Predicting the brown planthopper, *Nilaparvata lugens* (Stål) (Hemiptera: Delphacidae) potential distribution under climatic change scenarios in India

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The brown planthopper, *Nilaparvata lugens* (Stål) is the most serious pest of rice across the world. It is also known to transmit stunted viral disease; the insect alone or in combination with a virus causes the breakdown of rice vascular system, leading to economic losses in commercial rice production. Despite its immense economic importance, information on its potential distribution and factors governing the present and future distribution patterns is limited. Thus, in the present study we used maximum entropy modelling with bioclimatic variables to predict the present and future potential distribution of *N. lugens* in India as an indicator of risk. The predictions were mapped for spatio-temporal variation and area was analysed under suitability ranges. Jackknife analysis indicated that *N. lugens* geographic distribution was mostly influenced by temperature-based variables that explain up to 68.7% of the distribution, with precipitation factors explaining the rest. Among individual factors, the most important for distribution of *N. lugens* was annual mean temperature followed by precipitation of coldest quarter and precipitation seasonality. Our results highlight that the highly suitable areas under current climate conditions are 7.3%, whereas all projections show an increase under changing climatic conditions with time up to 2090, and with emission scenarios and a corresponding decrease in low-risk areas. We conclude that climate change increases the risk of *N. lugens* with increased temperature as it is likely to spread to the previously unsuitable areas in India, demanding adaptation strategies.

Keywords: Climate change, maximum entropy modeling, *Nilaparvata lugens*, potential distribution, rice.

CLIMATE change is among the most serious global challenges of the 21st century, and studies show that it will reduce crop yield by 3% ha^{-1} (refs 1, 2), change the suitability of crops[3] and increase the risk of pests and diseases[4–6], with all these impacts leading to food insecurity, livelihood and economic disruptions, migration and conflict. Although important for crop production, climate change is also expected to affect the distribution status of insect pests, which is neglected or underestimated in many impact studies. Climate change affects insect species abundance, distribution pattern, habitat suitability, niche area, reproduction capacity, invasion risk and outbreak frequencies[7,8]. The changes can be devastating for important pests of rice such as the brown planthopper (BPH) *Nilaparvata lugens*. In India, *N. lugens* was first recorded in 1950 from Tamil Nadu[9] and the first major outbreak occurred in Kerala during late 1960s. It is a phloem sucker of rice plants which has attained major insect status in the recent past across the rice-production regions[10]. Apart from causing direct loss, *N. lugens* also acts as the vector for stunted viral diseases. It has the capability of damaging rice cultivation from the vegetative to reproductive stage, which leads to the 'hopper burn' symptom[11]. India is the second largest producer of rice in the world. The country suffers severe yield losses to the tune of 70–100% due to repetitive outbreaks of *N. lugens* in Odisha, Punjab, Haryana, New Delhi, Telangana, Andhra Pradesh and Tamil Nadu, corresponding to a monetary value of US$ 2000 million[10,12]. In addition, earlier evidence suggests that its infestation is routine during the rainy season in northern and eastern India and outbreaks occur in almost every season[8–13].

The monophagy nature of *N. lugens* on rice plants makes its management more complex due to its remarkable resistance-breaking mechanism against varieties and insecticides[14]. Like other insect species, its survival, abundance and distribution are highly dependent on climatic factors and their seasonal variation. The effect of temperature is particularly important as it plays a crucial role in

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its survival, development and reproduction[15]. Piyaphongkul *et al*.[16] established that the upper lethal temperature (ULT_{50}) for nymphs and adults of *N. lugens* is 41.8°C and 42.5°C respectively. Another study showed that the feeding of *N. lugens* will increase under higher temperatures, implying more crop damage under climate change, although hatching rate will be reduced[6].

Pest response to climatic variables such as temperature may vary between controlled *in vitro* environments and field conditions because of many factors[17]. Hence determination of habitat suitability for pests under changing climate using forecast modelling could identify risk areas and facilitate development of appropriate strategies for their management and restrict their spread to new areas[18]. Empirical models are mostly location-specific. Hence there is a need to integrate species distribution models and ecological niche models to forecast the potential distribution and extended spread of pests with respect to climatic and environmental variables[19,20]. Computer-aided maximum entropy modelling (MaxEnt) is a combination of the above integrated modelling approaches and thus can be used to predict the potential distribution of economically important species, including agricultural pests[21,22].

The aim of this study is, therefore, to identify the bioclimatic determinants of *N. lugens* distribution, map this current distribution of this pest and quantify the changes in risk of the pest under projected climates. It is expected that the results of this study will ascertain on a large scale the drivers of *N. lugens* distribution, help to identify pest hotspots for targeted control, and assist in anticipating changes in the pest for adaptation of technical and policy planning to enhance food security and livelihood in rice-based agroecosystems.

Material and methods

Occurrence data source and point selection

N. lugens incidence data were acquired from the existing sources[8–13,23–25] and field observational data that we collected from 2012 to 2020 for potential occurrence points in different states of India. Hotspot location-specific, geocoded (i.e. latitude and longitude) data on the occurrence of *N. lugens* were verified with Google Earth open software version 7.3 (Google Inc, Mountain View, CA, USA) for the collected samples. The spatial resolution of environmental variables used in this study was 2.5 arc-min, covering about 21.0 sq. km, with the radius of the buffer zone set to 5 km (ref. 26). If the difference between the two occurrence points was less than 50 km, then only one occurrence point was used. Hence, in the present study, after excluding spatially auto-correlated samplings, a total of 60 well-spaced records were selected for predicting the spatial and temporal distribution of *N. lugens* over different Indian states (Supplementary Table 1). These samples were checked to ensure that they are distributed across the rice-producing areas to avoid sampling bias[27].

Environmental variables

The 19 bioclimatic variables on current climatic conditions (1969–2000) and future climate data were acquired from WorldClim database (ver. 1.4) at a spatial resolution of 2.5 arc min (refs 28, 29). Further, the required data of the Indian region were extracted from world data by masking the India boundary in ArcGIS™ (ver. 10.4) environment. Four future representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) were selected in this study[30]. Future climate data for the years 2050 and 2070 pertaining to these four scenarios were downscaled from the Hadley Global Environment Model 2-Atmosphere Ocean (HADGEM2-AO) global climate model[31] due to its reliable range in climate prediction for Asia[32], especially for India[33]. Multi-collinearity among the 19 bioclimatic variables was assessed using ENM Tools ver. 1.0 (refs 34, 35). When pairwise comparison of two variables had a value of Pearson's coefficient $|r| \geq 0.85$, then only the one with higher relative importance and higher predictive power for determining *N. lugens* distribution was used to develop the model[22]. Based on significance, only ten environmental variables were further selected for analysis (Table 1). The current bioclimatic variables included temperature (minimum, maximum, average monthly, average quarterly, average annual) and rainfall gathered during the period 1970–2000. Details of these bioclimatic variables are well explained in the published literature[29].

Maximum entropy model optimization

Maximum entropy model version 3.3.3 was used to evaluate the possible geographical distribution of *N. lugens* in India[36]. The present study used replication method and sub-sampling for validation of the model and minimizing errors which may occur due to random splitting of data into training and test subsets. Accordingly, 100 replicates were run till the end and model performance was evaluated by further computing the average area under the curve (AUC) values for both test and training datasets. In order to explore the significance of various bioclimatic predictors, jackknife and per cent variable contribution tests were performed. Likewise, the collected data were randomized to depict 10,000 random background points in MaxEnt with the help of kernel density estimator surface procedure[37]. The potential of the present model was estimated using AUC or the receiver operating characteristic (ROC) curve that is threshold-independent.

Table 1. Relative contribution of different bioclimatic variables to the MaxEnt model for *Nilaparvata lugens*

Bioclimatic variables	Type	Relative contribution (%)
Annual mean temperature (Bio 01; °C)	Temperature	39.0
Precipitation of coldest quarter (Bio 19; mm)	Precipitation	11.5
Precipitation seasonality (Bio 15; mm)	Precipitation	10.5
Mean diurnal range (Bio 02; °C)	Temperature	10.4
Precipitation of warmest quarter (Bio 18; mm)	Precipitation	09.1
Temperature seasonality (Bio 04; °C)	Temperature	05.5
Annual precipitation (Bio 12; mm)	Precipitation	04.9
Isothermality (Bio 03; °C)	Temperature	03.3
Precipitation of wettest month (Bio 13; mm)	Precipitation	03.2
Precipitation of driest month (Bio 14; mm)	Precipitation	02.7

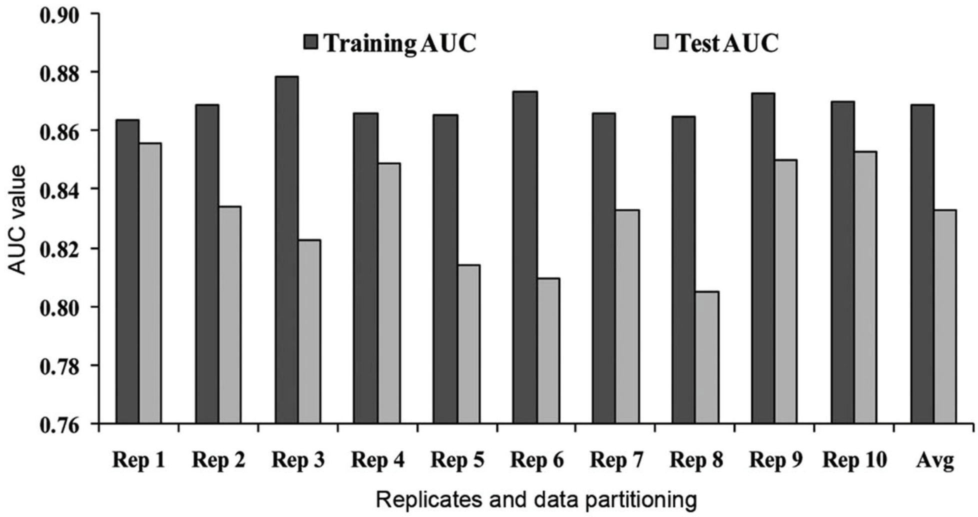


Figure 1. Evaluation statistics from test and training area under the curve (AUC) values of cross-model run validation and from random data partitioning.

Classification of potentially suitable area and prediction accuracy of MaxEnt

We used the lowest presence threshold (LPT) of *N. lugens* to define the suitable and unsuitable distribution areas[38]. Model prediction of all locations was imported to geographic information system (GIS) and maps were generated using ArcMap. *N. lugens* occurrences at current and future scenarios were defined based on the predicted habitat suitability, and the potential suitability areas were divided into four categories, viz. low (<0.265), mild (0.265–0.4), moderate (0.4–0.6) and high (0.6–1.0). Spatial analyst tool in ArcGIS was used for computing area (sq. km) under each polygon. Fade by clapping approach was used to remove any flawed prediction of suitable habitat. Generally, AUC range between 0.5 and 0.7 is considered bad or failed predictive power; value between 0.7 and 0.8 denotes acceptable model and that above 0.8 represents a fair ability to discriminate and is considered a good model[39–41].

Results

Model performance and impact of bioclimatic variables

MaxEnt performed well for predicting the potential distribution of *N. lugens* as revealed by higher mean training AUC value of 0.87 (range 0.86–0.88) with test AUC value of 0.83 (range 0.81–0.86; Figure 1). The AUC-based performance evaluation of the model gave confidence for projection across the study area and under future climate conditions. Temperature-based factors explained 68.7% of the suitability of *N. lugens* in India, with precipitation based factors explaining the remainder. This is despite the fact that the collinearity variable exclusion resulted in 6 of the 10 variables being precipitation-based and 4 being temperature based. The most important variable for *N. lugens* prediction was annual mean temperature (Bio 01; 39.2%); this was nearly four times as important as the second most important variable which was precipitation

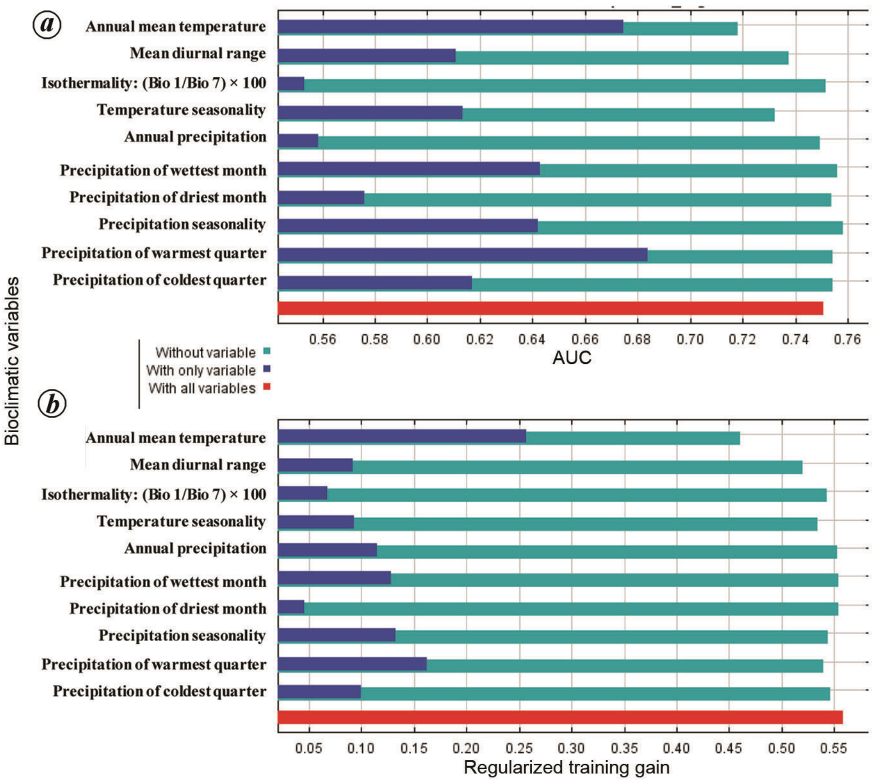


Figure 2. Relative importance of bioclimatic variables based on results of jackknife tests in the development of the MaxEnt model. Graphics show variable contributions to (***a***) AUC (area under the receiver operating characteristic (ROC) curve) and (***b***) regularized training gain. Values shown are averages over ten replicate runs.

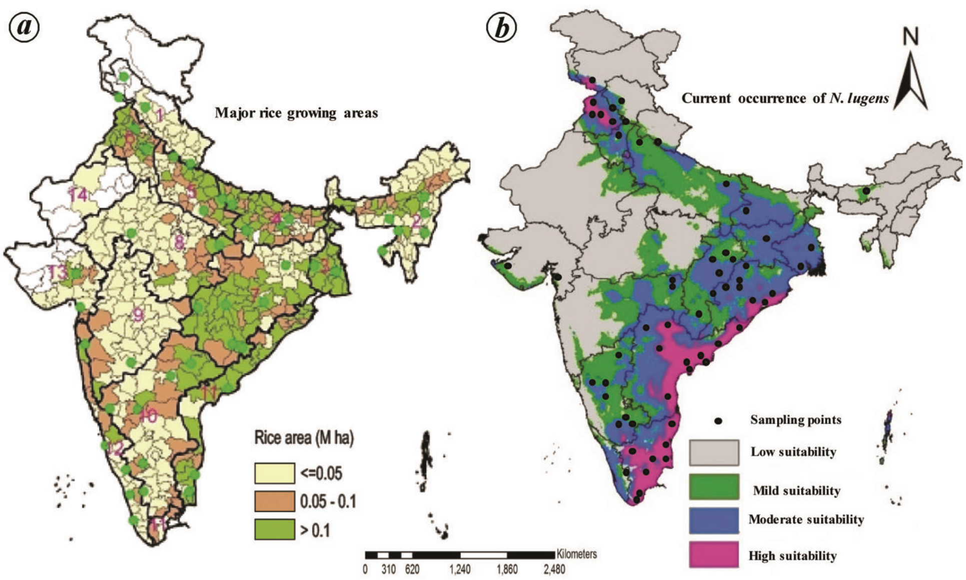
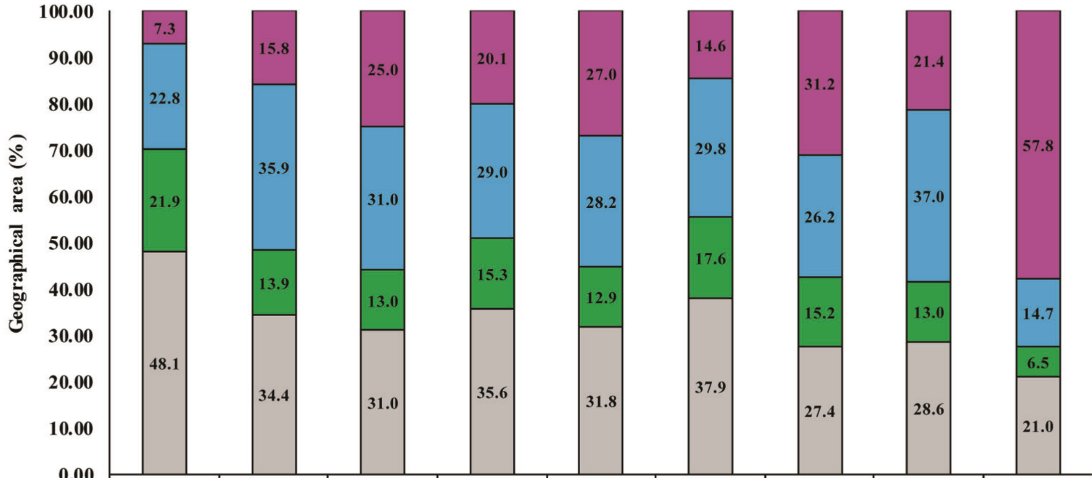


Figure 3. ***a***, Rice-growing areas in India (m ha). ***b***, Current occurrence and distribution of *Nilaparvata lugens* in India, and predicted suitability area under present climatic condition.

of coldest quarter (Bio 19; 11.5%), followed by precipitation seasonality (Bio 15; 10.5) and mean diurnal temperature range (Bio 02; 10.4%; Table 1 and Figure 2). These four variables could explain 71.6% of the model contribution. The remaining six variables offered <10% each to the model (Table 1).

The omission of Bio 19 as the prime explanatory variable reduced the model gain significantly, highlighting its



	Current scenario	RCP 2.6 2050	RCP 4.5 2050	RCP 6.0 2050	RCP 8.5 2050	RCP 2.6 2070	RCP 4.5 2070	RCP 6.0 2070	RCP 8.5 2070
High suitability	7.25	15.79	25.00	20.14	27.01	14.64	31.18	21.37	57.79
Moderate suitability	22.78	35.95	31.01	28.96	28.23	29.81	26.22	37.00	14.73
Mild suitability	21.86	13.86	12.96	15.27	12.93	17.62	15.17	13.04	6.48
Low suitability	48.12	34.40	31.03	35.64	31.84	37.93	27.43	28.59	21.01

Figure 4. Area statistics of the current and projected shift of *N. lugens* in India under different representative concentration pathway (RCP) during the 2050 and 2070 climate scenarios. The table shows the area (sq. km) covered under the four possible climate outcomes. Numbers in the staked bars represent percentage area under each outcome.

relative importance to the other ten selected variables in deciding the potential distribution of *N. lugens*. The individual response curves of different bioclimatic variables revealed that the probability of *N. lugens* presence decreased with increasing mean diurnal temperature up to 10°C, but increased over 10°C. The predicted probability of *N. lugens* was positively correlated with precipitation seasonality. Overall, annual temperature fluctuations and precipitation patterns contribute significantly and act as the major factors in determining the probability of *N. lugens* distribution in India.

Potential distribution pattern of N. lugens under current climate scenario in India

The potential suitability areas of *N. lugens* as predicted by the maximum entropy model were divided into four categories, viz. high, moderate, mild and low suitability (Figure 3). The results of the present study reveal that highly suitable habitats of *N. lugens* are predicted in the southern and eastern coasts of India as well as small patches in northern India. These are in Tamil Nadu, Andhra Pradesh, Telangana, Odisha and Punjab. The southern parts of Karnataka and coastal regions of Kerala have moderate suitability, while like Gujarat, Rajasthan, Madhya Pradesh, Himachal Pradesh, Nagaland, Manipur, Meghalaya and Jammu and Kashmir are presently not suitable for *N. lugens* distribution.

The southern and eastern rice-growing areas of the Indian mainland are predicted with high risk of *N. lugens* spread and dispersion against very low to nil risk in northwestern India. The current predicted area of high suitability was 238,192.6 sq. km, accounting for 7.3% of the total land area of India; followed by predicted area of low suitability being 1,581,788.9 sq. km, accounting 48.1% of the total land area, and moderate suitability area covering 748,675.7 sq. km, accounting for 22.8% of the total land area. The total area predicted suitable for *N. lugens* establishment in India was 1,705,442.7 sq. km, accounting for 51. 9% of the total land area of the country (Figure 4).

Future distribution potential of N. lugens in India

Results revealed that the total area under high risk was 7.5% (i.e. ~238,192.6 sq. km) under the current climate scenario, which is expected to increase to the tune of 15–27% (i.e. ~519,046.905.1 to 887,744.5 sq. km) in 2050 and 15–58% (i.e. ~481,090.5 to 1,899,556 sq. km) in 2070. The predicted high habitat suitable areas for *N. lugens* at present is less than 10% in India, whereas in the projected climate scenario high habitat suitable area of *N. lugens* is expected to be >25% in 2050 and >50% in 2070 (Figure 4). Likewise, moderate habitat suitable area is also projected to increase from 20% at present to 30–40% in future scenarios respectively, for 2050 and 2070 (Figures 4 and 5). Percentage change in area suitable for *N. lugens* over the current scenario exhibited a unique trend as low and mild habitat suitable areas showed negative trend, whereas moderate and high habitat suitable areas

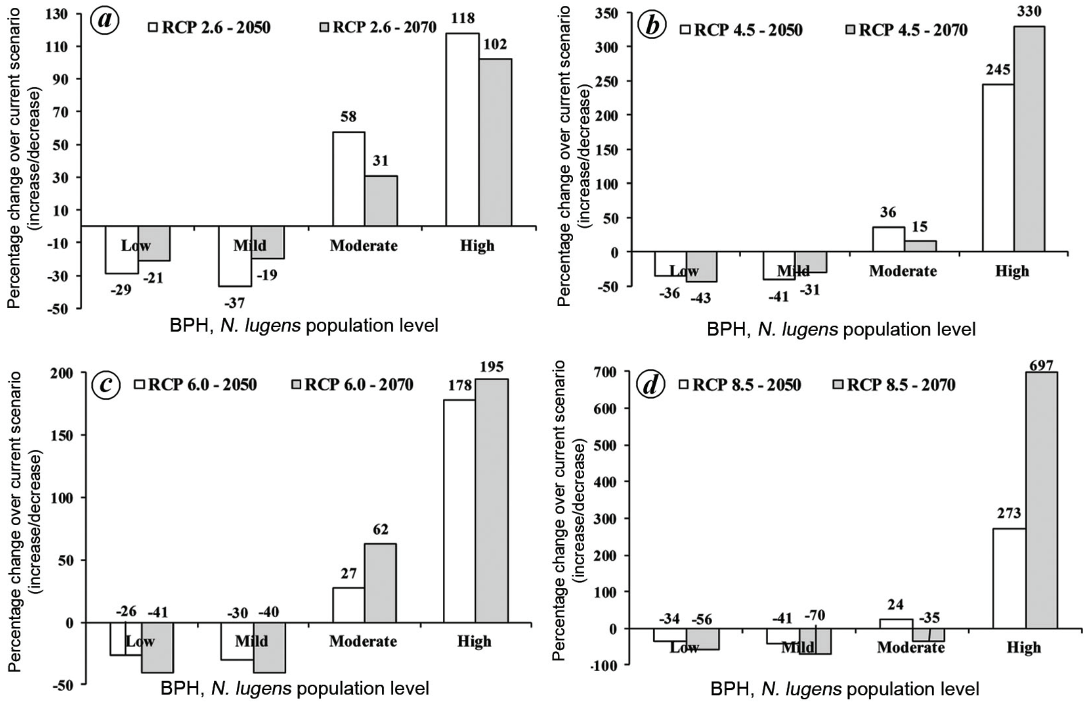


Figure 5. Percentage of *N. lugens* population changes in India during the projected climate scenarios (2050 and 2070) over the current scenario.

had increased for both the projected scenario of 2050 and 2070 in all four RCPs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5; Figure 5).

Figure 6 *a* depicts the MaxEnt model results of RCP 2.6 emission scenario for the probable distribution of *N. lugens* in 2050. The model predicted that the area of suitable habitat for moderate and high levels increased to 12% and 8% respectively, over the present suitable area. The model further predicted the highest risk of *N. lugens* dispersion and spread under RCP 4.5, RCP 6.0 and RCP 8.5 climate scenarios. The results indicated that the highest suitable area increased approximately 17%, 13% and 18% respectively, in Chhattisgarh, Bihar and Haryana by 2050, as against the current high suitability areas in the mentioned states (Figure 6 *b* and *d*). Likewise, highly suitable areas based on RCP 2.6 in 2070 increased to 8%, whereas RCP 4.5 and RCP 8.5 gained 24% and 50% more area (Figure 7). Thus, the prediction for 2070 depicts that more than 50% of Indian rice cultivated areas under severe threat by heavy BPH infestation in RCP 4.5 scenario, whereas the trend increased to 70% under RCP 8.5 scenario. The potential suitable area for *N. lugens* habitat is predicted to increase all over the country by 2070 (Figure 7), whereas by 2050 it will increase in parts of Karnataka, Chhattisgarh, Bihar, West Bengal, Haryana, Mizoram, Tripura, Arunachal Pradesh, Kerala and Tamil Nadu (Figure 6). Presently, *N. lugens* suitable areas are predicted under a high-risk class by 2050 and 2070 under both scenarios RCP 4.5 and RCP 8.5 (Figure 7). Moreover, low suitable areas decreased from 48% at present to 31% and 21% respectively, under RCP 4.5 (2050) and RCP 8.5 (2070).

Discussion

The results of the present study predict the distribution status of *N. lugens* in both present and future climate scenarios and suggest that climate change would affect the distribution and population of *N. lugens* in India. The MaxEnt model revealed that this pest has the potential to spread to previously low suitable and moderately suitable habitats in the future (2050 and 2070). The model also predicted that a large number of highly suitable areas in India in 2050 and 2070 are outside the current distribution range of *N. lugens*. MaxEnt was accurate in predicting *N. lugens* occurrence in the present study even with a small sample sizes[42] and the same was used earlier for plant, insect pest, mammal, avian and aquatic species suitability studies[43–45]. Corresponding to our model for *N. lugens*, annual mean temperature, precipitation seasonality, precipitation of the coldest quarter and mean diurnal range were the variables with the maximum influence on habitat suitability. Mean annual precipitation and temperature isothermality exerted, significant influence on *N. lugens* distribution. More than 30°C temperature and 500 mm precipitation were found to be detrimental to *N. lugens* distribution. Further, it was also noticed that <10°C temperature were also unsuitable for *N. lugens*. Projections of the present study are corroborated by previous studies for *N. lugens* distribution[18,46].

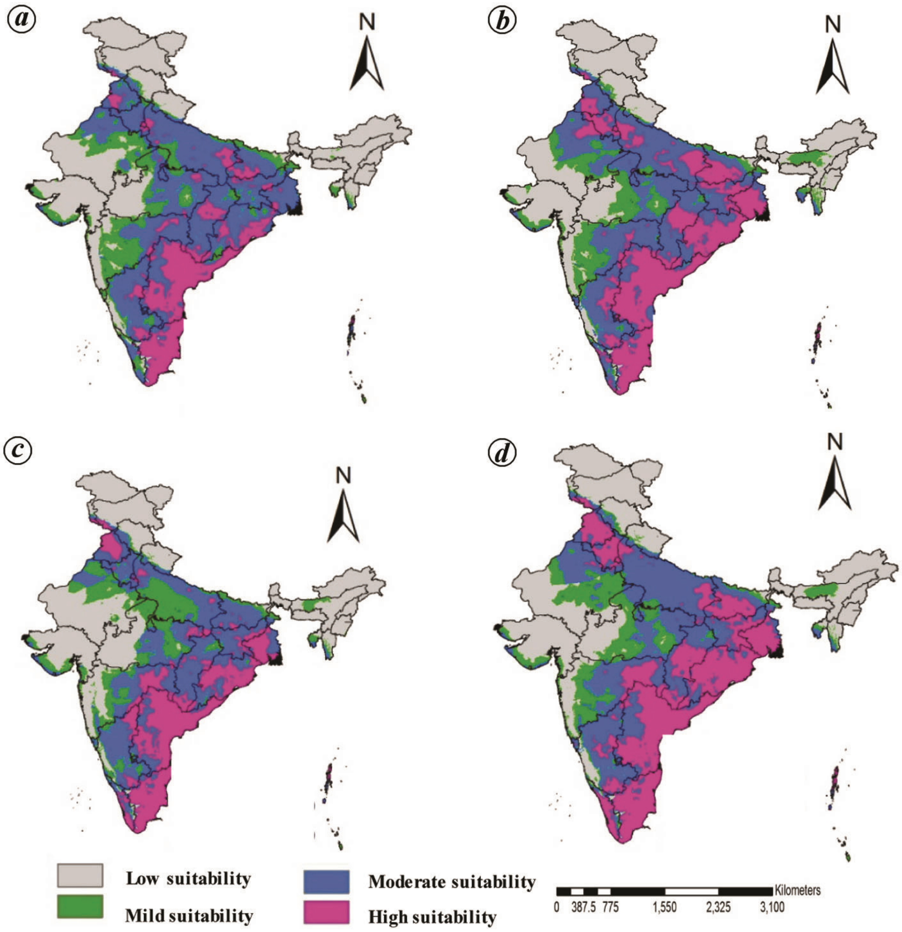


Figure 6. Projected changes in the distribution map of *N. lugens* in India during 2050, based on the HADGEM2-AO GCM model for (***a***) RCP 2.6, (***b***) RCP 4.5, (***c***) RCP 6.0 and (***d***) RCP 8.5 scenarios.

N. lugens infestation in the Gangetic Plain and Punjab area occurs only during the rainy season and their survival is limited in these areas by winter temperature. Earlier workers reported that the variation of *N. lugens* populations within months was due to oscillations in monthly temperature and precipitation[16,46]. Increased outbreak of *N. lugens* in Asian countries was due to increased temperature in the recent decade compared to earlier and the rigorousness of such outbreaks is likely to increase if there is no change in the predicted climate change scenarios. Despite the present and future potential distribution of *N. lugens* logically predicted by our study, there are certain factors limiting the model prediction precision such as model parameterization, selection of bioclimatic variables, low-resolution predictor data, area assessed in the study and the small number of occurrence records[22]. Among the above, sample size is not a problem in our study and spatial autocorrelation was also scrutinized by providing the geographic coordinates of *N. lugens* location before running the model.

In regard to future distribution of *N. lugens*, the present study using Maxent modelling suggests that geographic area would increase with more chance of spread into new areas compared to the present. We consider that the general warming is more representative than 'black swan' temperature events that can lead to large-scale mortality of the pest as predicted by Piyaphongkul *et al.*[16]. The earliest record of *N. lugens* in India was back in 1950s, and it has now expanded 1826 km west, 2750 km north and 2570 km northeast from the earlier recorded location[9]. This pest has a migration tendency which enhances the adult *N. lugens* to cover a few 1000 km during the monsoon period with average flight hours of 10 h at a stretch[47]. The excellent passive flying coupled with continuous availability of large areas of the host has helped in the long-distance spread of *N. lugens*.

In the present study, we have used the occurrence locations under the current climate scenario and predicted the suitable areas in future climate scenarios for India. The study revealed considerable agreement across climate scenarios that southern and eastern India will remain a highly suitable habitat for *N. lugens*, until at least 2070. Similarly, the areas of the Indo-Gangetic Plain currently with mild *N. lugens* infestation are predicted to become

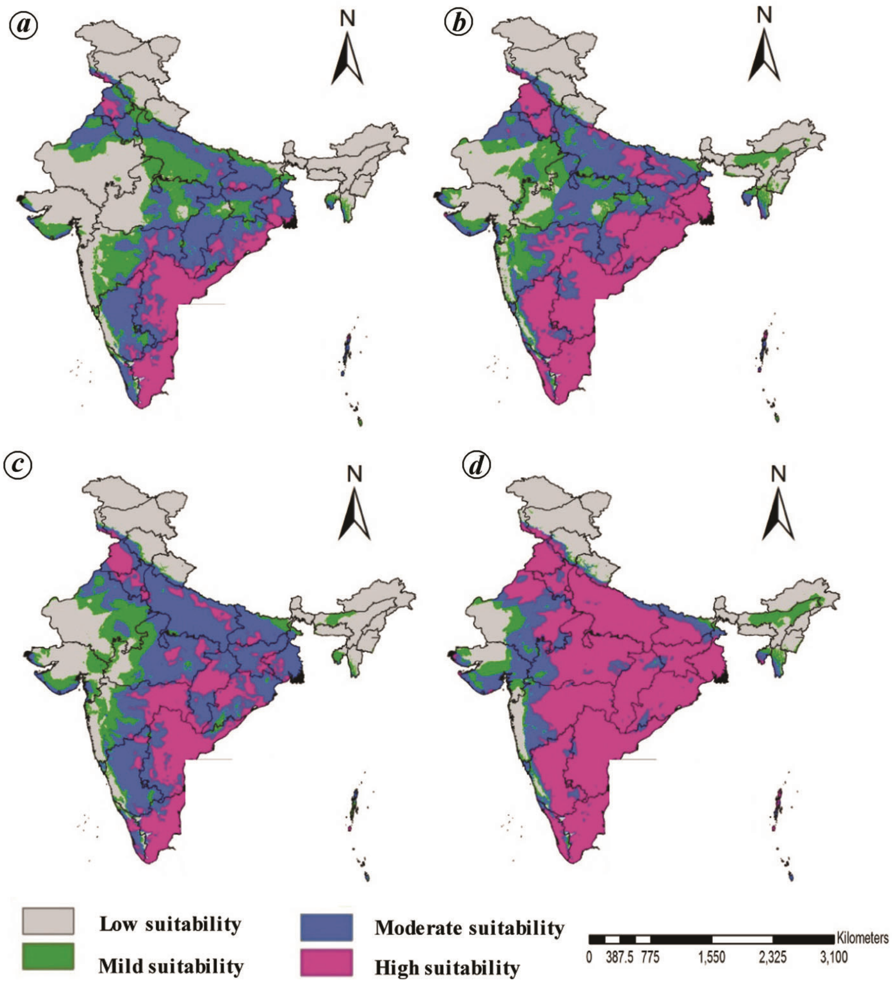


Figure 7. Projected changes in the distribution map of *N. lugens* in India during 2070, based on the HADGEM2-AO GCM model for (***a***) RCP 2.6, (***b***) RCP 4.5, (***c***) RCP 6.0 and (***d***) RCP 8.5 scenarios.

high suitable habitat areas in all the future climate scenarios. However, among the rice-producing North Indian regions, Uttarakhand, Himachal Pradesh and Jammu and Kashmir are projected to be less suitable until at least 2070. The results of the present study could not be compared with the published literature due to absence of projections model-based studies in India on *N. lugens*. An exception is the report by Yadav *et al.*[48], where multiple linear regression analysis has been carried out between *N. lugens* trap catches and weather variables (temperature and relative humidity) to divide the study region into severe, high, moderate and low outbreak potential areas. Earlier studies on the effect of climate change on *N. lugens* distribution have mainly focused only on local regions (within states/districts areas) and used one or two climate variables (mainly temperature and relative humidity)[48]. However, the present study aims to understand *N. lugens* distribution and habitat suitability under the changing climate scenarios in India using the MaxEnt model with ten bioclimatic variables.

While we have confidence in the results and implications of the model, it is important to point out some potential limitations and sources of uncertainty that should be considered in applying the results. The MaxEnt model is run with climate data and observed current infestation areas, both of which can be incomplete or subject to errors. Climate change also affects plant–insect and insect–insect (other Arthropods, predators, parasites, etc.) interactions in a similar manner. Earlier reports suggest that rice production is also under severe threat due to these anticipated environmental changes[1,2]. Likewise, insects are affected by climate change due to their ectothermic nature and sensitivity to temperature[15]. Climate change directly affects the insects through their physiology and behaviour[16] and indirectly through host plants, natural enemies and other competitors[17,18]. Further, natural enemies of pests that play an important role in their biological suppression are also liable to be affected by climate change. Increasing CO_2 and temperature affect the herbivore quality that ultimately alters the natural enemy fitness[49,50]. Changing climate may alter the abundance and activity of natural enemies directly through the changes in quality of the herbivores[8,11] and indirectly through adoption of new management strategies by farmers to cope with climate change. These strategies may create a spatio-temporal asynchrony between pests and their natural enemies, thus adversely affecting biocontrol efforts. Due to the multifarious effects of climate change on natural enemies, predictions about climate impacts are not easy unless there is a good understanding of the environmental impacts on tri-trophic interactions. Secondly, the presence of insect pests has the same weight between high incidence and low incidence areas, which can bias the results. Future projections of pest suitability are from suitable models and global climate models, both of which may also contain errors. It is also difficult to capture pest–host interactions, as it is assumed that the current rice-producing areas will remain suitable for the crop even in the future, which may not be the case. Finally, the area derivations include other lands that may not be available for rice and thus not directly linked to the cropped area, and thus the present study results should be considered as relative changes in the infestation areas rather than the absolute changes. Despite these limitations, this study shows the spatially explicit quantitative risk of climate change on *N. lugens* affecting rice, an important crop from India. Adaption planning like design of IPM strategies should be intensified in observed risk hotspots.

Conclusion

The present study provides a clear and accurate potential distribution map of *N. lugens* under current and future climate scenarios with more environmental factors. Hence the outcome of the study could clearly reveal the survivability of *N. lugens*. Future modelling efforts for *N. lugens* distribution should include a new set of high-resolution bioclimatic variables generated using recent climatic data, detailed knowledge of host availability during the crop and soil data. Results of the present study can be used by researchers, agriculture departments and policy makers for designing national-level *N. lugens* management strategies.

Conflict of interest: The authors declare no conflict of interest.

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