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Population dynamics modelling of *Scirpophaga incertulas* based on climatic factors in Mardingding, Karo, North Sumatra, Indonesia

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Abstract. *Ginting TY, Triwidodo H, Winasa IW, Maryana N. 2025. Population dynamics modelling of* Scirpophaga incertulas *based on climatic factors in Mardingding, Karo, North Sumatra, Indonesia. Biodiversitas 26: 5003-5011.* The yellow stem borer (*Scirpophaga incertulas*) is a major rice pest in Southeast Asia whose outbreaks are strongly influenced by climatic conditions. This study developed and evaluated dynamic models of *S. incertulas* populations in Mardingding Sub-district, Karo District, North Sumatra, Indonesia, during a single cropping season (January-April 2025). Field monitoring was conducted weekly at three sites using light traps, accompanied by assessments of infestation intensity and incidence. Climate data, including temperature, relative humidity, and rainfall, were obtained from NASA POWER (Prediction of Worldwide Energy Resources). To assess whether population differences among sites were statistically significant, an Analysis of Variance (ANOVA) was performed. The results revealed a significant difference in *S. incertulas* populations across locations ($F = 8.10$, F-critical = 3.28, $p < 0.05$), underscoring the influence of site-specific agroecosystem conditions. The relationships between climate variables and pest dynamics were further analyzed using multiple linear regression and a discrete logistic growth model. Results indicated that the logistic model provided more accurate estimates of *S. incertulas* population dynamics compared to linear regression, with the lowest prediction error (18.45%) observed at Tanjung Pamah. At this site, populations remained low (1.5-4.5 individuals) under average conditions of 22.89°C, 89.44% relative humidity, and 5.90 mm rainfall. Peak infestation intensity and incidence across sites occurred approximately six weeks after planting, under mean conditions of 23°C, 89% relative humidity, and 5-6 mm rainfall. These findings demonstrate that integrating climatic drivers with logistic models improves forecasting of *S. incertulas* outbreaks, particularly in relatively homogeneous rice systems. Such approaches support early-warning systems, reduce reliance on chemical control, and strengthen biodiversity-friendly rice pest management.

Keywords: Climatic factors, discrete logistic model, linear regression, population dynamics, *Scirpophaga incertulas*

INTRODUCTION

Rice (*Oryza sativa* L.) is the staple food for more than half of the global population, including Indonesia, where it serves as the main source of carbohydrates. Any reduction in rice productivity, therefore, poses a direct threat to national food and nutritional security (Triwidodo et al. 2023). Rice productivity is highly vulnerable to biotic and abiotic constraints, among which insect pests remain one of the most persistent challenges, requiring continuous monitoring and management efforts (Nawaz et al. 2022).

Among rice pests, the yellow stem borer *Scirpophaga incertulas* (Walker, 1863) is one of the most destructive in Southeast Asia. It causes “dead hearts” in the vegetative stage and “white heads” in the reproductive stage, leading to yield losses (Katel et al. 2023). Infestation reduces productive tillers and damages panicle and grain development. With high reproductive potential under favorable conditions, this species remains a persistent threat in tropical Asian rice ecosystems.

Climatic variables such as temperature, relative humidity, and rainfall play a central role in shaping the life cycle and survival of *S. incertulas*. Suboptimal temperatures can disrupt egg, larval, and pupal development, while variations in humidity and rainfall affect host colonization and larval survival (Ma et al. 2025). Weekly and seasonal fluctuations in these factors generate uncertainty in predicting outbreaks, which complicates management. Hence, integrating climate data into pest population studies is increasingly recognized as a prerequisite for developing weather-based forecasting systems and precision management strategies.

Previous studies on *S. incertulas* mostly focused on laboratory conditions or general aspects of its biology and ecology. However, these overlook field-level complexities where microclimate, crop phenology, and landscape heterogeneity shape pest abundance. Few field studies have integrated climatic variables into population models (Hernández-Ochoa et al. 2022), and most rely on simple regressions that ignore real-world population constraints—leaving major gaps in predicting pest dynamics in tropical rice systems.

Regression-based methods are widely used in ecological studies to quantify relationships between environmental variables and population dynamics. Linear regression remains useful for identifying which climatic factors most strongly influence pest abundance (Domingues et al. 2022).

However, linear models assume unrestricted growth and thus may fail to capture density-dependent processes and environmental limits. Logistic models, in contrast, incorporate the concept of carrying capacity, thereby providing a biologically realistic framework for modeling pest populations in resource-limited environments. Logistic modeling has been successfully applied in ecology and epidemiology to describe non-linear, density-dependent growth (Hosmer et al. 2013). Yet, its application to insect pests in tropical rice ecosystems remains scarce.

This knowledge gap highlights the need to develop dynamic pest population models that integrate climatic drivers while accounting for ecological limits on pest growth. Such approaches are particularly important in tropical rice systems, where climate variability and monoculture practices interact to intensify pest outbreaks and threaten ecosystem stability. By advancing modeling approaches, it is possible not only to improve the accuracy of pest forecasting but also to design more sustainable strategies that minimize chemical reliance and conserve biodiversity through Integrated Pest Management (IPM).

This study aimed to fill the existing gap by integrating climatic factors into population modeling of *S. incertulas* during a rice cropping season in Mardingding, North Sumatra, Indonesia. Dynamic population models using linear and logistic approaches were developed to assess climatic influences on pest dynamics across three locations and relate infestation to plant age. By comparing both models under field conditions, this study offers new insights for ecological forecasting and supports early-warning systems and biodiversity-friendly pest management in tropical rice ecosystems.

MATERIALS AND METHODS

Population observation of *Scirpophaga incertulas*

This study was conducted from January to April 2025 in three paddy field locations in Mardingding Sub-district, Karo District, North Sumatra, Indonesia: Lau Kasumpat, Mardingding, and Tanjung Pamah Villages. Ciherang rice, commonly grown by local farmers, was cultivated at all sites. The villages represent rice-based polyculture systems, though cropping patterns varied: Lau Kasumpat (maize–rice), Mardingding (cocoa–maize–rice), and Tanjung Pamah (watermelon–maize–shallot–banana–rice). These differences in vegetation structure provided a basis for interpreting variations in *S. incertulas* populations across sites.

Population observations of *S. incertulas* were conducted using light traps installed at each site within a 500 m² (50 × 10 m) rice field plot. One light trap was installed per location. The trap consisted of an LED SMD light source with an intensity of 400 lumens (40 W), operated daily from 6:00 PM to 6:00 AM local time (Western Indonesian Time). A container filled with soapy water was placed beneath the lamp to capture moths attracted to the light. Captured *S. incertulas* moths and other insects were separated by species, placed into 30 cc vials containing 70% alcohol, and subsequently identified using an Olympus SZ5 stereo microscope before being subjected to data analysis.

Observation of infestation incidence and infestation intensity of *Scirpophaga incertulas*

The infestation incidence and infestation intensity of *S. incertulas* were observed by selecting five observation points in each paddy plot, marked with bamboo fences. Each bamboo-marked plot contained six rice clumps, resulting in a total of 30 clumps observed regularly once a week until eight weeks after planting. The five observation points in each plot were arranged diagonally to ensure a representative distribution of samples. The infestation intensity was calculated based on the number of infested tillers relative to the total number of observed tillers, as shown in equation 1. Infestation incidence was calculated based on the number of infested clumps relative to the total number of sampled clumps, as shown in equation 2. These methods were based on relevant literature sources (Pedigo and Rice 2009; Bock et al. 2021; Madden and Ojiambo 2024).

$$\text{Infestation Intensity (\%)} = \left(\frac{\text{Number of Infested Tillers}}{\text{Total Number of Tillers}}\right) \cdot 100 \quad [1]$$

$$\text{Infestation Incidence (\%)} = \left(\frac{\text{Number of Infested Clumps}}{\text{Total Number of Observed Clumps}}\right) \cdot 100 \quad [2]$$

Observation of climate factors

Climate data, including daily air temperature (°C), daily relative humidity (%), and daily rainfall (mm), were used as supporting variables to analyze the climatic factors influencing the population dynamics, infestation incidence, and infestation intensity of *S. incertulas*. Since no local weather stations were available at the study sites, climate data were obtained from the official NASA Prediction of Worldwide Energy Resources (POWER) database, which provides reliable, location-specific historical climate records. Previous studies have demonstrated that NASA POWER data are consistent with ground-based meteorological measurements in tropical regions, particularly for temperature and humidity, although rainfall estimates may show higher variability due to spatial heterogeneity (Tan et al. 2023). Despite these limitations, NASA POWER has been widely used as a dependable alternative for ecological and agricultural modeling where direct field measurements are unavailable (Jiménez-Jiménez et al. 2021; Araghi et al. 2022).

Location point data were recorded using the geographic coordinates of each rice field. The coordinates were 3°14'37.7" N, 98°00'03.0" E for Lau Kasumpat, 3°13'21.6" N, 98°00'23.5" E for Mardingding, and 3°12'40.6" N, 98°00'46.6" E for Tanjung Pamah. The data collection period extended from January 28, 2025, to April 24, 2025, encompassing the entire growing season until the completion of a single rice cropping cycle. All climatic variables were first compiled into daily datasets and subsequently aggregated into weekly averages to correspond with the schedule of pest population and infestation monitoring.

Population dynamics modelling of *Scirpophaga incertulas*

The population dynamics of *S. incertulas* were modeled using climate variables (temperature, relative humidity, and

rainfall) in relation to actual field observations during a single rice cropping season. Two modeling approaches were employed: multiple linear regression and a discrete logistic growth model (Montgomery et al. 2021).

The multiple linear regression model was formulated as follows:

$$N_t = \alpha_0 + \alpha_1 \cdot T + \alpha_2 \cdot RH + \alpha_3 \cdot RF + \varepsilon t \quad [3]$$

N_t is the observed pest population (number of individuals) in week t, T is temperature (°C), RH is relative humidity (%), RF is rainfall (mm), α_0 is the intercept, and α_1, α_2, and α_3 are regression coefficients for each climatic variable. εt is the error term (assumed mean zero).

The discrete logistic growth model was formulated as follows:

$$N_{t+1} = N_t + r_t \cdot N_t \cdot \left(1 - \frac{N_t}{K}\right) \quad [4]$$

$$r_t = \ln\left(\frac{N_{t+1}}{N_t}\right) \quad [5]$$

$$K = \text{Max } N_t \quad [6]$$

N_t and N_{t+} represent the population sizes at weeks t and t+1, respectively, while r_t denotes the intrinsic (per-capita) growth rate for interval t. The weekly variation of r_t was calculated dynamically from observed population data using the natural logarithm formula. The carrying capacity (K) was defined as the highest weekly population size recorded at each site, representing the maximum field density.

Finally, the accuracy of both models was evaluated by comparing predicted population values against observed data using Mean Absolute Percentage Error (MAPE) (Pramoedyo et al. 2022). The model with the lowest prediction error was considered the most accurate and thus suitable for estimating *S. incertulas* population dynamics in subsequent cropping seasons.

$$\text{MAPE (\%)} = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{\text{Actual}_i - \text{Predited}_i}{\text{Actual}_i}\right| \cdot 100 \quad [7]$$

All statistical analyses were conducted using standard software. Population differences of *S. incertulas* among the three sites were tested using one-way ANOVA ($\alpha = 0.05$) in IBM SPSS Statistics 27 (IBM Corp., Armonk, NY, USA). Descriptive statistics and the implementation of both multiple linear regression and discrete logistic growth models were performed in Microsoft Excel (Microsoft Corp., Redmond, WA, USA) using built-in functions and iterative calculations. Model performance was assessed using the Mean Absolute Percentage Error (MAPE) in Excel.

RESULTS AND DISCUSSION

Population differences among study sites

The summarized data on climatic variables, pest population, infestation intensity, and incidence are presented in Tables 1-3. ANOVA results (Table 4) showed significant differences in *S. incertulas* populations among the three locations ($F = 8.10 > F_{(crit)} = 3.28$, $p < 0.05$), indicating that population means varied significantly across sites.

Table 1. Summary of climatic factors, pest population, and infestation parameters of *Scirpophaga incertulas* during the vegetative stage of rice in Lau Kasumpat, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Variable	Mean	Standard deviation	Peak week
Temperature (°C)	22.91	0.25	Week 3 (23.40)
Relative humidity (%)	89.44	1.33	Week 5 (90.94)
Rainfall (mm)	5.69	3.80	Week 9 (14.60)
Population (individuals)	19.50	11.65	Week 8 (45.00)
Infestation intensity (%)	0.72	1.23	Week 10 (3.28)
Infestation incidence (%)	11.39	18.67	Week 4 (60.00)

Table 2. Summary of climatic factors, pest population, and infestation parameters of *Scirpophaga incertulas* during the vegetative stage of rice in Mardingding, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Variable	Mean	Standard deviation	Peak week
Temperature (°C)	22.89	0.28	Week 2 (23.40)
Relative humidity (%)	89.44	1.33	Week 4 (90.94)
Rainfall (mm)	5.90	3.93	Week 8 (14.60)
Population (individuals)	12.50	13.50	Week 3 (54.00)
Infestation intensity (%)	2.12	2.21	Week 5 (7.30)
Infestation incidence (%)	24.44	19.76	Week 5 (66.67)

Table 3. Summary of climatic factors, pest population, and infestation parameters of *Scirpophaga incertulas* during the vegetative stage of rice in Tanjung Pamah, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Variable	Mean	Standard deviation	Peak week
Temperature (°C)	22.89	0.28	Week 2 (23.40)
Relative humidity (%)	89.44	1.33	Week 4 (90.94)
Rainfall (mm)	5.90	3.93	Week 8 (14.60)
Population (individuals)	2.63	1.13	Week 2 & 5 (4.50)
Infestation intensity (%)	1.45	1.45	Week 6 (4.77)
Infestation incidence (%)	16.11	12.38	Week 6 (43.33)

Table 4. ANOVA results comparing *Scirpophaga incertulas* population among three observation sites in Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Source of variation	SS	df	MS	F	P-value	F crit
Between groups	1725.13	2	862.56	8.10	0.00	3.28
Within groups	3512.06	33	106.43			
Total	5237.19	35				

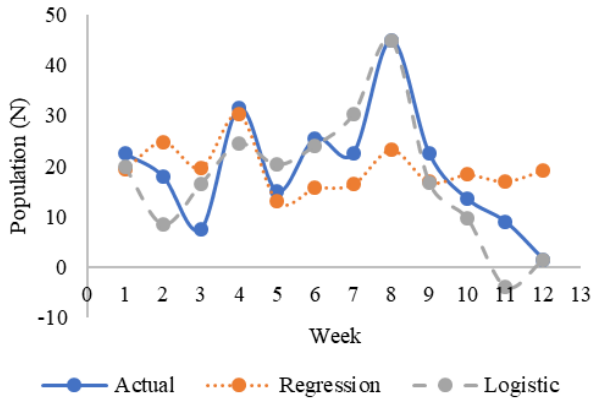

Figure 1. Comparison of actual vs. predicted population dynamics in Lau Kasumpat, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia, using multiple linear regression and discrete logistic models

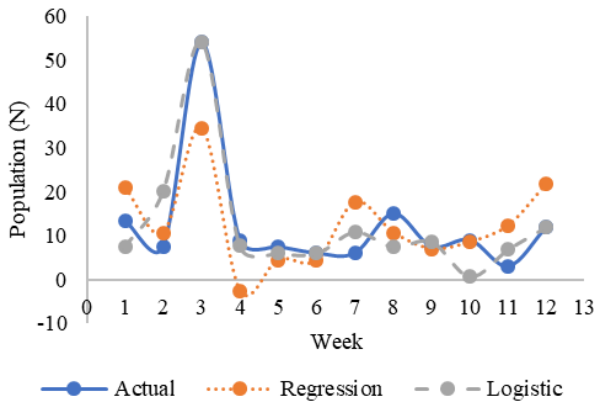

Figure 2. Comparison of actual vs. predicted population dynamics in Mardingding, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia, using multiple linear regression and discrete logistic models

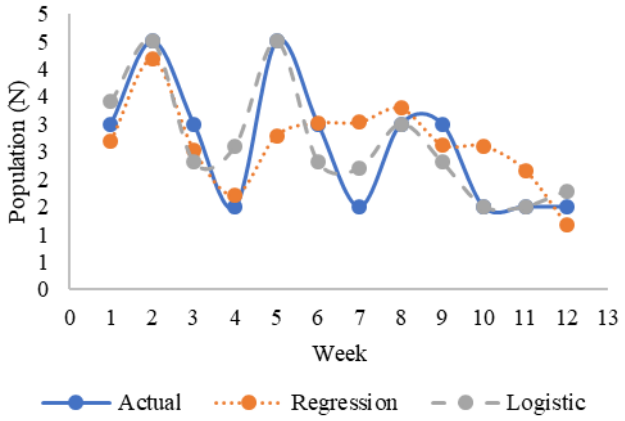

Figure 3. Comparison of actual vs. predicted population dynamics in Tanjung Pamah, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia, using multiple linear regression and discrete logistic models

Descriptive statistical analysis revealed distinct fluctuation patterns of *S. incertulas* populations among the study sites. In Lau Kasumpat, populations ranged from 0 to 45 individuals, with a peak in week 8. The highest temperature (23.40°C) occurred in week 3, peak relative humidity (90.94%) in week 5, and maximum rainfall (14.60 mm) in week 9. In Mardingding, population density varied between 3 and 54 individuals, with the peak observed in week 3. Climatic peaks occurred earlier and at different intervals—temperature (23.40°C) in week 2, relative humidity (90.94%) in week 4, and rainfall (14.60 mm) in week 8. In contrast, Tanjung Pamah exhibited markedly lower *S. incertulas* populations, ranging from 1.5 to 4.5 individuals, with peaks in weeks 2 and 5. At this site, temperature peaked in week 2 (23.40°C), relative humidity in week 4 (90.94%), and rainfall in week 8 (14.60 mm).

These descriptive findings not only illustrate the temporal variability in *S. incertulas* population dynamics but also indicate that the markedly higher population peaks recorded in Lau Kasumpat and Mardingding are more plausibly attributable to differences in vegetation composition and habitat fragmentation factors that alter resource continuity (Aguilar et al. 2025), host-plant availability, and natural-enemy dynamics rather than to microclimatic variation (Aguila et al. 2023), which was broadly similar across the three sites.

Predictive modelling of population dynamics based on climatic factors

The regression analysis between *S. incertulas* population dynamics (Y) and climatic variables from the three study sites produced a multiple linear regression model. This model was then applied to predict pest populations using temperature, relative humidity, and rainfall as predictor variables. In parallel, a discrete logistic growth model was also developed to estimate *S. incertulas* populations (Nt+1) based on the intrinsic growth rate (rt) at time t, with rt varying dynamically each week according to regression outputs, and with carrying capacity (K) determined from the maximum observed population density. Figures 1-3 present the comparisons between observed population dynamics and model predictions from both linear regression and logistic growth models, while predictive accuracy was evaluated using Mean Absolute Percentage Error (MAPE) as summarized in Tables 5-7.

In Lau Kasumpat, both models were able to reproduce the general trend of population fluctuations throughout the growing season. However, differences in the magnitude of predictions became apparent during peak infestation periods. The linear regression model tended to overestimate population densities, particularly during weeks of rapid pest buildup, while the logistic model underestimated peak densities by constraining growth within its assumed carrying capacity. This divergence can be attributed to the biological nature of pest outbreaks, where population surges are often influenced by sudden favorable weather conditions or localized availability of host plants (Soubeyrand et al. 2024). The regression model, being purely statistical, responded more directly to short-term variability in climatic inputs, thereby amplifying peak values (Zhang and Jánošík 2024). In contrast, the logistic framework imposed a ceiling effect, resulting in underestimation when actual populations

temporarily exceeded the predicted carrying capacity (Bradshaw and Herrando-Pérez 2023). These differences highlight the limitations of each model type when applied to real agroecosystem conditions with fluctuating environments.

In Mardingding, deviations between observed and predicted values were greater for both models. The site's heterogeneous cropping system, mixed planting schedules, and variable management likely caused inconsistent pest dynamics. Under such complex conditions, climatic factors alone could not explain population changes, as other ecological drivers—such as alternative host availability, microclimatic variation, and natural enemies—also influenced pest growth. The higher MAPE values indicate the challenge of modeling pest populations in highly variable agroecosystems, highlighting the need to include additional ecological and agronomic parameters for better predictive accuracy (Cai et al. 2023).

In Tanjung Pamah, the logistic growth model closely matched the observed population trends, showing higher predictive reliability under uniform conditions. The homogeneous cropping system, with synchronized planting and consistent management, produced stable climatic responses. Consequently, climatic factors sufficiently explained most variations in pest populations, while the logistic model effectively captured non-linear growth patterns (Fischbein and Corley 2022). The low MAPE value (18.45%) confirmed its robustness, indicating that logistic models are well suited for forecasting in stable rice agroecosystems.

MAPE analysis confirmed these findings by quantifying model performance. The logistic model showed the highest accuracy in Tanjung Pamah (18.45%), while errors were greater in Lau Kasumpat (39.85%) and Mardingding (51.51%). This indicates that climatic factors predict pest dynamics effectively in stable systems but are less reliable in heterogeneous environments with complex ecological interactions (Stell et al. 2022). The contrasting results highlight the role of landscape complexity in population modeling (Briscoe et al. 2023) and demonstrate that MAPE effectively identifies the ecological contexts where logistic models perform best.

Overall, the results demonstrate that while both linear regression and logistic growth models have value in forecasting *S. incertulas* dynamics, their accuracy is site-dependent. The logistic model, in particular, shows promise as a tool for early-warning systems in rice agroecosystems where climatic conditions and planting practices are relatively uniform. However, in more diverse landscapes, integrating additional ecological variables beyond climate will be necessary to enhance model robustness and ensure reliable pest forecasting.

Relationship between plant age and pest infestation

The relationship between plant age (weeks) and *S. incertulas* population dynamics at the Tanjung Pamah site was modeled using a 5th-order polynomial to capture observed fluctuations across crop growth stages. The model yielded an R^2 of 0.4033 for population size, 0.7356 for infestation intensity, and 0.6692 for infestation incidence during the single rice-cropping season. The higher-order polynomial was chosen because lower-order models (e.g., quadratic or cubic) could not adequately represent the non-linear variations associated with plant growth and pest dynamics. Figures 4 and 5 illustrate these relationships.

Table 5. MAPE of the *Scirpophaga incertulas* population prediction model in the paddy field at Lau Kasumpat, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Week	Population			Error	
	Actual	Predicted models			
		Regression	Logistic	Regression	Logistic
1	23	19.36	19.99	13.98%	11.16%
2	18	24.86	8.54	38.13%	52.53%
3	8	19.75	16.47	163.33%	119.59%
4	32	30.41	24.49	3.45%	22.26%
5	15	13.12	20.31	12.51%	35.38%
6	26	15.65	24.12	38.63%	5.42%
7	23	16.46	30.30	26.84%	34.66%
8	45	23.28	45.00	48.26%	0.00%
9	23	16.91	16.75	24.83%	25.54%
10	14	18.38	9.67	36.17%	28.38%
11	9	17.06	-3.90	89.53%	143.34%
12	2	19.28	1.50	1185.47%	0.00%
MAPE				140.09%	39.85%

Table 6. MAPE of the *Scirpophaga incertulas* population prediction model in the paddy field at Mardingding, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Week	Population			Error	
	Actual	Predicted models			
		Regression	Logistic	Regression	Logistic
1	14	20.89	7.55	54.74%	44.08%
2	8	10.64	20.25	41.86%	169.99%
3	54	34.54	54.00	36.04%	0.00%
4	9	-2.52	7.63	127.96%	15.19%
5	8	4.52	6.06	39.69%	19.22%
6	6	4.32	6.00	27.99%	0.00%
7	6	17.65	10.89	194.24%	81.45%
8	15	10.71	7.49	28.63%	50.06%
9	8	6.99	8.68	6.81%	15.70%
10	9	8.54	0.76	5.06%	91.55%
11	3	12.31	6.93	310.20%	130.93%
12	12	21.83	12.00	81.92%	0.00%
MAPE				79.59%	51.51%

Table 7. MAPE of the *Scirpophaga incertulas* population prediction model in the paddy field at Tanjung Pamah, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Week	Population			Error	
	Actual	Predicted models			
		Regression	Logistic	Regression	Logistic
1	3	2.70	3.41	10.12%	13.52%
2	5	4.18	4.50	7.22%	0.00%
3	3	2.53	2.31	15.66%	23.10%
4	2	1.71	2.60	13.69%	73.24%
5	5	2.79	4.50	37.92%	0.00%
6	3	3.02	2.31	0.63%	23.10%
7	2	3.03	2.19	102.17%	46.21%
8	3	3.29	3.00	9.63%	0.00%
9	3	2.62	2.31	12.54%	23.10%
10	2	2.60	1.50	73.31%	0.00%
11	2	2.16	1.50	44.16%	0.00%
12	2	1.17	1.79	21.72%	19.18%
MAPE				29.06%	18.45%

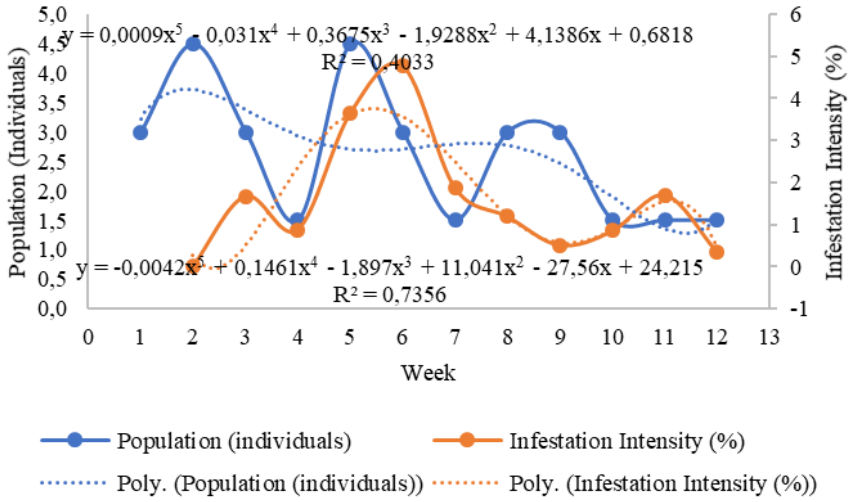

Figure 4. The relationship between the population and infestation intensity of *Scirpophaga incertulas* and plant age (per week) in Tanjung Pamah, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

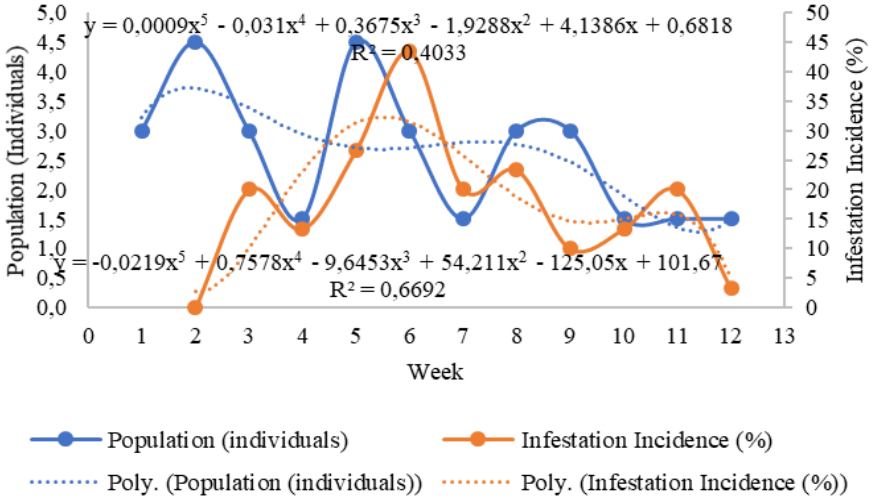

Figure 5. The relationship between the population and infestation incidence of *Scirpophaga incertulas* and plant age (per week) in Tanjung Pamah, Mardingding Sub-district, Karo District, North Sumatra Province, Indonesia

Discussion

This study represents the first attempt to integrate logistic growth modeling of *S. incertulas* with climatic variables in the rice agroecosystems of Mardingding, Karo, North Sumatra. Such integration provides a novel contribution to pest ecology and management, as most earlier research has relied either on regression-based climate pest correlations or on empirical field monitoring, without embedding population dynamics in a predictive framework. By predicting growth rates with linear regression and discrete logistic models, this study captures the density-dependent nature of stem borer growth while testing how far climatic variables alone can explain population fluctuations. The novelty of this approach lies not only in the methodological design but also in its application to highly diverse and fragmented agroecosystems, where the interaction of climate and ecology produces distinct outcomes.

Vegetation composition and habitat fragmentation were central determinants of observed site-specific variation. Lau Kasumpat, with only rice and maize, represented a relatively homogeneous system. At the same time, Mardingding supported cacao, maize, and rice, and Tanjung Pamah displayed the highest crop diversity, including watermelon, onion, banana, maize, and rice. Such variation is not trivial: previous studies have demonstrated that increasing vegetation heterogeneity expands food resources, nesting and oviposition sites, and microhabitats, which collectively enhance arthropod abundance and richness (Maestracci et al. 2025). At the same time, diversified systems strengthen ecological networks, stabilizing food webs and offering refugia for both pests and their natural enemies (Fernández-Martínez et al. 2020). In our study, the higher pest predictability in the more homogeneous Tanjung Pamah suggests that reduced diversity simplifies ecological interactions, allowing climatic factors to dominate. Conversely, in Lau Kasumpat and Mardingding, the complexity of cropping systems reduced the explanatory power of climate-only models, underscoring the regulating role of biotic interactions.

Habitat fragmentation exerted an additional, independent effect. In Tanjung Pamah, *S. incertulas* populations declined in conjunction with the reduction of paddy field area, which was partly converted into residential land. Habitat fragmentation is widely known to reduce host plant continuity, restrict pest dispersal, and limit population persistence, particularly for specialist herbivores like stem borers (Gámez-Virués et al. 2020). Didham et al. (2020) similarly emphasized that agricultural land-use change to urban areas alters insect community structures and weakens host–pest interactions. This finding provides direct evidence that population decline cannot be explained solely by climate but must also account for spatial processes of habitat reduction and isolation. Thus, agroecological dynamics diversity and fragmentation directly interact with climatic influences in determining pest trajectories.

The regression analysis revealed that climatic variables, particularly temperature, relative humidity, and rainfall, had negative coefficients in the models. While counterintuitive at first glance, this outcome indicates that beyond optimal thresholds, increasing temperature or humidity can suppress population growth, consistent with threshold-based responses described in ecological theory. Ali et al. (2020) previously noted that while increases in temperature and rainfall individually promote *S. incertulas*, their combined effects may reduce abundance, reflecting non-linear relationships. Fanani et al. (2019) further argued that pest responses to abiotic variables are often unimodal, peaking at intermediate levels and declining under extreme conditions. The study results, therefore, align with broader ecological principles, showing that climate can both promote and suppress populations depending on its alignment with optimal ranges.

Model performance highlighted the contexts where logistic approaches are most and least useful. In Tanjung Pamah, the logistic model achieved an MAPE of 18.45%, closely tracking observed trends. This confirms that in relatively stable and homogeneous systems, population dynamics can be approximated by climate-driven, density-dependent models. By contrast, in Lau Kasumpat and Mardingding, errors exceeded 39% and 51%, respectively. This underperformance illustrates a critical limitation: logistic models assume that population growth is shaped primarily by abiotic drivers and density dependence, neglecting biotic interactions. In polyculture systems, multiple host crops create a dynamic habitat mosaic, while natural enemies exert strong regulatory pressures that decouple pest abundance from climate alone.

Natural enemies are particularly important in explaining these discrepancies. Parasitoids such as *Trichogramma* spp. and predators like *Cheilomenes sexmaculatus* (Fabricius, 1781) are well documented as suppressors of lepidopteran stem borers (Buchori et al. 2008). Zhu et al. (2022) reported that natural enemy activity can reduce stem borer populations by 30–50%, depending on landscape structure. Excluding such biotic regulation leads climate-only models to overestimate pest potential, particularly in diverse landscapes where natural enemies thrive. This underlines the need for hybrid models that integrate both abiotic and biotic regulation, thereby capturing the ecological realism absent in logistic approaches.

Crop diversification itself modulates pest–climate dynamics. In monoculture, host plants are continuously available, so populations respond more directly to climate. In polycultures, host limitation and interspecific competition weaken climate–pest associations. This is why Lau Kasumpat and Mardingding showed reduced model accuracy compared with Tanjung Pamah. The finding echoes Gawdiya et al. (2025), who demonstrated that diversification enhances resistance to pest outbreaks by stabilizing ecological interactions. Thus, vegetation heterogeneity not only influences biodiversity but also reduces the predictive reliability of climate-based models, challenging the assumption that pests always respond uniformly to abiotic drivers.

Rice plant phenology provided additional explanatory power. A fifth-order polynomial regression indicated that plant age was strongly associated with infestation levels, particularly at six weeks after planting, when structural resistance is low (Bandong and Litsinger 2005). Abbas et al. (2023) similarly observed peak stem borer densities around 63 days after sowing. In our study, this stage coincided with climatic conditions (23.12°C, 89.71% RH, 5.27 mm rainfall) favorable for pest growth, creating a window of opportunity for outbreaks. The synergism between plant phenology and climate highlights why prediction improves when both dimensions are integrated. Jha and Prasad (2021) further emphasized that variations in transplanting time alter infestation patterns precisely through shifts in growth stage relative to weather.

Importantly, these results point to practical implications. Pest management should not rely exclusively on climate monitoring. Instead, early-warning systems should integrate crop phenology, vegetation diversity, and natural enemy abundance. This approach would enable farmers to optimize planting schedules, apply interventions during vulnerable crop stages, and conserve natural enemies. Such integration aligns with the principles of ecological intensification, which emphasize ecosystem services for sustainable pest regulation, and climate-smart agriculture, which prioritizes resilience to variability (Haan et al. 2020).

The novelty of this study lies in its demonstration that discrete logistic growth models, when parameterized with climatic variables, are capable of reproducing the population dynamics of *S. incertulas* within relatively stable monoculture systems. This represents the first attempt to apply such an approach within rice agroecosystems in Mardingding, Karo, North Sumatra. The findings contribute to the advancement of pest population modeling by highlighting not only the predictive potential of climate-based models but also their inherent limitations. Furthermore, the study emphasizes the necessity of developing integrated climate–ecology hybrid models that account for natural enemies, habitat fragmentation, and vegetation heterogeneity. Such integrative frameworks would enhance predictive accuracy while simultaneously providing a more robust basis for agroecological management under conditions of land-use change and biodiversity decline.

In conclusion, this study highlights both the promise and the limitations of climate-based logistic models for predicting *S. incertulas* dynamics. While such models can effectively capture pest trends in stable monocultures, their

accuracy declines in heterogeneous landscapes where ecological interactions exert a stronger influence. These findings emphasize that pest management cannot rely solely on climatic predictors but must integrate biodiversity-based strategies that harness natural enemies and habitat diversity to suppress pest populations. Strengthening agroecosystem resilience requires management practices that buffer against climatic variability, reduce vulnerability to pest outbreaks, and maintain stable rice yields. Equally important, conserving biodiversity through refugia plants, landscape heterogeneity, and the protection of natural enemies is not only an ecological necessity but also a practical pathway to sustainable pest regulation. Thus, the implications of this study extend beyond modeling: they call for integrated pest management approaches that are climate-smart, ecologically grounded, and biodiversity-supportive, ensuring both the productivity and the long-term sustainability of rice systems in Mardingding, Karo, North Sumatra, and comparable agroecosystems.

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