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Spatial Analysis of Environmental Factors for Modeling Plant Hopper Potential Risk Prediction

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ABSTRACT

Agricultural insect pests reduce crop productivity, causing a gap between global food demand and production. Early detection and early response can improve pest control efficiency. The study aimed to investigate the spatial correlations between brown plant hopper (BPH) occurrence and affected factors using field data collection in Can Tho City, Vietnam. The data on cultivation practices and meteorological conditions at 120 weekly monitoring sites at Can Tho city during the rice cropping season of 2016–2017 were collected to find the correlation between the occurrence frequency and density of BPH. Besides, GIS and spatial interpolation were applied to assess the current status of harmful situations, predict the impact trends of crop pests or diseases in space and time to serve a community's needs, as well as forecast plant protection. As a result, in the 2nd rice cropping stage, the population of brown planthoppers was found to be highly significantly influenced by the following factors: (1) planthopper age, (2) natural enemy density, (3) air temperature, (4) field water level, and (5) number of leaves, which is highly positively correlated with brown hopper density. There is a lower correlation between leaf color code (6) and air humidity (7) and a negative correlation between pesticides used (8). The variables of rice leaf color code (6) and air humidity (7) correlate with the BPH population, although the field water level (4) and leaf count (5) do not correlate for the whole crop. It can be used to predict the changing trend of BPH in rice fields. However, the factors influencing the brown planthopper would determine the accuracy of the prognosis.

Keywords: geographic information system, potential risk, geostatistic, interpolation, brown plant hopper.

INTRODUCTION

Nowadays, climatic changes can impact pest risk patterns in various direct and indirect ways, most notably where future climatic changes enable a pest to expand its range into the pest risk area (Szyniszewska et al., 2024). New insect pests from overseas cause annual problems in several nations. Field detection and local treatment could improve agricultural insect pest control. Early and accurate insect pest as well as infestation border field data are needed (Rano et al., 2022). A manual survey utilizing a variety of conventional traps is the most popular and traditional way to monitor insect pests in the field. In the event of larger areas and lower accuracy rates, these conventional techniques of insect pest monitoring are quite time-consuming (Ranjan and Vinayak, 2020).

According to Andrewartha and Birch (1986), there is a wealth of scientific data available for analysis, and this information, along with the complex biological processes at play when pests and habitats interact, make it very challenging to reconcile the risk pests pose to environments. Nonetheless, multivariate regression analysis estimation of an event likelihood is helpful since these models can process enormous amounts of data and convert them into realistic, relevant, and scientifically supported predictions. Bradshaw et al. (2019) state that climate indices can assess pest risks directly or indirectly via comparisons with areas where the pest has already been established. Climate change can majorly affect the relationships between agricultural pests and their dispersal. If the control strategy is analytically offered to a heavily contaminated region, it might not be essential to submit a realistic control approach to the remaining area. According to Dengmasa et al. (2022), both human activities and climate change are impacted by natural processes. As their name suggests, climate-matching models match climates between one or more reference locations and the climate at one or more locations in the pest risk area (Liu et al., 2023). Risk managers now simulate possible pest establishment zones and places where the species can be present only part of the year and complete at least one generation (Akrivou et al., 2021; Weinberg et al., 2022).

Agro-ecosystem forecasting systems for insect-plant disease enable farmers to be aware of possible outbreaks, which helps them promptly plan and apply bio-control agents, mechanical methods, and pesticides. It lowers production costs and is a valuable tool for precision farming (Ranjan and Vinayak, 2020). Pedersen and Lind (2017) noted that farmers can research the spatial-temporal variability of important plant health and production traits owing to GIS and remote sensing. Digital platforms aggregate sensor data to facilitate decision-making. Dobesberger (2002) states that the output can be easily shown in a GIS format. Even novice GIS users easily visualize the output maps with descriptive labels as well as diverse color and pattern groups (Paramasivam, 2019). According to Acharya et al. (2018), GIS is a helpful tool for managing and manipulating data to estimate the hopper density of brown plants.

The practical implications of this study are significant. Using GIS and geostatistical methods to find the regression and spatial correlations of the BPH population with the climate factors of the study area in Can Tho City, Vietnam, the occurrence of BPH can be predicted. This prediction can be used as an early warning of rice pests and diseases, providing valuable information for plant protection and other majors.

MATERIALS AND METHODS

The data collection and study location

The study was conducted in Can Tho City, Vietnam, a region known for its intensive rice cultivation as well as frequent pest and disease issues. This location was chosen to represent a typical rice-growing area, making the findings applicable to similar regions (Figure 1).

The data collection

At each of the 120 sites, the data on BPH density, rice growth stages, cultivation techniques, and meteorological conditions were collected by the Plant Protection Department of Can Tho City every ten days. This rigorous and systematic approach ensured a comprehensive dataset for analysis.

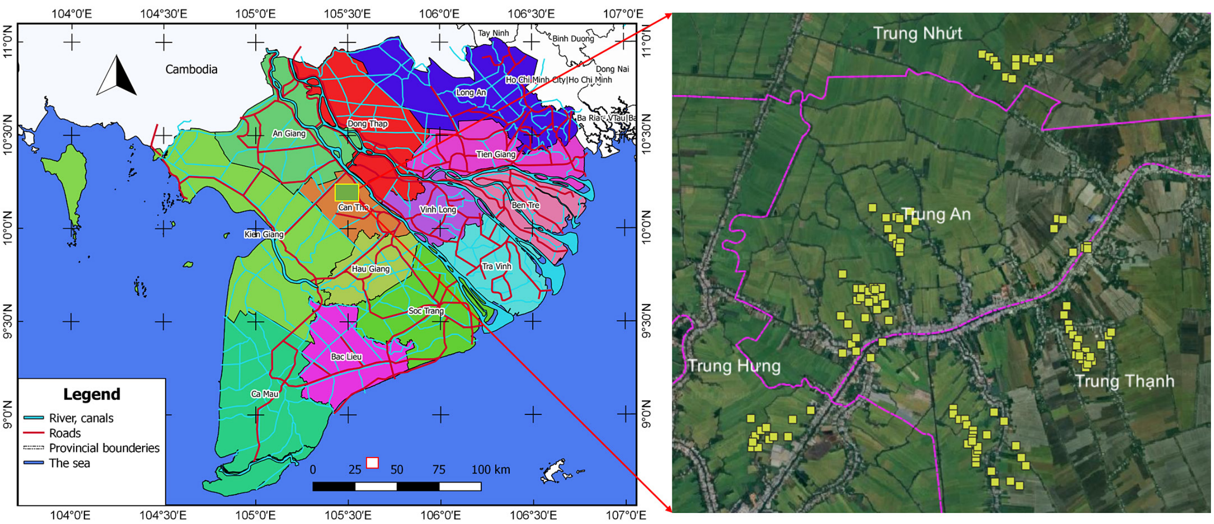

Figure 1. Study sites in Can Tho, Viet Nam

The Can Tho Department of Plant Protection classified the warning criteria for BPH in rice into 3 levels, from slight to strongly affected, corresponding from 750 to greater than 3000 BPH number/m^2 and 250 to 1000 BPH eggs/m^2

Five random quadrants in a rice field were selected; the sample quadrate size was 0.25 m^2, and the BPH density (per m^2) was determined based on the average BPH density in the five quadrants, then multiplied by four quadrants.

$$BPH\ density = \frac{Total\ of\ BHP\ collected}{5} 4 \quad (1)$$

The regression analysis

The regression analysis and prediction models were created based on the parameters linked to agriculture methods, climate, and the density of BPH in rice.

$$Number\ of\ BPH/m^2 = (ax_1) + (bx_2) + + (cx_3) + (dx_4) + \ldots + (zx_n) \quad (2)$$

where: x_1,..., and x_n are factors affecting and a, b, c, d,.., and z are constants.

The predicted and actual BPH densities as well as their relationship to the second period and current season were determined using observations and data collected at 120 sites at ten-day intervals throughout the rice cropping seasons. The expected and actual BPH densities for each monitored location during the second period and throughout the cropping season were compared.

Variogram and geostatistical (kriging) interpolation

According to Evan (2022), using the terms variogram and semi-variogram interchangeably is common. There is a distinction. After the 1/2 component is subtracted, the word variogram is appropriate to enable a direct comparison between the variogram and covariance function; this 1/2 factor is used. According to Western and Blöschl (1999), variograms, a key concept in geostatistics, assess spatial variation of parameters. Nugget, sill, and decorrelation length make up the variogram structure.

Figure 2 shows the schematization of the variogram, with the points representing the measured data points and the curve representing the model function utilized. Range denotes the desired range, sill represents the plateau value at maximum range, and nugget denotes the nugget impact. As Li and Zhao (2014) suggested, the variograms, spatial variation of variables, and actual and anticipated BPH distribution were interpolated and compared using GIS and geospatial analysis tools. The variogram represents the Z(x) variables regionalized at x, where $x + h$ = half of the variance.

To determine the spatial distribution of the BPH density, a semi-variogram study of the second phase, the predicted season as a whole, and the actual BPH density was used.

Interpolating using a geostatistical (Kriging) method requires semi-variogram modeling (Long et al., 2018). The factors affect how each observation affects the kriging prediction of the three main factors that determine data configuration include: 1) the spatial arrangement of observations (e.g., clustering in over-sampled areas); 2) their geographic closeness to the unsampled zone; and 3) the geographical association of data with one another. The development of kriging models is appropriate for spatially linked data. (BioMedware, Inc. & Goovaerts, 2019). Combining five

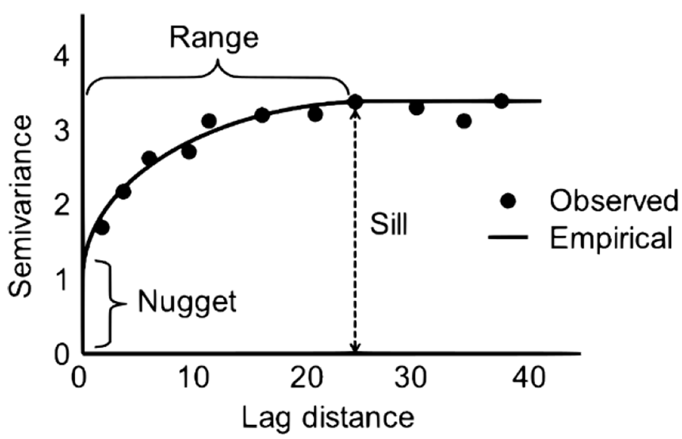

Figure 2. Illustration of semi-variogram parameter (Biswas et al., 2013)

data in a straightforward linear manner yields the kriging estimate, z*(u0).

$$z^*(\boldsymbol{u}_0) = \sum_{\alpha=1}^{5} \lambda_\alpha \times z(\boldsymbol{u}_\alpha) \quad \text{with} \quad \sum_{\alpha=1}^{5} \lambda_\alpha = 1 \quad (3)$$

RESULTS AND DISCUSSION

In the study, the correlation analysis between the second period and the entire season was made from the data collected at ten-day intervals at six periods. The regression and linear correlation of rice BPH density, climate, and farming methods were investigated. After estimating the density using the regression equation, the estimated population of BPH was interpolated and utilized to draw geographic boundaries. Furthermore, a comparison between the expected and actual BPH density was performed. Among those selected for result interpretation and delineation were the second period and the cropping season. The results and discussion of the study are presented below.

The relationship between BPH and related effect factors

From the survey results in 120 fields, in the 2nd rice cropping stage, five factors that affect the population of brown planthoppers with a high level of significance were found, including the factors of (1) planthopper age, (2) natural enemy density, (3) air temperature, (4) field water level, (5) number of leaves and are high positively correlated with the BPH density, while (6) leaf color (7) air humidity are lower correlation, and pesticide used (8) has negative correlation. However, for the whole rice crop, the field water level (4) and the number of leaves (5) do not correlate with the BPH population, while the factors of rice leaf color code (6) and air humidity (7) correlate with the BPH population (Table 1). It implies that the BPH density decreases with more targeted pesticide treatment intervals. Unfortunately, the failure of the applied broad-spectrum insecticides to lower BPH density may be ascribed to hopper burn, the development of insecticide resistance in BPH, and farmer application practices (Matsukawa-Nakata et al., 2019).

Generally, there were different factors influencing the BPH density at every period. The developmental stage and cultural practices of rice crops at different times determined the crop resistance to pests or pest control attacks.

Regression of BPH with affected factors

According to the multivariable analysis, the regression of BPH with affected factors was developed and shown in Table 2. It shows that the determination factor for BPH for the entire cropping season (R^2 = 0.41) was lower than the BPH density expected by the regression equation for the 2nd period.

The regression analysis of the predicted BPH regression for the 2nd period and the entire season in Table 2 shows that the reduced R^2 of the cropping season may result from the factors affecting its density or multiple causes acting in concert.

Table 1. Linear relationships between the impacted variables and the BPH density in the 2nd phase and the winter-spring season

Factors	BPH age	Enemy	Air temp	Field water level	Leaf number /m^2	Leaf color	Air humidity	Pesticide used
		Density/m^2	^{0}C	cm	Number	Color code	%	Times
2nd period	0.80**	0.60**	0.42**	0.31**	0.21*	-	-	-
Season	0.39**	0.45**	0.36**	-	-	0.24**	0.22**	- 0.32**

Note: ** significant at 1%, * significant at 5%.

Table 2. The predicted BPH regression for the 2nd period and the entire season

Predicted BPH (number/m^2)	Regression formula
2nd phase	a + (b × BPH age) + (c × enemy density) + (d × air temperature) – (e × level of field water) + (f × leaf number/m^2)
Season	a + (b × enemy density) + (c × BPH age) + (d × air temperature) + (e × leaf color code) – (f × air humidity) - (g × number of times of pesticide used)

Note: *a*, *b*, *c*, *d*, *e*, *f*, *g* – constants.

Several variables, such as climate, cultural customs, diversity, etc., frequently influence BPH. Knowing the problematic aspects and how they relate to one another allows it to forecast the incidence and density. As a result, warning farmers and the local government about hopper occurrences is essential for plant protection efforts; nonetheless, the main limitation is prediction accuracy. However, rather than being accurate, the overall pattern of its frequency helps farmers or local governments in the form of an early warning. From this angle, features and regression equations affected by BPH density can be anticipated and applied to early warning systems.

Prediction of BPH density

On the basis of observations and data gathered at 120 places throughout seasons at ten-day intervals, the results of correlation analysis show that the estimated actual BPH density and its relationship to the second period and current season are computed. The expected and actual densities of BPH for each observed location during the second period (a) and the entire cropping season (b) are closely correlated (Figure 3). However, the R^2 (0.666) of predicted BPH in the second phase was higher than the whole season (0.404). It can be due to several factors affecting the occurrence of BPH.

The data collection results show that every observation site had a distinct BPH density. There was a relationship between the BPH density and several influencing elements, like the climate and cultivation techniques, which can be used to forecast the region's density. The pattern of its occurrence is also provided (Figure 3), even though the projected accuracy cannot be approximated. As a result, it can help the government create crop protection plans and establish early warning systems.

The variogram of BPH density

The results of the analysis of the BPH density show that the spatial distribution of BPH density can be certified using a semi-variogram analysis of the second phase, the anticipated entire season, and the actual BPH density (Table 3). It demonstrates that the distribution of the actual BPH

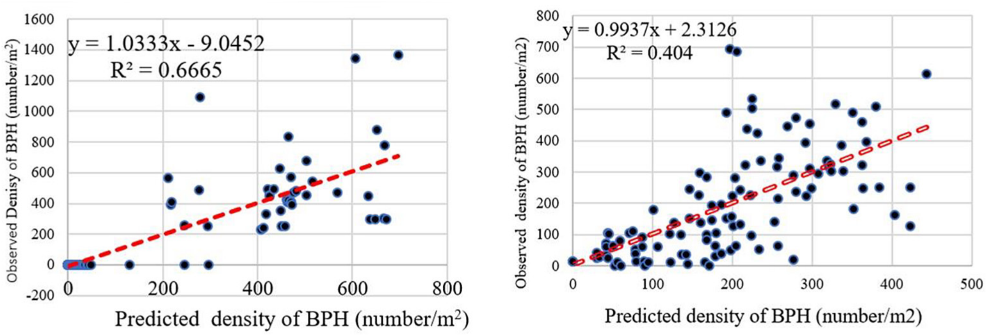

Figure 3. The correlation of predicted and observed densities of BPH during the second period (a) and the entire cropping season (b)

Table 3. Semi-variogram of the 2nd period and whole season predicted and actual BPH density (Winter-Spring, 2016–2017)

BPH density (Hopper number/m²)	2nd period (Exponential model)		Whole cropping season (Gaussian model)	
	Expected	Actual	Expected	Actual
C_o	13.900	43.800	1.970	9.870
$C_o + C$	70.800	96.400	18.840	34.330
R^2	0.814	0.438	0.94	0.74
$C/C + C_o$	0.804	0.546	0.895	0.712
A_o (m)	1.257	1.129	1.747	889
A (m)	3.771	3.387	3.025	1.539

Note: R^2 – determination factor; A – range (effective range); A_o – range parameter; C_o – nugget; $C+C_o$ – sillC/C+C_o – proportion.

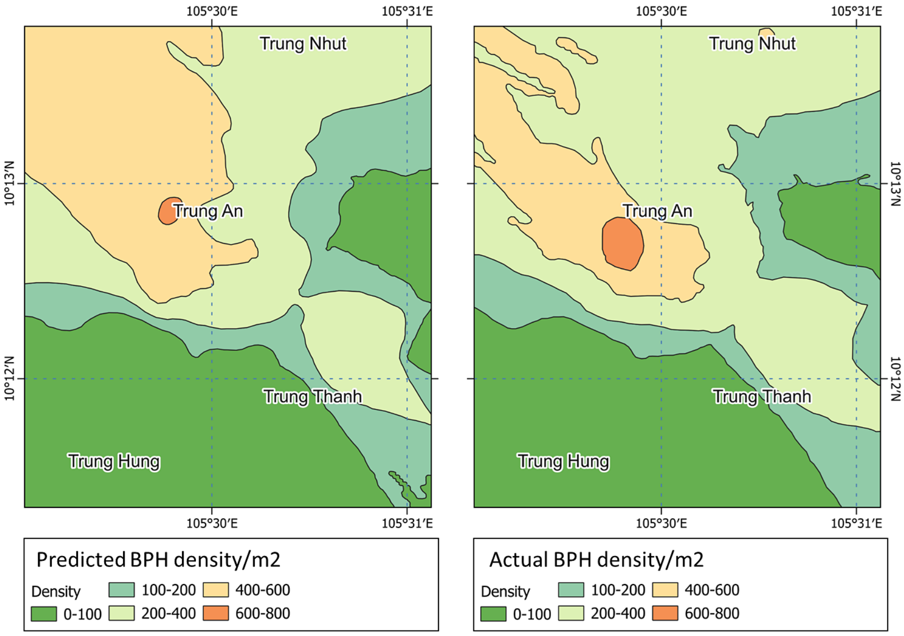

Figure 4. Spatial distribution of actual and predicted BPH density of 2nd period

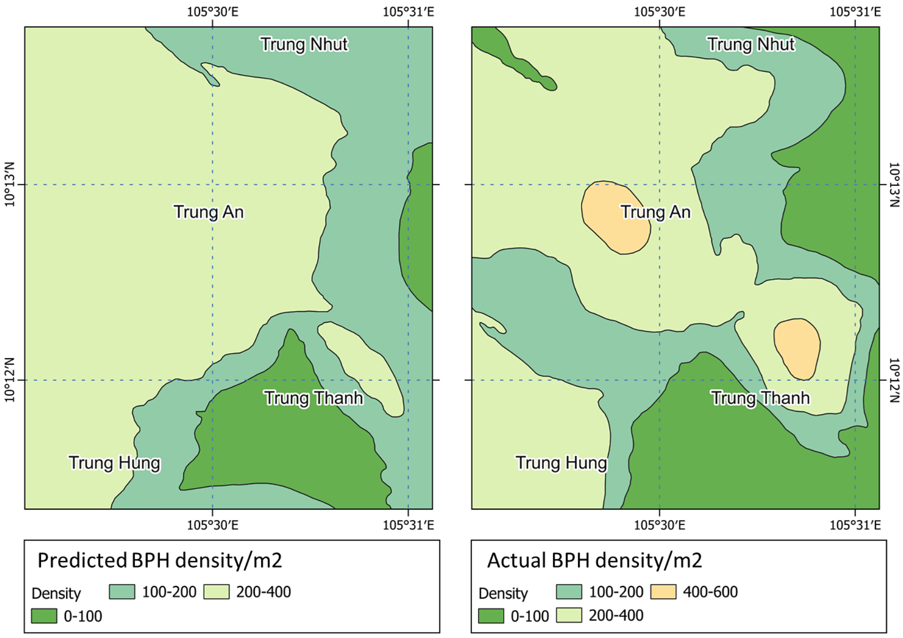

Figure 5. Spatial distribution of actual and predicted BPH density of the whole Winter-Spring season

density is comparatively consistent with the expected BPH density of phase 2 and the entire season based on influencing factors. During the 2nd period, the predicted R^2 was 0.814, and the actual R^2 was 0.438. During the entire season, the actual R^2 was 0.740, and the predicted R^2 was 0.940. The semi-variogram model for the 2nd period is exponential, and for the whole season, it is Gaussian. The density was then interpolated using the kriging method. Figures 4 and 5 show the results of the interpolation of predicted BPH density distribution based on the correlation of factors affecting it, as well as the results of the spatial interpolation of the actual BPH density of the second phase and the whole crop season. In which the predicted BPH population is lower than the actual population, possibly because many factors influence the actual population to cause outbreaks. Besides climatic factors and farming techniques, there are also influencing factors that cannot be controlled, such as the influence of wind, rice thunderstorms, care techniques, etc.

CONCLUSIONS

This study discovered that the regression equation significantly corresponds with the BPH population and affects factors at specific growth stages and culture seasons using GIS and geostatistics techniques. In the 2nd rice cropping season, the following variables were found to have a highly significant impact on the population of brown planthoppers: (1) planthopper age; (2) natural enemy density; (3) air temperature; (4) field water level; and (5) number of leaves, which is highly positively correlated with brown hopper density. Additionally, there is a negative correlation between leaf color code (6), air humidity (7), and pesticide use (8). Although the field water level (4) and leaf count (5) do not include the whole rice crop season, the variables of rice leaf color code (6) and air humidity (7) correspond with the BPH population. This correlation can serve as an early warning system and predict how BPH changes over time in rice fields. Every rice growing stage and cultivation season can have a different impact on the factors and levels of influence. The prediction accuracy depends on the variables that affect the occurrence of BPH, such as cropping stages, crop kinds, and cultivation seasons.

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