BIO Web of Conferences **234**, 01009 (2026) https://doi.org/10.1051/bioconf/202623401009
FiSAED 2025

Projected changes in climate suitability for the Brown Planthopper (*Nilaparvata lugens*) in West Java under future climate scenarios

Yon Sugiarto[*], *Yonny* Koesmaryono, Impron, and Perdinan

Department of Geophysics and Meteorology, Faculty of Mathematics and Natural Science, IPB University, Bogor, 16680, Indonesia

Abstract. One of the impacts of climate change in the agricultural sector in Indonesia is the shift in the distribution of the brown planthopper (*Nilaparvata lugens*), a significant threat to rice cultivation in Indonesia. This study provides one of the first CLIMEX-based assessments of brown planthopper climatic suitability in West Java using multi-model CMIP6 projections and spatial autocorrelation analysis. Baseline (1990-2020) and future climate conditions (2040–2060) were simulated under the SSP2-4.5 and SSP5-8.5 scenarios using four CMIP6 models (ACCESS-CM2, EC-Earth3-Veg, GISS-E2-1-G, and HadGEM3-GC31-LL). Climatic suitability was quantified using the Ecoclimatic Index (EI), while spatial clustering was evaluated using Moran's statistics. Under baseline conditions, high-suitability zones (EI 51–75) are predominantly concentrated along the northern coastal regions, especially in Indramayu, Karawang, and Subang. Under future scenarios, suitable areas expand southward and into middle-altitude regions, increasing from approximately 40% at present to nearly 80% under SSP5-8.5. Spatial analysis indicates significant clustering of suitability across neighboring districts. These findings indicate that rising temperatures increasingly support brown planthopper development, thereby elevating pest risk in major rice-producing areas of West Java.

1 Introduction

Climate change poses a growing threat to global food production and food accessibility. Increasing frequencies of droughts, floods, and climate-driven pest and disease outbreaks are raising food security risks, particularly in vulnerable regions. Tropical areas are expected to experience a global temperature increase of about 1–2 °C, which may lead to food shortages and unstable agricultural production [1]. Food crops in tropical countries such as Indonesia are especially vulnerable to future pest outbreaks, as climate change alters temperature, rainfall, and humidity patterns. These climatic changes can create favorable conditions for insect pests and other crop-damaging organisms. In Southeast Asia, the brown planthopper has emerged as a major threat to rice production, and numerous studies have reported

---

[*] Corresponding author: yons@apps.ipb.ac.id

frequent and severe population outbreaks. This pest is widely recognized as one of the most destructive insects affecting rice cultivation.

Previous studies have shown that pest growth, spatial distribution, reproduction, and survival are strongly influenced by climatic factors such as heavy rainfall during dry seasons, wind patterns, and increased atmospheric or soil moisture [2]. In Indonesia, climate projections indicate a rise in the frequency and intensity of extreme weather events, which may reduce crop yields and increase the risk of pest and disease outbreaks. West Java is one of Indonesia's most important food-producing regions, particularly for rice. Climate variability and long-term climate change are expected to reduce rice and maize production by up to 30% in major production areas, including West Java, Central Java, and South Sulawesi. Some districts in northern West Java may even experience crop failure for two consecutive planting seasons, highlighting the urgency of climate-related agricultural risk assessments.

Understanding how climate change affects pest distribution is therefore critical for supporting sustainable rice production and national food security. Reliable information on future pest risk can help improve early warning systems, guide pest management strategies, and support climate adaptation planning in agriculture. However, in Indonesia, climate-based assessments of pest distribution remain limited, especially those using process-based or semi-mechanistic models. This research addresses the gap by providing a climate-informed analysis of brown planthopper suitability under future climate scenarios, with a specific focus on West Java, a key rice-producing region.

Climatic factors play a central role in determining the distribution and spread of agricultural pests, and various Species Distribution Models (SDMs) have been developed to assess these patterns [3]. Among them, CLIMEX and MaxEnt are the most widely used tools for evaluating changes in climatic suitability under climate change scenarios [4]. This study applies CLIMEX, a semi-mechanistic bioclimatic model developed by Sutherst and Maywald, which estimates species distribution based on physiological tolerance to temperature and moisture conditions [5]. CLIMEX has been widely used to assess the potential distribution of plant and animal species by integrating climate variables, elevation, and biological characteristics. Despite several regional studies on brown planthopper dynamics, climate-based suitability assessments using semi-mechanistic models remain limited in West Java, Indonesia's major rice-producing region [6]. The primary objective of this study is to assess how future climate scenarios may influence the climatic suitability and spatial distribution of the brown planthopper across West Java Province, Indonesia.

2 Materials and methods

2.1 Study area

The study area covers West Java Province, Indonesia, which consists of 27 regencies, located between 6.0°–7.5° South Latitude and 106.5°–108.5° East Longitude.

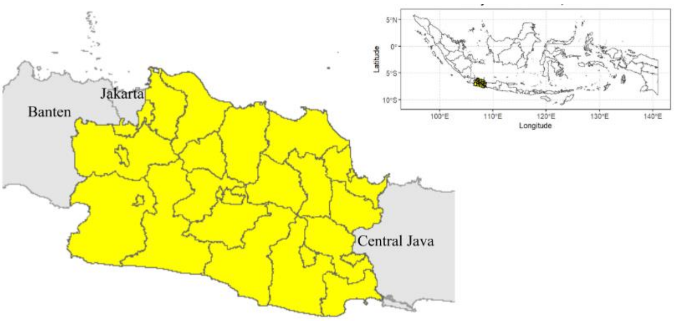

Fig. 1. Study area of West Java Province, Indonesia

The lowlands surrounding West Java on the northern side are relatively flat and almost at sea level, while those in the south are generally below 100 meters above sea level. The mountain ranges of West Java, located in the central–southern region, rise to elevations exceeding 1,500 meters above sea level and extend from western Bogor to eastern Kuningan. Rice fields in West Java are widely distributed in areas near the coast, stretching from Bekasi to Cirebon and Cianjur.

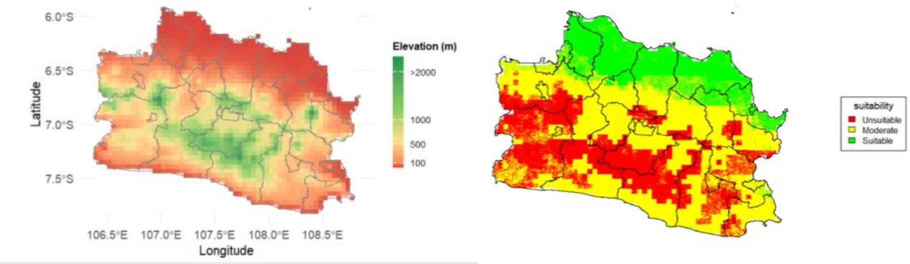

Fig. 2. Elevation map (left) and rice land suitability (right) in West Java Province, Indonesia

2.2 Data sources

Geographic input data were prepared using coordinate points covering West Java, adjusted to match the spatial resolution of the climate data. Altitude information was derived from average air temperature using the Braak formula. Baseline and future climate data, including minimum, maximum, and mean air temperature as well as precipitation, were obtained from the WorldClim database. Because WorldClim does not provide relative humidity data at 09:00 and 15:00, these variables were estimated using the recommended approach based on the Magnus equation.

Historical climate data for the period 1990–2020 and future projections for 2041–2060 were used, with a spatial resolution of 2.5 arc-minutes (approximately 21 km). CMIP6 Global Climate Models (GCMs) under Shared Socioeconomic Pathways (SSPs), including SSP2-4.5 (medium greenhouse gas emissions) and SSP5-8.5 (high greenhouse gas emissions), are used to represent future climate conditions [7]. Four GCMs were selected for this study: ACCESS-CM2, EC-Earth3-Veg, GISS-E2-1-G, and HadGEM3-GC31-LL. Data processing and spatial analysis were conducted using RStudio, CLIMEX, and ArcMap, while biological and physiological parameters of *N. lugens* were applied in the CLIMEX simulations. CLIMEX parameters were adopted from previous validated studies on *N. lugens* to ensure biological realism and comparability of results. The initial parameters were determined using a humid tropical template as a basis, and previous studies were also adjusted to the actual field distribution due to limited research on the biology and climate influences of *N. lugens* under field conditions [3]. The parameters were calibrated iteratively to match the actual distribution data [3, 5].

Table 1. Input data parameters of *N. lugens* [3]

Category	CLIMEX Parameter	Code	Nilai
Moisture Index	Lower threshold soil moisture	SM0	0.08
	Lower optimum soil moisture	SM1	0.2
	Upper optimum soil moisture	SM2	0.8
	Upper threshold soil moisture	SM3	2.8
Temperature Index	Lower threshold temperature (°C)	DV0	11.6
	Lower optimum temperature (°C)	DV1	26
	Upper optimum temperature (°C)	DV2	35
	Upper threshold temperature (°C)	DV3	47
Cold Stress	Temperature threshold cold stress (°C)	TTCS	10
	Cold stress accumulation rate	THCS	-0.15
Heat Stress	Temperature threshold heat stress (°C)	TTHS	45
	Heat stress accumulation rate	THHS	0.00008
Dry Stress	Soil moisture threshold dry stress	SMDS	0.22
	Dry stress accumulation rate	HDS	-0.0015
Wet Stress	Soil moisture threshold wet stress	SMWS	2.5
	Wet stress accumulation rate	HWS	0.002
Degree-days per Generation	Degree-day for complete generation	PDD	389

2.3 CLIMEX model

CLIMEX version 4 is an ecological software tool widely used to predict the geographical distribution of plant and animal species. CLIMEX develops a semi-mechanistic simulation model that estimates climate suitability for the presence of *N. lugens*. The CLIMEX model is used across various fields, including ecology, agriculture, forestry, and epidemiology [8]. CLIMEX output provides a quantitative representation of climate suitability for a species in a given region via the Ecoclimatic Index (EI). The EI is derived from calculations of the annual Growth Index (GIA), annual Stress Index (SI), and Stress Interaction Index (SX). EI reflects a species' tolerance to specific climatic conditions. Higher EI values indicate more optimal climatic conditions for a species' long-term survival, and vice versa. The "compare locations" function in CLIMEX is used to develop the *N. lugens* simulation model. This function calculates the annual climatic suitability index for a species by combining the growth index, stress index, and stress interaction index [9]. The annual Growth Index (GIA) represents the potential for population growth and development. It is derived from the Temperature Index (TI) and Moisture Index (MI), which describe the temperature and soil moisture requirements necessary for species growth [5]. Stress indices, such as cold, wet, dry, and heat stress, indicate the likelihood or probability that a population can survive under unfavourable conditions. The EI is calculated using the following equation:

$$EI = GI_a \times SI \times SX \qquad (1)$$

The resulting EI values range from 0 to 100. Higher EI values indicate a greater potential risk of *N. lugens* infestation. EI values are classified as follows: unsuitable (0), marginal (1–25), moderate (26–50), suitable (51–75), and highly suitable (>75).

2.4 Moran's index

Moran's Index is a statistical test used to measure overall spatial autocorrelation to detect spatial patterns such as dispersion or clustering. The Moran's Index calculates how far the value at a given location deviates from the mean value and how far the values at neighboring locations deviate from the mean. Moran's I was selected to quantify spatial dependence among districts. It effectively captures clustering patterns at administrative scales. This index depends on the characteristics of surrounding locations [10], where:

$$I = \frac{N}{\Sigma_i \Sigma_j w_{ij}} \cdot \frac{\Sigma_i \Sigma_j w_{ij}\,(x_i-\bar{x})(x_j-\bar{x})}{\Sigma_i (xi-\bar{x})^2} \qquad (2)$$

I : Moran's Index
N : number of regencies
X_i : value at regency i
X_j : value at regency j
W_{ij} : standardized spatial weight between regencies i and j
Expected value of Moran's Index

$$E(I) = o = \frac{-1}{N-1} \qquad (3)$$

$$z_{calculate} = \frac{I - Io}{var\ (I)} \sim N(0,1) \qquad (4)$$

Spatial autocorrelation occurs among locations when:

I : Moran's Index coefficient
I_0 : expected value of Moran's Index
Var(I) : variance of Moran's Index

The range of values obtained from Moran's Index is $-1 < I < 1$. Values closer to +1 indicate stronger positive spatial autocorrelation, while values closer to −1 indicate stronger negative spatial autocorrelation. A more detailed interpretation is as follows:

$I_0 = -1/(N-1)$, which is approximately zero (0), indicates no spatial autocorrelation.
$I > I_0$ indicates positive spatial autocorrelation, forming clustered data patterns.
$I < I_0$ indicates negative spatial autocorrelation, forming dispersed data patterns.

3 Results

3.1 Climate characteristics and future projections

West Java exhibits clear spatial variation in elevation, with lowland areas dominating the northern region and mountainous terrain concentrated in the central to southern parts of the province. Baseline climate conditions (1990–2020) show mean annual air temperatures ranging from 24 to 27 °C and annual rainfall between 1,300 and 4,300 mm, with lower temperatures observed in high-elevation areas.

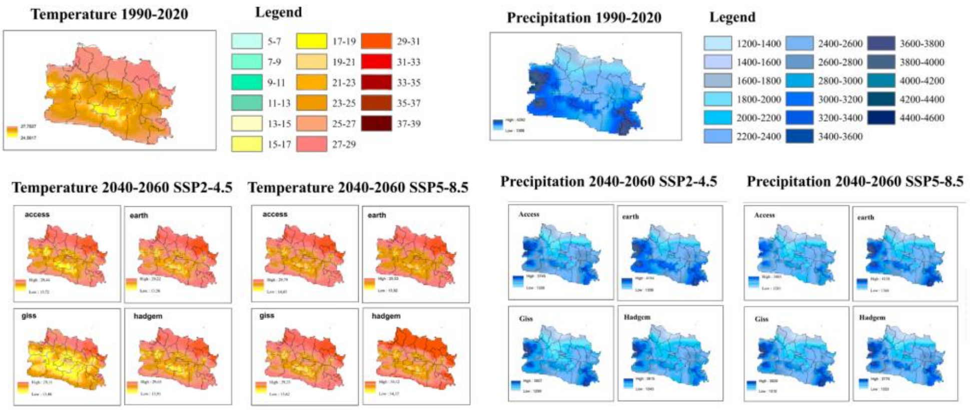

Fig. 3. Comparison of baseline temperature and precipitation (1990–2020) with mid-century projections for 2040–2060 under SSP2-4.5 and SSP5-8.5 scenarios.

Future climate projections for 2040–2060 show a consistent increase in near-surface air temperature across all four CMIP6 models under both SSP2-4.5 and SSP5-8.5 scenarios. Mean annual air temperature is projected to increase to approximately 29 °C over most of West Java, with greater warming under SSP5-8.5. Precipitation projections show higher spatial variability among models, although an overall tendency toward increased rainfall is observed, particularly in southern and mountainous regions.

3.2 Spatial distribution of Ecoclimatic Index (EI)

Baseline Ecoclimatic Index (EI) values indicate spatial heterogeneity across West Java. Areas with moderate to high climatic suitability (EI > 50) are concentrated in lowland and coastal regions, while mountainous areas show low or unsuitable EI values. High EI values are observed in major rice-producing districts such as Indramayu, Karawang, and Subang.

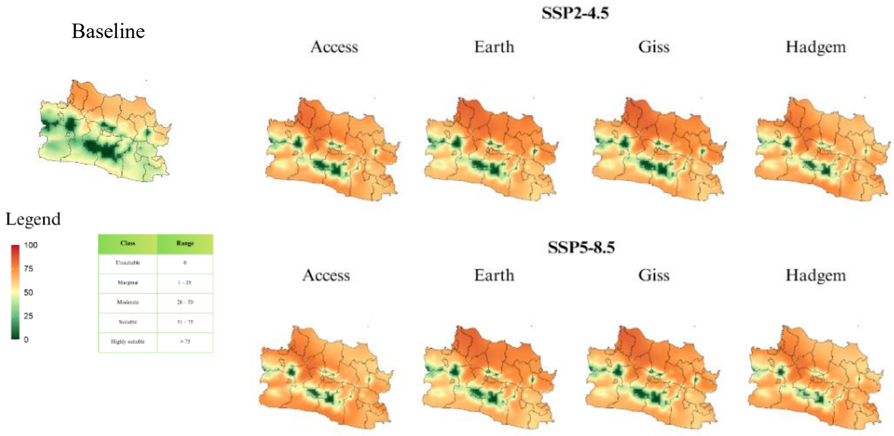

Fig. 4. Spatial distribution of Ecoclimatic Index (EI) for *N. lugens* under baseline and future climate scenarios in West Java Province, Indonesia.

Under future climate scenarios, both SSP2-4.5 and SSP5-8.5 show substantial changes in EI distribution. Suitable areas (EI 51–75, as defined in Section 2.3) expand toward central and southern regions and into middle-altitude zones. Under SSP5-8.5, the proportion of suitable areas increases from approximately 40% under baseline conditions to nearly 80%, depending on the climate model. Areas classified as unsuitable (EI = 0) remain limited and are confined mainly to high-elevation regions. Table 2 summarizes the expansion of suitable EI classes under future scenarios.

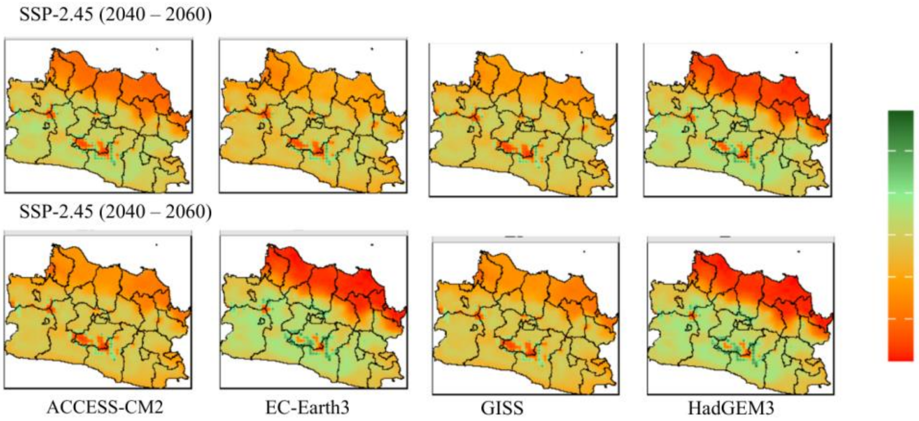

Fig. 5. Spatial distribution changes of Ecoclimatic Index (EI) for *N. lugens* under baseline and future climate scenarios in West Java Province, Indonesia.

Historical outbreaks observed indicate that brown planthopper attack areas in West Java during 2018–2022 were consistently concentrated in the northern coastal regencies, particularly Indramayu, Karawang, and Subang. These districts recorded the largest affected areas, especially in 2018 and 2019, and remained relatively more vulnerable than other regions even as overall infestation levels declined after 2019. In contrast, central and southern regencies such as Ciamis, Banjar City, and Pangandaran exhibited comparatively limited and more stable attack areas throughout the observation period.

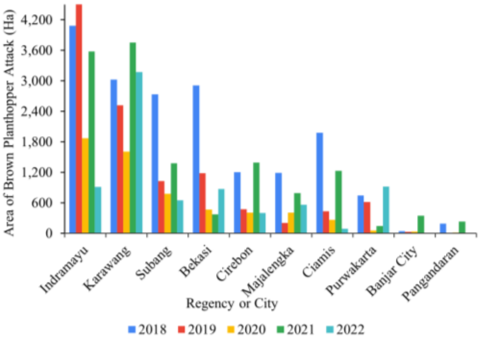

Fig. 6. Observed the brown planthopper attack areas across regencies in West Java (2018–2022) recorded by the Ministry of Agriculture.

This spatial distribution is consistent with historical outbreak reports and previous distribution studies in Indonesia, which identify the northern coastal belt of West Java as a recurrent hotspot of brown planthopper infestation. The agreement between observed outbreak records (2018–2022) and the baseline CLIMEX Ecoclimatic Index (1990–2020) outputs supports the model's reliability in capturing the established geographical pattern of brown planthopper risk. The baseline simulation results show high EI values (51–75) concentrated in these same districts, demonstrating spatial consistency between model outputs and observed pest occurrence patterns. This qualitative validation supports the biological plausibility of the selected CLIMEX parameterization.

3.3 Changes in EI classes under future climate scenarios

Quantitative analysis of EI classes shows a consistent reduction in marginal (EI 1–25) and moderate (EI 26–50) suitability classes under future scenarios. In contrast, the suitable class (EI 51–75) increases substantially across all models. The highly suitable class (EI > 75), absent under baseline conditions, emerges under both SSP2-4.5 and SSP5-8.5, with the largest proportions observed under SSP5-8.5. The largest increases in EI values are recorded in the HadGEM model under SSP5-8.5 (increase of 47 EI units) and in the GISS model under SSP2-4.5 (increase of 46 EI units). Slight decreases in EI are observed in northern coastal areas, with reductions of up to 2 EI units under SSP5-8.5 in the GISS and HadGEM models.

Table 2. Changes in percentage area of Ecoclimatic Index classes for *N. lugens* under baseline and future climate scenarios in West Java Province, Indonesia.

EI Value Class	**Baseline % Area**	**% Area for SSP2-4.5 Scenario**				**% Area for SSP5-8.5 Scenario**			
		Access	**Earth**	**Giss**	**Hadgem**	**Access**	**Earth**	**Giss**	**Hadgem**
0	0.57	0.06	0.09	0.12	0.04	0.04	0.05	0.09	0.00
1 - 25	9.82	3.43	4.03	3.91	2.88	2.65	3.18	3.64	1.86
26 - 50	50.16	10.89	12.40	11.92	10.47	8.93	11.84	11.52	9.33
51 - 75	39.46	74.08	63.68	66.77	79.36	78.39	64.54	68.89	81.68
> 75	0	11.54	19.79	17.29	7.25	9.99	20.39	15.87	7.12

3.4 Relationship between EI and elevation

Scatterplot analysis shows a clear negative relationship between EI values and elevation under baseline conditions. EI values above 60 are predominantly observed below 800–1,000 m above sea level, while elevations above 1,500–2,000 m are largely unsuitable (EI ≈ 0). This relationship persists under both future climate scenarios, although EI values show an overall downward shift, particularly under SSP5-8.5.

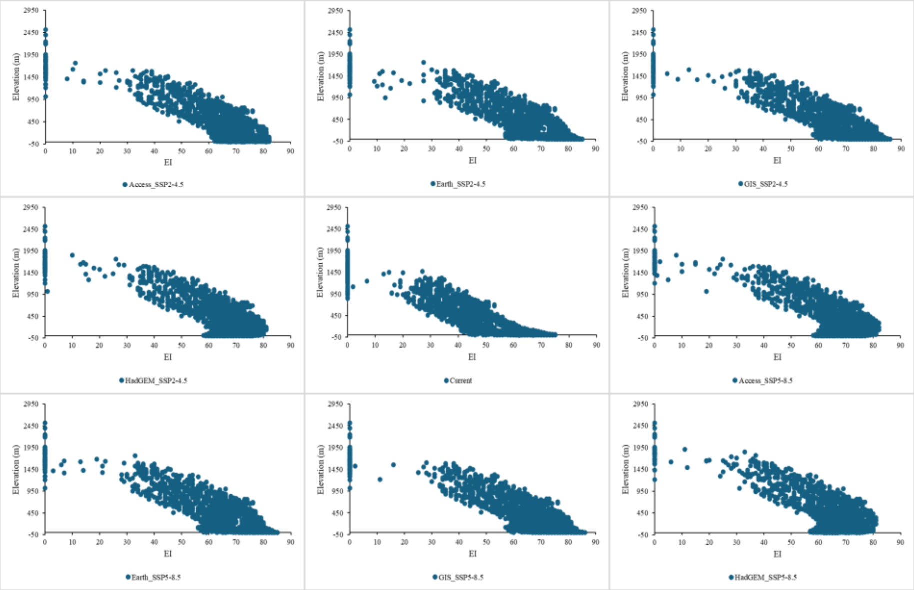

Fig. 7. Distribution of Ecoclimatic Index for *N. lugens* under baseline and future climate scenarios in West Java Province, Indonesia.

3.5 Spatial autocorrelation of climatic suitability

Moran's I analysis shows significant positive spatial autocorrelation of EI values across districts under baseline conditions and most future scenarios. Moran's I values range from 0.20 to 0.44, with statistically significant clustering observed in nearly all cases. Only the HadGEM SSP2-4.5 scenario shows a non-significant spatial pattern. These results indicate that districts with similar EI values tend to be spatially clustered.

Table 3. Moran's I result of Ecoclimatic Index under baseline conditions and future scenarios.

	Moran_I	Expectation	Variance	Z_score	P_value	Interpretation
Baseline	0.44	-0.04	0.02	3.40	0.00	Significant positive autocorrelation (clustered pattern)
Access SSP2-4.5	0.21	-0.04	0.02	1.86	0.03	Significant positive autocorrelation (clustered pattern)
Earth SSP2-4.5	0.32	-0.04	0.02	2.60	0.00	Significant positive autocorrelation (clustered pattern)
Giss SSP2-4.5	0.31	-0.04	0.02	2.52	0.01	Significant positive autocorrelation (clustered pattern)
Hadgem SSP2-4.5	0.17	-0.04	0.02	1.56	0.06	Not significant (random pattern)
Access SSP5-8.5	0.20	-0.04	0.02	1.80	0.04	Significant positive autocorrelation (clustered pattern)
Earth SSP5-8.5	0.31	-0.04	0.02	2.47	0.01	Significant positive autocorrelation (clustered pattern)

Giss SSP5-8.5	0.26	-0.04	0.02	2.19	0.01	Significant positive autocorrelation (clustered pattern)
Hadgem SSP5-8.5	0.19	-0.04	0.02	1.69	0.05	Significant positive autocorrelation (clustered pattern)

3.6 Agricultural and pest management implications

This research shows that the projected expansion of climatically suitable areas for *N. lugens* suggests an increased risk of regional-scale pest outbreaks in West Java. Thus, strengthening management responses becomes increasingly important. The Ministry of Agriculture needs to intensify efforts to enhance climate-informed early warning systems and broaden pest surveillance coverage to regions projected to become increasingly suitable in the coming decades, particularly in the central and southern parts of West Java. Proactive monitoring in these areas would facilitate earlier detection and enable more timely and effective responses to potential surges in pest populations.

At the same time, promoting rice varieties with stronger tolerance or resistance to brown planthopper infestation should be considered as part of longer-term adaptation efforts. Integrating seasonal climate information into Integrated Pest Management (IPM) practices may also enhance decision-making at the farm level, enabling farmers to align control measures with expected climatic conditions better. Under high-emission scenarios, where the expansion of climatically suitable habitats for *N. lugens* is projected to be more extensive, such forward-looking measures will become even more critical. Without appropriate adaptation strategies, the risk of production losses in central rice-growing districts may increase in the future.

4 Discussion

4.1 Climate drivers

The results demonstrate that climate warming is the dominant driver of changes in the brown planthopper climatic suitability in West Java, acting through temperature thresholds, moisture stress, and elevation-related gradients. West Java has a tropical climate, with air temperatures influenced by topography. Topography, location, wind patterns, and external factors such as the ENSO phenomenon may influence the high annual rainfall in these areas. Elevation significantly affects the climatic profile of a given area [6]. The magnitude of warming is stronger under SSP5-8.5 than under SSP2-4.5, reflecting the influence of higher greenhouse gas concentrations. This pattern aligns with regional and global assessments showing robust warming over Indonesia and Southeast Asia. Precipitation projections show greater spatial variability and inter-model differences, although a general tendency toward increased rainfall in many parts of West Java is visible under both scenarios, particularly under SSP5-8.5. Intensified precipitation in southern and mountainous regions may be linked to greater moisture availability and more vigorous convective activity in a warmer atmosphere.

Land suitability for rice cultivation in West Java shows clear spatial differences. Areas classified as highly suitable are mainly located in northern West Java, while moderately suitable areas are found in the central to southern regions. Unsuitable areas are generally associated with mountainous zones. Climatic and topographic conditions strongly influence this pattern. The northern region tends to experience higher air temperatures and lower rainfall than the central–southern areas, and it is characterized by relatively flat terrain. In contrast, the central–southern region is dominated by mountainous landscapes, which affect temperature, rainfall distribution, and land suitability. Overall, West Java has soil, rainfall, and temperature conditions that are generally favorable for rice cultivation. However, the region is also exposed to climate-related hazards. Floods and droughts occur frequently in northern West Java, while landslides are more common in the southern areas, and these hazards can cause crop failure. Climate change may further increase agricultural risks by extending dry seasons and shifting the onset of the rainy season, disrupting planting schedules. A temperature increase of 1 °C has been reported to reduce rice productivity by 5–7% [1]. These changes may indirectly influence brown planthopper dynamics by altering crop availability and growing conditions. In addition, climate change is expected to influence the distribution and intensity of plant pests and diseases. According to the study conducted by Lamba and Dono [11], brown planthoppers in tropical regions depend on actively growing rice plants. In rainfed rice fields in West Java, rice is not cultivated during the dry season.

4.2 Redistribution of spatial suitability

This study also demonstrates that climate change is likely to significantly influence the climatic suitability and spatial distribution of *N. lugens* in West Java. Under baseline climate conditions, areas with high climatic suitability are mainly located in northern coastal regions, where temperatures are relatively high and rice cultivation is intensive. These findings are consistent with previous studies showing that brown planthoppers develop optimally under warm and moderately humid conditions commonly found in lowland rice-growing areas [11, 12]. The concentration of high EI values in major rice production districts such as Indramayu, Karawang, and Subang further confirms the close relationship between climatic suitability, cropping intensity, and pest presence.

Future climate projections under SSP2-4.5 and SSP5-8.5 indicate a clear expansion of suitable climatic conditions toward the central and southern parts of West Java, including middle-altitude regions. This shift reflects the effect of increasing temperatures, which reduce thermal limitations in areas that were previously marginal for brown planthopper development. Similar distribution shifts toward cooler or higher-elevation regions under climate change have been reported in other tropical and subtropical studies using CLIMEX and related species distribution models [8, 13]. At the same time, some northern coastal areas show a slight decrease in suitability, particularly under the SSP5-8.5 scenario, suggesting that increased heat and moisture stress may begin to exceed optimal thresholds defined in the CLIMEX framework [8].

The expansion of suitable areas from approximately 40% under baseline conditions to nearly 80% under the high-emission scenario shows a substantial increase in future pest risk for rice production in West Java. This result is consistent with experimental and modelling studies showing that temperature increases within specific ranges can accelerate the life cycle and reproductive capacity of brown planthoppers, potentially leading to population outbreaks [13, 14]. Treatments examining rice resistance to brown planthoppers under elevated temperature and carbon dioxide conditions show that climate change may reduce the effectiveness of pest-resistant genes in rice [15].

Under future climate scenarios (2040–2060), both SSP2-4.5 and SSP5-8.5 preserve the overall negative EI–altitude relationship, but the scatter distributions indicate a systematic downward shift in EI values at nearly all elevations, particularly under SSP5-8.5. Across ACCESS, EC-Earth, GISS, and HadGEM, lowland areas that were highly suitable under the baseline increasingly transition toward moderate or marginal suitability, while higher elevations remain largely unsuitable, with little evidence of upward expansion of favorable conditions. This suggests that warming-induced heat stress and altered moisture balances outweigh any potential thermal relaxation at higher elevations. Under SSP5-8.5, the compression of EI values is strongest, reflecting intensified temperature stress and increased evapotranspiration that reduces adequate moisture availability. Thus, excessive warming may also reduce suitability in some lowland areas due to stress accumulation, highlighting that climate change redistributes suitable habitats rather than uniformly increasing pest suitability [8].

The spatial autocorrelation analysis shows that climatic suitability for the brown planthopper is spatially clustered across districts, with significant positive Moran's I values observed under most scenarios. This clustered pattern indicates that neighboring districts tend to experience similar levels of climatic suitability, increasing the likelihood of regional-scale pest outbreaks rather than isolated infestations. Similar spatial clustering patterns have been reported in other studies of climate-driven pest distribution, emphasizing the importance of considering spatial dependence in pest risk assessments [10]. From a management perspective, this suggests that pest monitoring and control strategies should be coordinated across administrative boundaries.

Overall, the findings highlight the value of climate-based pest suitability modelling for supporting agricultural risk assessment and climate adaptation planning in Indonesia. The integration of CLIMEX simulations with CMIP6 climate projections and spatial analysis provides a robust framework for anticipating future pest risks under different emission scenarios. Given that climate-based pest distribution studies in Indonesia remain limited [11], this research contributes important scientific evidence to support early warning systems and climate-informed pest management strategies for sustainable rice production.

4.3 Limitation

This study has several limitations. CLIMEX considers only climatic variables and does not incorporate land use, cropping intensity, natural enemies, or pesticide practices. CMIP6 projections contain structural and scenario uncertainties. Precipitation variability introduces additional modelling uncertainty. Biological parameters were based on the literature rather than locally calibrated. Future research integrating field survey data and ensemble modelling would improve robustness.

5 Conclusion

This study shows that climate change is likely to significantly affect the climatic suitability and spatial distribution of the brown planthopper in West Java Province. Under baseline climate conditions, areas with high suitability (EI 51–75) are mainly located in northern coastal rice-growing regions, especially in Indramayu, Karawang, and Subang. Future climate projections for 2040–2060 under both SSP2-4.5 and SSP5-8.5 indicate that suitable areas will expand southward and into middle-altitude regions. Under the high-emission scenario (SSP5-8.5), the proportion of suitable areas increases from about 40% at present to nearly 80%. This expansion is mainly driven by rising temperatures and changes in rainfall patterns that create more favorable conditions for brown planthopper development.

The spatial analysis results indicate that brown planthopper suitability is not randomly distributed but tends to form clusters across neighboring districts. This clustered pattern suggests that future brown planthopper outbreaks are likely to affect groups of districts simultaneously, particularly in major rice production areas. Overall, the findings indicate that rising temperatures will support the growth and spread of brown planthoppers, increasing pest risks in West Java. These results highlight the importance of using climate-based pest distribution models to support early warning systems and climate adaptation strategies for sustainable rice production in Indonesia.

Spatial clustering suggests coordinated monitoring across districts is necessary. Pest monitoring programs should be expanded in projected high-risk regions, and climate projections should be integrated into regional pest management planning to safeguard sustainable rice production.

The authors would like to thank the Department of Geophysics and Meteorology, IPB University, for providing institutional support and research facilities. The authors thank Fitri Rizki Amaliah, a research assistant of IPB University, for assistance with data processing and GIS-based spatial analysis. The authors also acknowledge the providers of the WorldClim database and CMIP6 climate model outputs for making climate data openly accessible.

References

1. L. Nazaruddin, Dampak perubahan iklim terhadap produktivitas padi di Pulau Jawa di masa mendatang. J. Widya. Climango. **6**, 42 – 53 (2024)
2. E. Surmaini, Y. Sarvina, E. Susanti, I.N. Widiarta, M. Misnawati, S. Suciantini, Y.R. Fanggidae, R. Rahmini, E.R. Dewi, Climate change and future distribution of brown planthopper in Indonesia: a projection study. J. Saudi Soc. Agric. Sci. **23**, 130 – 141 (2024). https://doi.org/10.1016/j.jssas.2023.10.002
3. J. Hong, M. Lee, Y. Kim, Y.-S. Lee, J. Wee, J.-J. Park, W.-K. Lee, Y. Song, K. Cho, Potential range shift of a long-distance migratory rice pest, *Nilaparvata lugens*, under climate change. Sci. Rep. **14**, 11531 (2024). https://doi.org/10.1038/s41598-024-62266-x
4. J.-M. Jung, W.-H. Lee, S. Jung, Insect distribution in response to climate change based on a model: review of function and use of CLIMEX: review of CLIMEX functions and its applications. Entomol. Res. **4**, 223 – 235 (2016). https://doi.org/10.1111/1748-5967.12171
5. S. Taylor, L. Kumar, Sensitivity analysis of CLIMEX parameters in Modelling potential distribution of *Lantana camara* L. Plo. One. **7,** e40969 (2012). https://doi.org/10.1371/journal.pone.0040969
6. M.V. Lantschner, G.D.L. Vega, J.C. Corley, Predicting the distribution of harmful species and their natural enemies in agricultural, livestock and forestry systems: an overview. Int. J. Pest. Manage. **65**, 190 – 206 (2018). https://doi.org/10.1080/09670874.2018.1533664
7. K. Riahi, D.P.V. Vuuren, E. Kriegler, J. Edmonds, B.C. O'neill, S. Fujimoori, N. Bauer, K. Calvin, R. Dellink, O. Fricko, W. Lutz, A. Popp, J.C. Cuaresma, K.C. Samir, M. Leimbach, L. Jiang, T. Kram, S. Rao, J. Emmerling, K. Ebi, T. Hasegawa, P. Havlik, F. Humpenoder, L.A.D. Slva, S. Smith, E. Stehfest, V. Bosetti, J. Eom, D. Gernaat, T. Masui, J.Rogelj, J. Strefler, L. Drouet, V. Krey, G. Luderer, M. Harmsen, K. Takahashi, L. Baumstark, J.C. Doelman, M. Kainuma, Z. Klimont, G. Marangoni, H.-L. ampen, M. Obersteiner, A. Tabeau, M. Tavoni, The shared s ocioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob. Environ. Change. **42**, 153 – 168 (2017). https://doi.org/10.1016/j.gloenvcha.2016.05.009
8. D.J. Kriticos, B.L. Webber, A. Leriche, N. Ota, I. Macadam, J. Bathols, J.K. Scott, CliMond: global high-resolution historical and future scenario climate surfaces for bioclimatic modelling.Methods. Ecol. Evol. **3**, 53–64 (2012). https://doi.org/10.1111/j.2041-210X.2011.00134.x
9. L. Chen, W. Lu, B.B. Lamont, Y. Liu, P. Wei, W. Xue, Z. Xiong, L. Tang, Y. Wang, P. Wang, Z. Yan, Modeling the distribution of pine wilt disease in China using the ensemble models MaxEnt and CLIMEX. Ecol. Evol. **14**, e70277 (2024). https://doi.org/10.1002/ece3.70277
10. Y. Chen, An analytical process of spatial autocorrelation functions based on Moran's index. P. One. **16**, e0249589 (2021). https://doi.org/10.1371/journal.pone.0249589
11. K. Lamba, D. Dono, A review on brown planthopper (*Nilaparvata lugens* Stål), a major pest of rice in Asia and Pacific. Asian J. Res. Crop Sci. **6**, 7 – 19 (2021). https://doi.org/10.9734/AJRCS/2021/v6i430122
12. X. Xiu, Y. Zhao, M. Yu, Y. Gao, G. Yang, J. Wang, X. Shi, X. Wang, Dispersal patterns and potential distribution prediction of three rice planthopper species in China based on

the ensamble model. J. Appl. Entomol. **148**, 1015 – 1026 (2024). https://doi.org/10.1111/jen.13317

13. G.G.-P. Pandi, J.S Choudhary, A. Chemura, G.-B. Gowda, M. Annamalai, N. Patil, T. Adak, P.C. Rath, Predicting the brown planthopper, *Nilaparvata lugens* (Stål) (hemiptera: delphacidae) potential distribution under climate change scenarios in India. Curr. Sci. **121**, 1600 – 1609 (2021). https://doi.org/10.18520/cs/v121/i12/1600-1609
14. S. Sahoo, G.-P.-P. Govindharaj, J.S Choudhary, D. Panigrahi, B.-G. Gadratagi, S.D. Mohapatra, Temperature-dependent development and reproduction models of rice brown planthopper, *Nilaparvata lugens* (Stål). Ann. Appl. Bio. **187**, 215 – 226 (2025). https://doi.org/10.1111/aab.70008
15. Y.-H. Kuang, Y.-F. Fang, S.-C. Lin, S.-F. Tsai, Z.-W. Yang, C.-P. Li, S.-H. Huang, S.L. Hechanova, K.K. Jena, W.-P. Chuang, The impact of climate change on the resistance of rice near-isogenic lines with resistance genes against brown planthopper. Rice. **14**, 64 (2021). https://doi.org/10.1186/s12284-021-00508-6