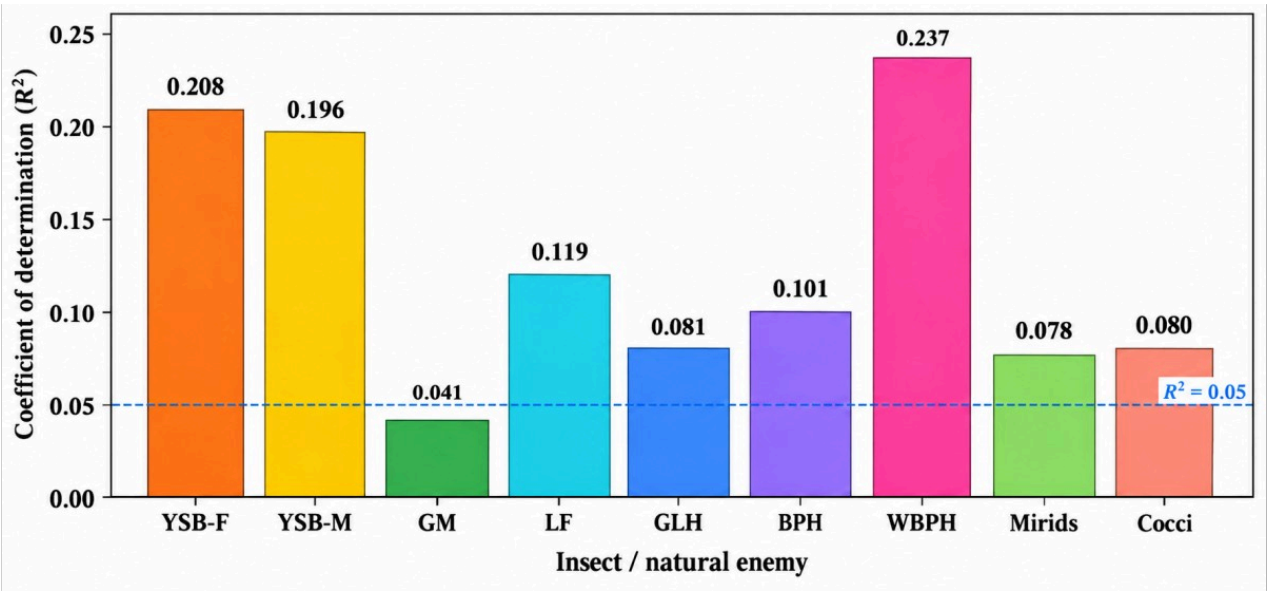


Figure 2. Coefficient of determination (R^2) of the contemporaneous species-specific multiple regression models.

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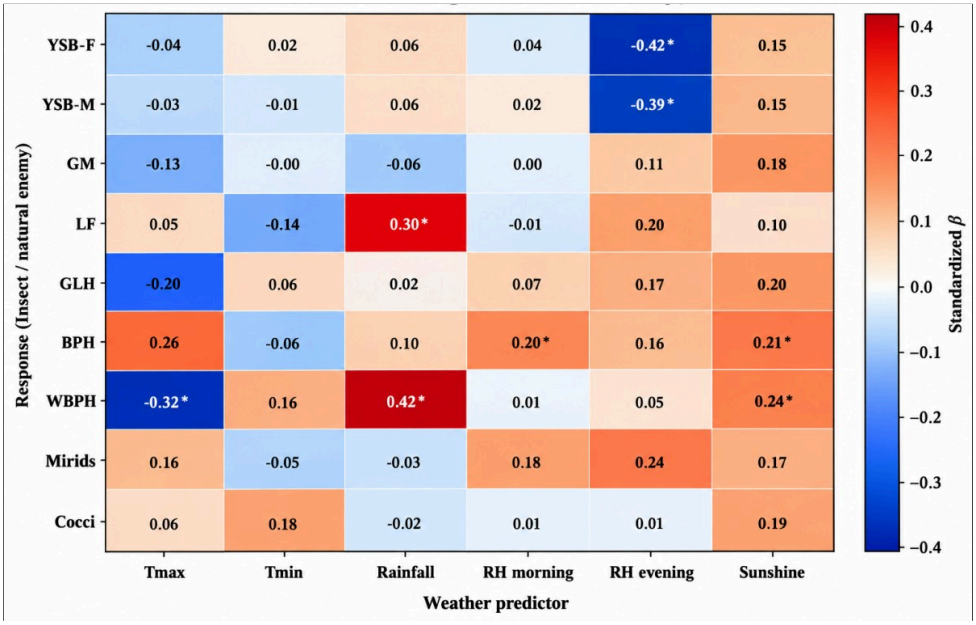


Figure 3. Standardized regression coefficients (β) for the six weather variables. * $P < 0.05$.

Table 2. Regression equations and significant predictors for the Rice insect pests and natural enemies

Insect variable	Regression equation
YSB female	Y = 662.909 − 2.854Tmax + 1.334Tmin + 0.234Rainfall + 1.964RH_morning − 10.167RH_evening* + 16.077Sunshine
YSB male	Y = 196.357 − 0.592Tmax − 0.260Tmin + 0.064Rainfall + 0.354RH_morning − 2.584RH_evening* + 4.476Sunshine
GM	Y = 178.671 − 13.601Tmax − 0.348Tmin − 0.309Rainfall + 0.139RH_morning + 3.505RH_evening + 26.232Sunshine
LF	Y = -83.278 + 1.583Tmax − 4.121Tmin + 0.491Rainfall* − 0.189RH_morning + 1.933RH_evening + 4.324Sunshine
GLH	Y = -924.274 − 70.751Tmax + 18.604Tmin + 0.429Rainfall + 15.924RH_morning + 18.056RH_evening + 94.028Sunshine
BPH	Y = -43888.469 + 495.573Tmax − 95.049Tmin + 9.663Rainfall + 258.142RH_morning* + 95.562RH_evening + 565.742Sunshine*
WBPH	Y = 1190.799 − 106.207Tmax* + 48.026Tmin + 7.170Rainfall* + 1.463RH_morning + 4.974RH_evening + 106.982Sunshine
Mirids	Y = -20895.907 + 162.746Tmax − 49.502Tmin − 1.755Rainfall + 127.002RH_morning + 76.653RH_evening + 241.488Sunshine
Coccinellids	Y = -275.303 + 2.157Tmax + 6.510Tmin − 0.032Rainfall + 0.289RH_morning + 0.070RH_evening + 10.095Sunshine

YSB = Yellow stem borer; GM = gall midge; LF = leaf folder; GLH = green leafhopper; BPH = brown planthopper; WBPH = white-backed planthopper; * Significant predictors at $P \geq 0.05$

Table 3. Variance Inflation Factor (VIF) values for weather variables

Weather variable	VIF
Maximum temperature (T_{max})	4.72
Minimum temperature (T_{min})	3.97
Rainfall	1.33
Morning relative humidity (RH morning)	1.56
Evening relative humidity (RH evening)	2.57
Sunshine hours	1.90

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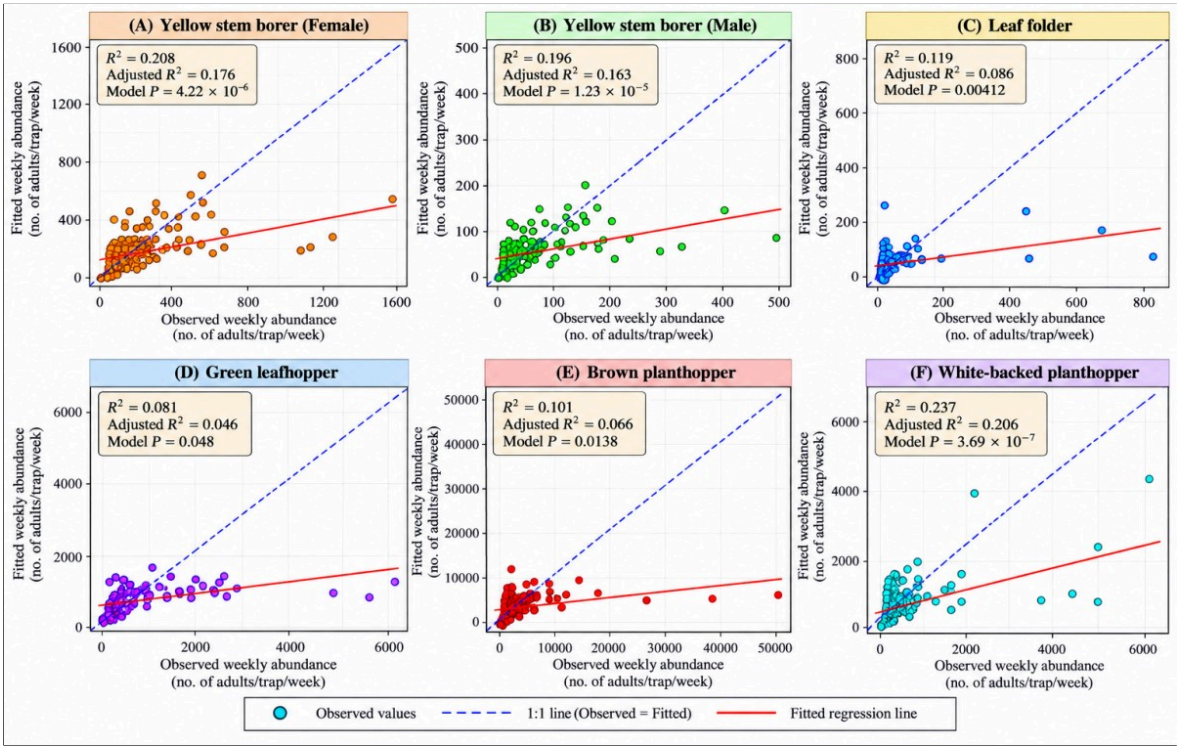


Figure 4. Observed versus fitted values for the statistically significant contemporaneous regression models.

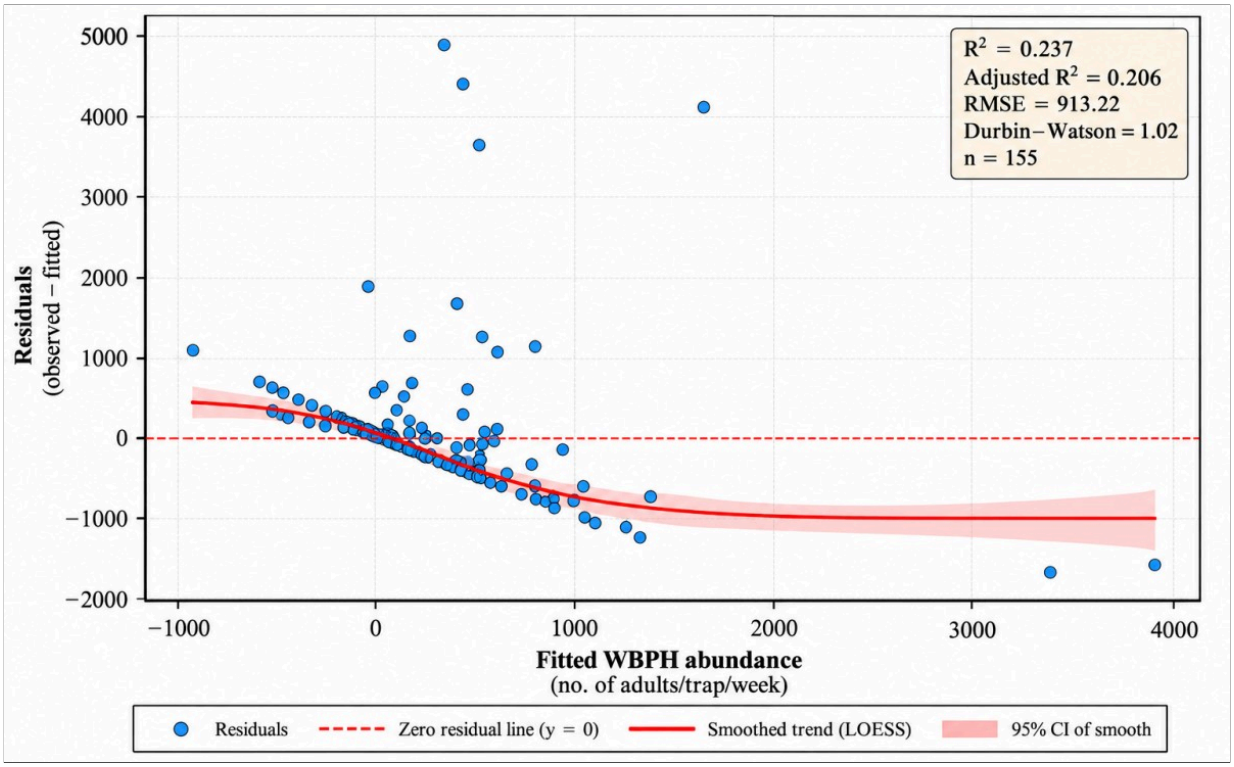


Figure 5. Residual-versus-fitted plot for the WBPH contemporaneous multiple regression model.

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