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SHORT COMMUNICATION

Assessing the risk of mango quarantine pest *Deanolis sublimbalis* Snellen under different climate change scenarios

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Abstract
Considering the quarantine importance of the red-banded mango caterpillar, *Deanolis sublimbalis* (Crambidae: Lepidoptera), studies were carried out to predict the impact of climate change on its geographical distribution using the ecological niche modeling. Predictions were made based on the analysis of the relationship between occurrence points of *D. sublimbalis* and the corresponding current and future climate data of the study area, which was retrieved from the worldclim database. Spatial analysis software DIVA-GIS was used for visualization of the maps. The maximum entropy algorithm provided reasonable estimates of the species range in respect of discrimination of suitable and unsuitable areas for its occurrence in both present and future climatic conditions. The model provided a good fit for species distribution with a high value of area under the curve (0.971). Jackknife test indicated temperature seasonality to be the most important bioclimatic variable determining the potential geographical distribution of *D. sublimbalis.* The model predicted higher suitability areas for the pest occurrence in eastern parts of Andhra Pradesh, coastal regions of Orissa, southern parts of West Bengal, and some parts of Tripura. In future climate scenarios of 2030, 2050, 2070, and 2080, model-predicted relative increase in its distribution. Prediction of likely changes in the pest distribution with climate change will be useful in formulating effective management strategies against mango fruit borer.

Keywords Climate change · Ecological niche modeling · Pest distribution · Quarantine pest · Red-banded mango caterpillar

Introduction

Climate change has been accepted as a clear and emerging global issue, and its adverse impacts on biological elements of the ecosystem have been reported worldwide (Bellard et al. 2012). Climate change effects have been documented for both human populations and biodiversity (Chang et al. 2015); examples of the latter include pest and disease outbreaks (Woods et al. 2005), temporal reproductive isolation (Lowry and Willis 2010), and changes in species' distribution and phenology (Peterson et al. 2008). The situation is predicted to become more serious as the pace and magnitude of environmental changes intensifies (Meehl et al. 2007) and may prove to be more adverse in developing countries as compared to developed countries (IPCC 2014).

Ecological niche modeling is a rapidly evolving field to study the species distribution under different climate change scenarios (Peterson 2011). Many methods are available for predicting species distribution using geo-referenced species presence data with environmental variables (Elith et al. 2006; Guisan and Zimmermann 2000). One of the currently most popular methods is MaxEnt (Halvorsen et al. 2015; Elith et al. 2011; Phillips et al. 2006), which is based upon the maximum entropy principle, estimating a probability distribution for the modeled target species (Elith et al. 2011; Phillips et al. 2006, 2009). MaxEnt has proved to provide models with acceptable predictive ability even when few presence records are available (Peterson 2011; Elith et al. 2006; Hernandez et al. 2006). Species distribution models have many applications, such as mapping and monitoring of rare and endangered species (Edvardsen et al. 2011),

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assessment of the impact of climate change on the niche expansion of the geographically limited species (Baradevanal et al. 2020), and suitability assessment and risk zoning of quarantine pest (Choudhary et al. 2019).

Red-banded mango caterpillar (RBMC), *Deanolis sublimbalis* Snellen (Crambidae: Lepidoptera), is a designated quarantine pest. It has recently assumed serious status in the Indian states of Andhra Pradesh, Odisha, and West Bengal (Krishnarao et al. 2019). In severe cases, it can cause up to 40% loss in fruit production. Mango (*Mangifera indica* L.) fruits are the primary host of the RBMC but also have wild hosts like coco grass or nut grass, *Cyperus rotundus* (Family: Cyperaceae) and kwini/kurwini mango, *Mangifera odorata* Griffith (Family: Anacardiaceae). Besides India, it is distributed throughout the tropical regions of South and South-East Asia comprising Indonesia, Papua New Guinea, Burma, Thailand, China, Brunei, Philippines, and some parts of Australia (Sengupta and Behura 1955; Kalshoven et al. 1981; Golez 1991; Zaheruddeen and Sujatha 1993; Waterhouse 1998; Krull and Basedow 2006; Tenakanai et al. 2006; Krishnarao et al. 2019). Though the RBMC has been reported in India since more than a half-century ago, its geographical distribution largely restricted to the eastern coast of India, very little information is available concerning the effect of bioclimatic variables and likely impact of climate change on its distribution. Hence, the objective of the present study was to assess change in the distribution of RBMC under the different climate change scenarios.

Materials and method

Pest occurrence records

Data on pest occurrence were collected along with geographic coordinates with latitude and longitude using global positioning system (GPS) through roving surveys as well as from published literature (Golez 1991; Zaheruddeen and Sujatha 1993; Waterhouse 1998; Krull and Basedow 2006; Tenakanai et al. 2006; Krishnarao et al. 2019). Duplicate occurrence records were removed to reduce geographical bias and spatial autocorrelation. The 'spThin' package in R software version 3.5 was used with 100 iterations for a given thinning distance of 1 km within species occurrence range to reduce bias caused by occurring agglomerate points. A total of 49 valid points of *D. sublimbalis* occurrence were used to predict its potential distribution under different climate change scenarios (Fig. 1).

Current and future climate data

Data on current climatic conditions of 19 'bioclimatic' variables were collected from the WorldClim database, version 1.4 (http://www.worldclim.org/), at a spatial resolution of 2.5 min. Data were processed by the requirement of the study using 'raster' and 'rgeos' R package. Multicollinearity among the environmental variables was assessed as it

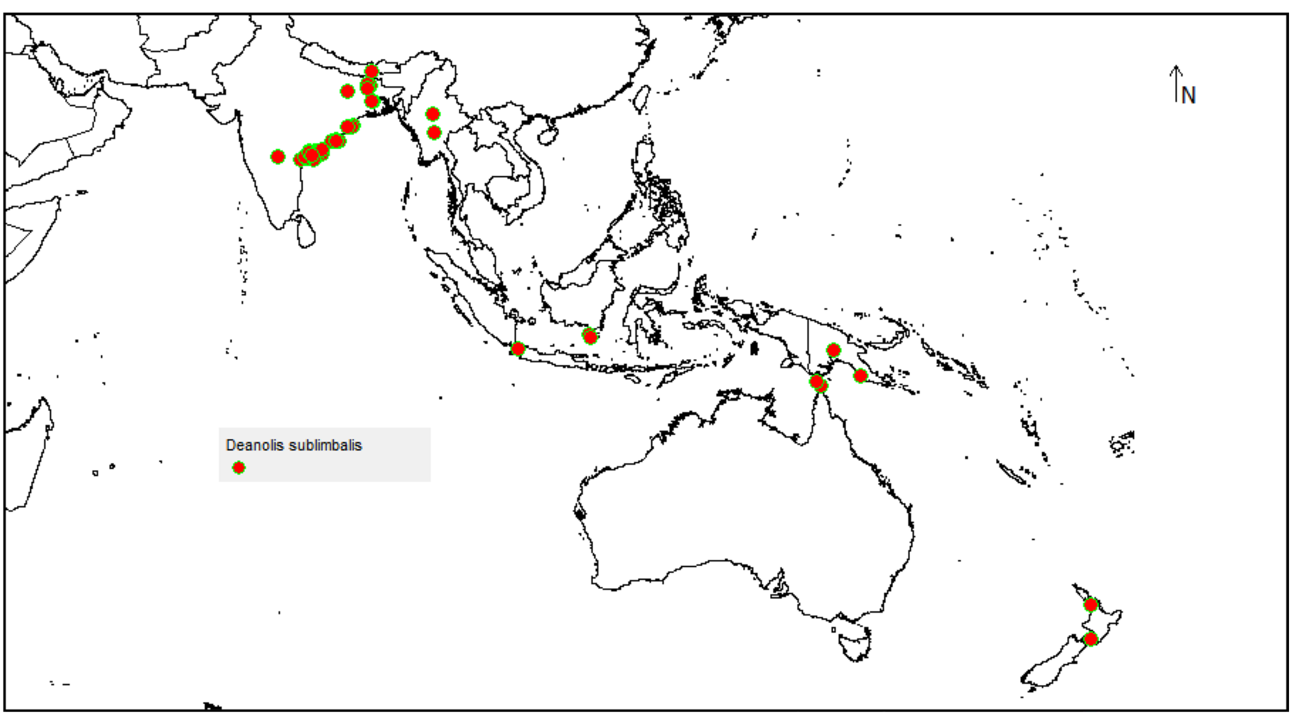

Fig. 1 Occurrence records of red-banded mango caterpillar (RBMC), *Deanolis sublimbalis* Snellen (Lepidoptera: Crambidae)

hinders the detection of species environmental relationships. Pearson correlation coefficient was used to classify and remove the highly correlated variables through pairwise comparisons, and out of paired variables having Pearson's coefficient (r) value of ≥ 0.80, only one was retained for model development considering its predictive power in terms of percent contribution and jackknife gain and relative importance in determining *D. sublimbalis* distribution. Consequently, six environmental variables were observed annual mean temperature (BIO1), mean diurnal range (BIO2), temperature seasonality (BIO4), annual precipitation (BIO12), precipitation of driest month (BIO14), and precipitation of coldest quarter (BIO19).

Statistically downscaled and bias-corrected future climate data were collected from the CCAFS database (http://ccafs-climate.org/) at a spatial resolution of 2.5 min. The global climate model (GCM) Commonwealth Scientific and Industrial Research Organization (CSIRO.MK3) that represent simulations for two representative concentration pathways (RCP 2.6 and RCP 8.5) from the 5th assessment of the Intergovernmental Panel for Climate Change (CMIP5) were selected for representing the future climatic scenario by 2030, 2050, 2070, and 2080. Each scenario represents the radiative force estimated for the corresponding years based on the predicted greenhouse gas emissions.

Maximum entropy species distribution modeling (MaxEnt) is a species-presence-only method developed for mapping species distributions (Phillips et al. 2006, 2009) the information generated by species-presence data while making minimal assumptions about the unknown information. Here, we used MaxEnt version 3.4.1, specifying a tenfold cross-validation approach with the linear, quadratic, product, and hinge features selected. Additionally, we selected a regularization multiplier value of one (default value) and the multivariate environmental similarity surfaces (MESS) analysis options. We selected these final settings after running several models and examining response curves for realistic representation (over-fitted response curves are unrealistic) and evaluating the area under the receiver characteristic curve (AUC) values for model accuracy (models with AUC values close to one are considered more reasonable than models with AUC values close to 0.5, which are considered random) (Pearson et al. 2007). Response curves were used to study the relationships between various bioclimatic variables and the predicted probability of the presence of *D. sublimbalis*. The effect of environmental variables in the model was assessed using the Jackknife test (Sarikaya and Örücü 2019). This provides estimates of the bias and a standard error of an estimate from subsamples of the available samples. The values 0 and 1 were used while creating the potential distribution maps, and accordingly, while 1 showed the most suitable area where the species may be found, 0 meant that the presence of the species in that area was impossible (0.0–0.1, not suitable habitat; 0.1–0.3 less suitable habitat; 0.3–0.5 moderately suitable habitat; 0.5–0.7 highly suitable habitat; 0.7–1 excellent suitable habitat). The final MaxEnt model predictions were projected into a spatial map by using Diva-GIS (V.7.3).

Results

In this study, the distribution of *D. sublimbalis* was predicted satisfactorily with 0.971 AUC and had a high power of estimation (Fig. 2). Considering the training gain, test gain, and AUC values, the jackknife test revealed that three environmental variables that affected the species distribution were annual mean temperature, temperature seasonality, and annual precipitation (Fig. 3). The probability of presence was exponentially increased according to the increase in the most important environmental variables (Fig. 4). The model predicted that precipitation-related bioclimatic variables such as annual precipitation (28.8%), precipitation of the driest month (12.7%), precipitation of the coldest quarter (7.8%), and temperature-related bioclimatic variables such as annual mean temperature (27.7%), temperature seasonality (11.2%), and mean diurnal range of the temperature (9.3%) played a vital role in determining the *D. sublimbalis* distribution. Annual mean temperature (38.2%) and mean diurnal range (23.5%) had the highest permutation importance in the model (Fig. 5). In the current climate scenario suitability areas for the pest, the occurrence was predicted in Southeast Asian countries (India, Bangladesh, Laos, Sanya, Myanmar, Thailand, Cambodia, and Vietnam) and Australia. High suitability areas were predicted in India and Bangladesh. In India, most suitable areas were predicted on the east coast of the country particularly in the states of Andhra Pradesh, Orissa, and West Bengal (Fig. 6).

In the future climate predictions by the year 2030 and 2050 under optimistic scenario (RCP 2.6), high and excellent suitability areas were reduced compared to the current scenario for the D. *sublimbalis* occurrence, whereas under a pessimistic scenario (RCP 8.5) enhanced area of occurrence was predicted for high and excellent habitat suitability of *D. sublimbalis* (Fig. 7). The potential distribution of *D. sublimbalis* was also predicted for the climate change scenario by 2070 and 2080. In both the year's enhanced shift in the occurrence of the pest was predicted, particularly by the year 2080 more excellent suitability areas were predicted for the pest occurrence under RCP 8.5 scenario (Fig. 8). Future climate predicted habitat suitability for the pest follows

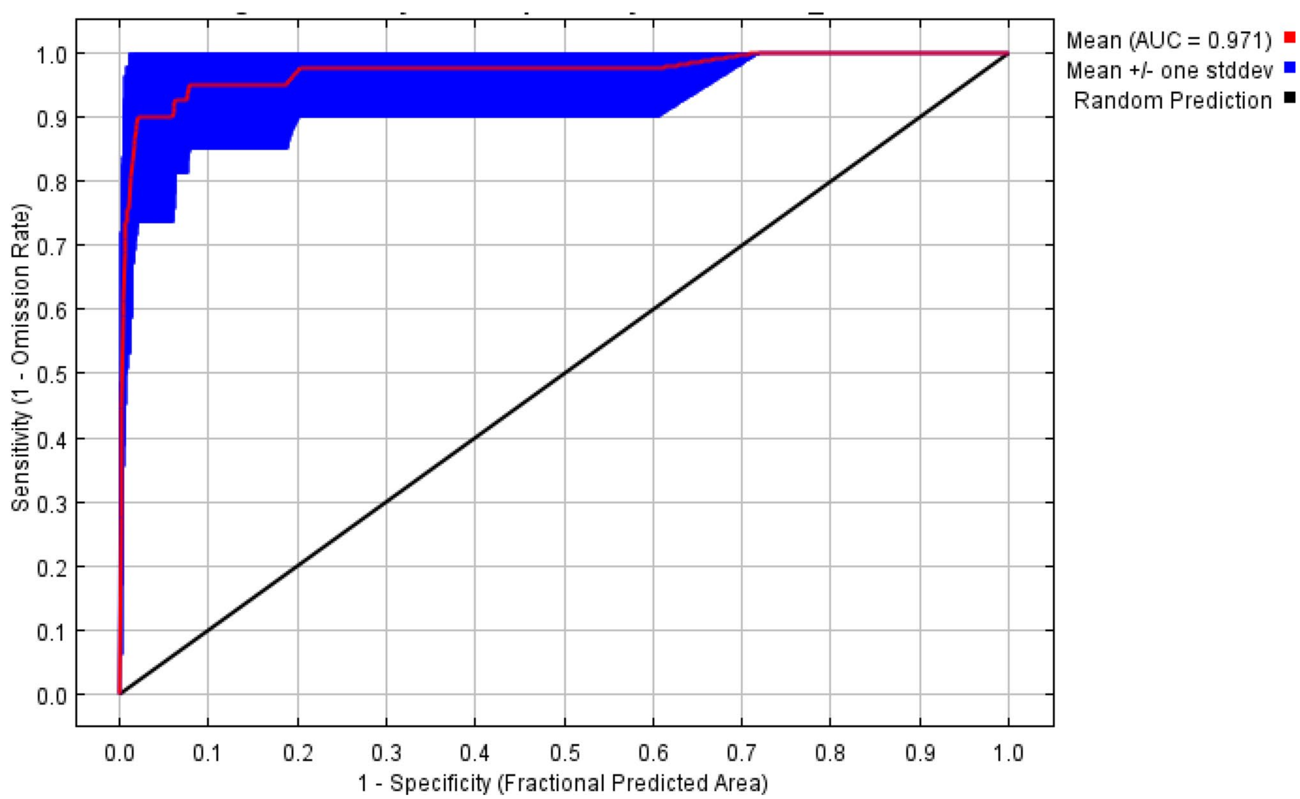

Fig. 2 Receiver operating characteristic (ROC) curve for *D. sublimbalis*. Red curves show the AUC and blue margins are ± standard deviation calculated over 10 replicates

as that of current climate predictions except in the years of 2070 and 2080 under RCP 8.5 pest occurrence which was not predicted in Australia,

Discussion

Climate is one of the important abiotic factors that influence the global distribution of a species (Elith and Leathwick 2009). Ecological niche models (ENMs) based on the quantitative relationship between environmental variables and species occurrence are used to predict areas of possible introduction, establishment, and spread of a species (Kumar et al. 2014). Correlative ENMs characterize the relationship between occurrence locations of a species with environmental characteristics of those locations and use this to assess the environmental suitability for a species in a specific location.

Recent studies have demonstrated the predictive value of correlative ecological models, and they are widely used tools for assessing the risk of the establishment of a variety of species including insects, aquatic organisms, plants, human diseases, vertebrates, and pathogens (Jiménez-Valverde et al. 2011; Galdino et al. 2016). The information on a species potential risk of establishment helps develop strategy or methodology. In the present study, we used MaxEnt modeling to assess the potential risk of *D. sublimbalis* under different climate change scenarios. The model revealed that temperature-related bioclimatic variables such as annual mean temperature, diurnal range of the temperature, and precipitation-related bioclimatic variable annual precipitation had higher predictive importance. Earlier several workers have studied the activity of the pest during the crop season. Golez (1991) reported that the larval population of mango fruit borer started to buildup in the middle of January, reached its peak in April, and gradually declined towards the end of mango season. Likewise, Sahoo and Das (2004) observed the first brood of the pest during the second to the third week of March and the second brood from April 4th week to May 1st week. Similarly, Bhattacharyya (2014) found that the infestation of *D. sublimbalis* started during the first week of April when mango fruits were of a pea to marble size and peak infestation occurred during April second fortnight when temperature ranged from of 29.0–42.5 °C and relative humidity of 14–100%. The present study indicated that temperature is the key factor in pest distribution. Intermittent rains have a greater influence on the buildup of humidity, which

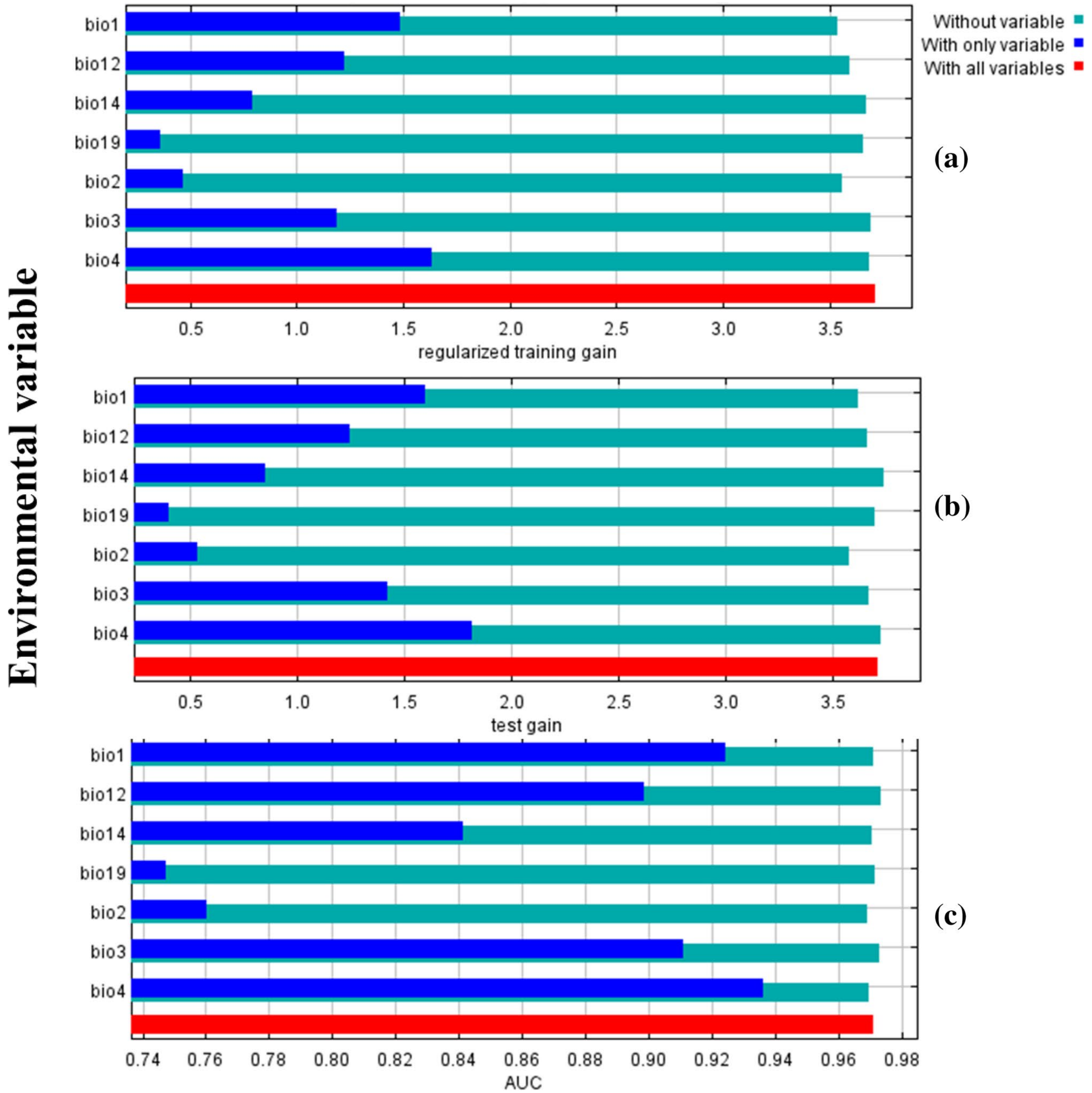

Fig. 3 Jackknife test of variable importance for *D. sublimbalis* under current climatic conditions. The relative importance of bioclimatic variables based on the results of jackknife tests in the development of MaxEnt model. Graphics show variable contributions to **a** regularized training gain and **b** regularized test gain **c** AUC (area under the receiver operating characteristic (ROC) curve). Values shown are averages over ten replicate runs

further makes the microclimate congenial for the pest buildup and spread.

The likely distribution pattern of *D. sublimbalis* was varied across the different RCPs from optimistic (RCP 2.6) to pessimistic (RCP 8.5) estimates of climate change. The probability of the spread of the pest is the conventional areas of its occurrence which will be more in the RCP 8.5 scenario in all the future climate predictions. This change may be attributed to the high-temperature projection, which favors the growth and development of the pest. Variations in the expansion of pests in new areas are also expected from different RCPs because there is inherent uncertainty in forecasting anthropogenic climate change (Pearson et al. 2006; Thuiller 2004). Based on the probability of distribution of pests in current and future

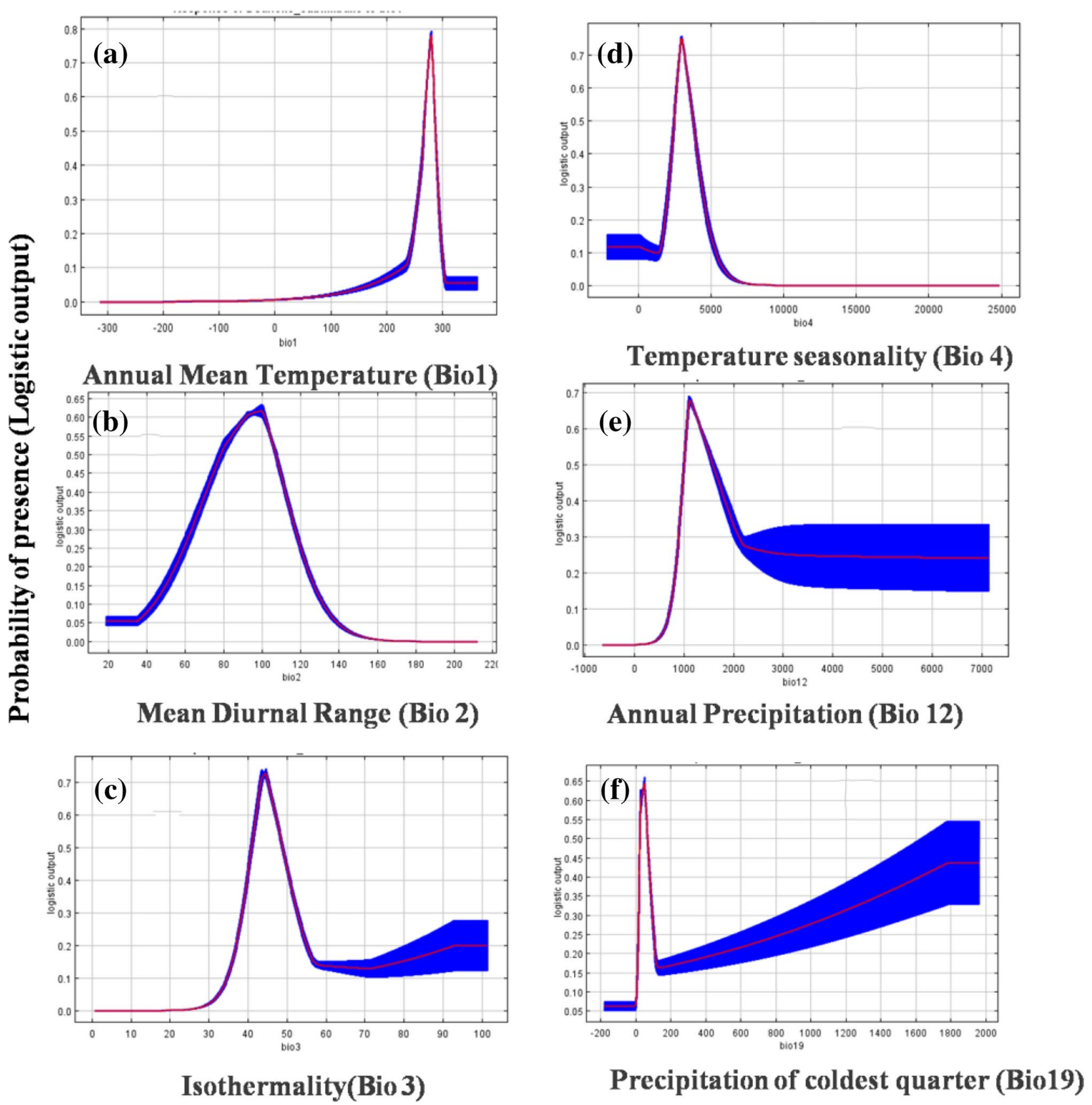

Fig. 4 Relationships between important bioclimatic variables such as annual mean temperature (**a**), mean diurnal range (**b**), isothermality (**c**), temperature seasonality (**d**), annual precipitation (**e**), precipitation of coldest quarter (**f**) and the probability of the presence of *D. sublimbalis*. Red curves show the mean response and blue margins are ± standard deviation calculated over 10 replicates

climate scenarios, India and Bangladesh were more vulnerable to its spread.

The results of the present study need to be interpreted with caution. Correlative niche models such as MaxEnt may have prediction uncertainties (Jarnevich et al. 2015). These uncertainties are primarily due to the quality of pest occurrence data, sampling bias, resolution of spatial data layers, species characteristics, and spatial autocorrelation (Anderson 2013). However, several calibrations can be made, which can have a great influence on the model and consequently on its accuracy (Kumar et al. 2015). These calibrations include the selection of background points and

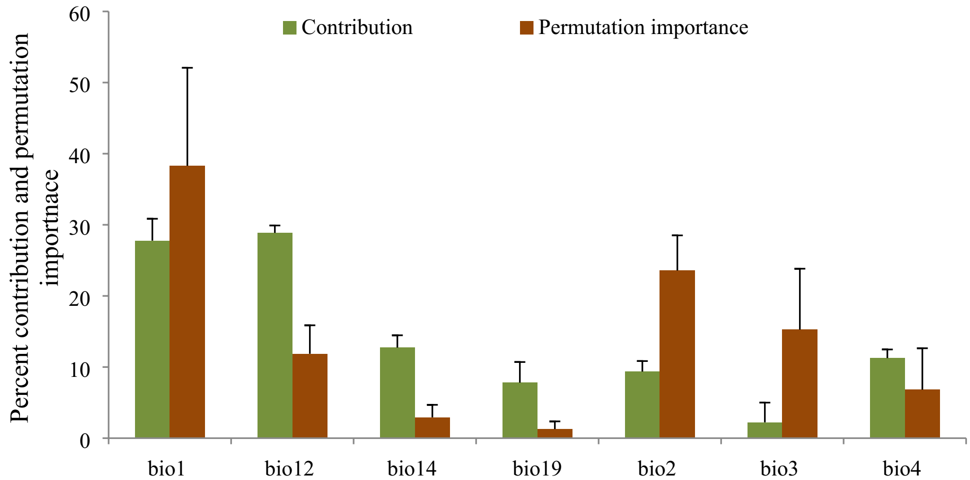

Fig. 5 Percent contribution and permutation importance of bioclimatic variables (bio1 = annual mean temperature; bio2 = mean diurnal range; bio3 = isothermality; bio4 = temperature seasonality; bio12 = annual precipitation; bio14 = precipitation of driest month; bio19 = precipitation of coldest quarter) to the fitted model of *D. sublimbalis* under current climatic conditions. Vertical bars on the histogram represents the standard deviation of tenfold cross validation

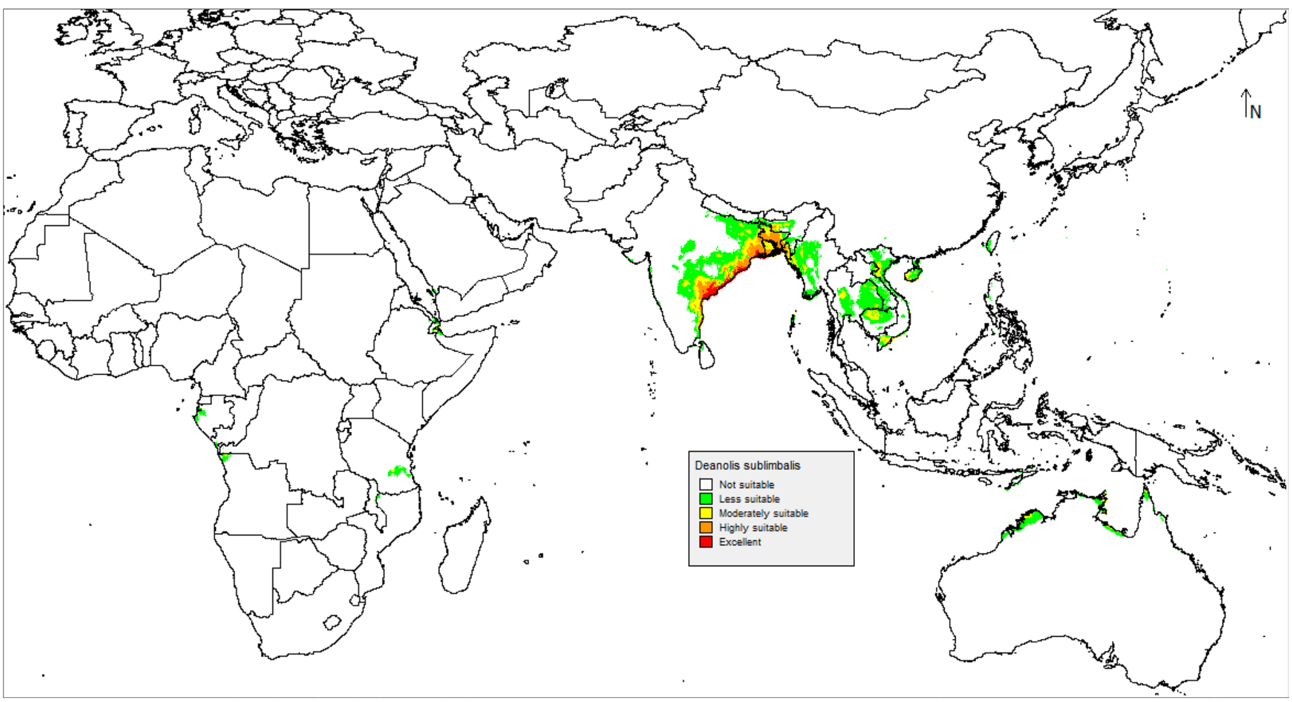

Fig. 6 Prediction of distribution of *D. sublimbalis* under the current scenario

extent, the value of regularization multiplier, and the selection of feature types (Phillips et al. 2006). Considering these potential pitfalls in the modeling process, we took utmost care in model calibration, and thus, generating predictive models that were consistent with the current known distribution of the species in terms of satisfactory validation of predicted distribution of the pest, this is evinced by the response curves.

The present study provides deeper insight into the potential distribution of *D. sublimbalis* under different climate change scenarios. It revealed likely changes in the distribution and activity of *D. sublimbalis* in response to climate change. The results can be used in designing pest management strategies to suppress the pest in conventional areas and the establishment of pest in newer areas.

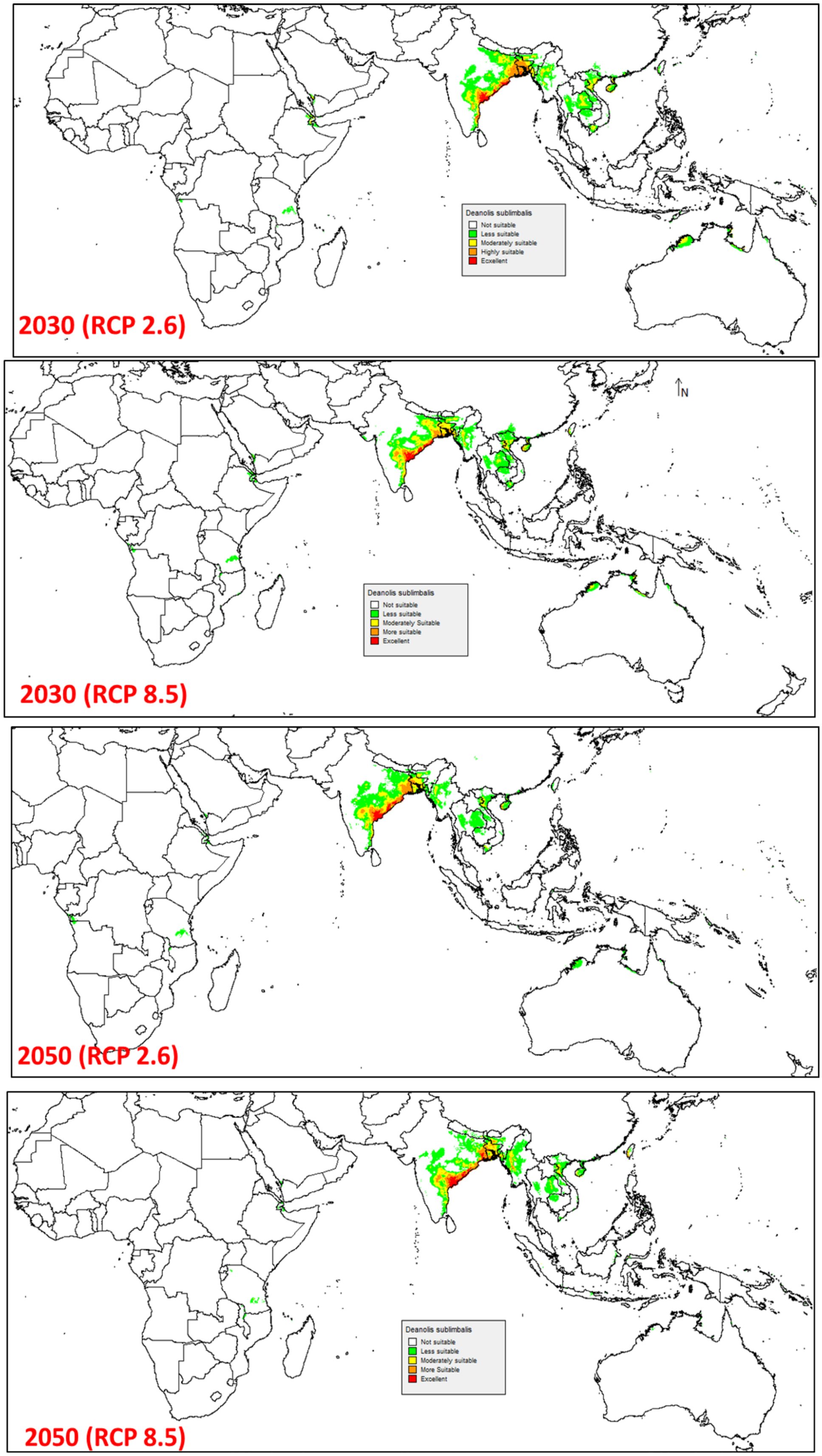

Fig. 7 Prediction of distribution of *D. sublimbalis* under future climate scenario of 2030 and 2050

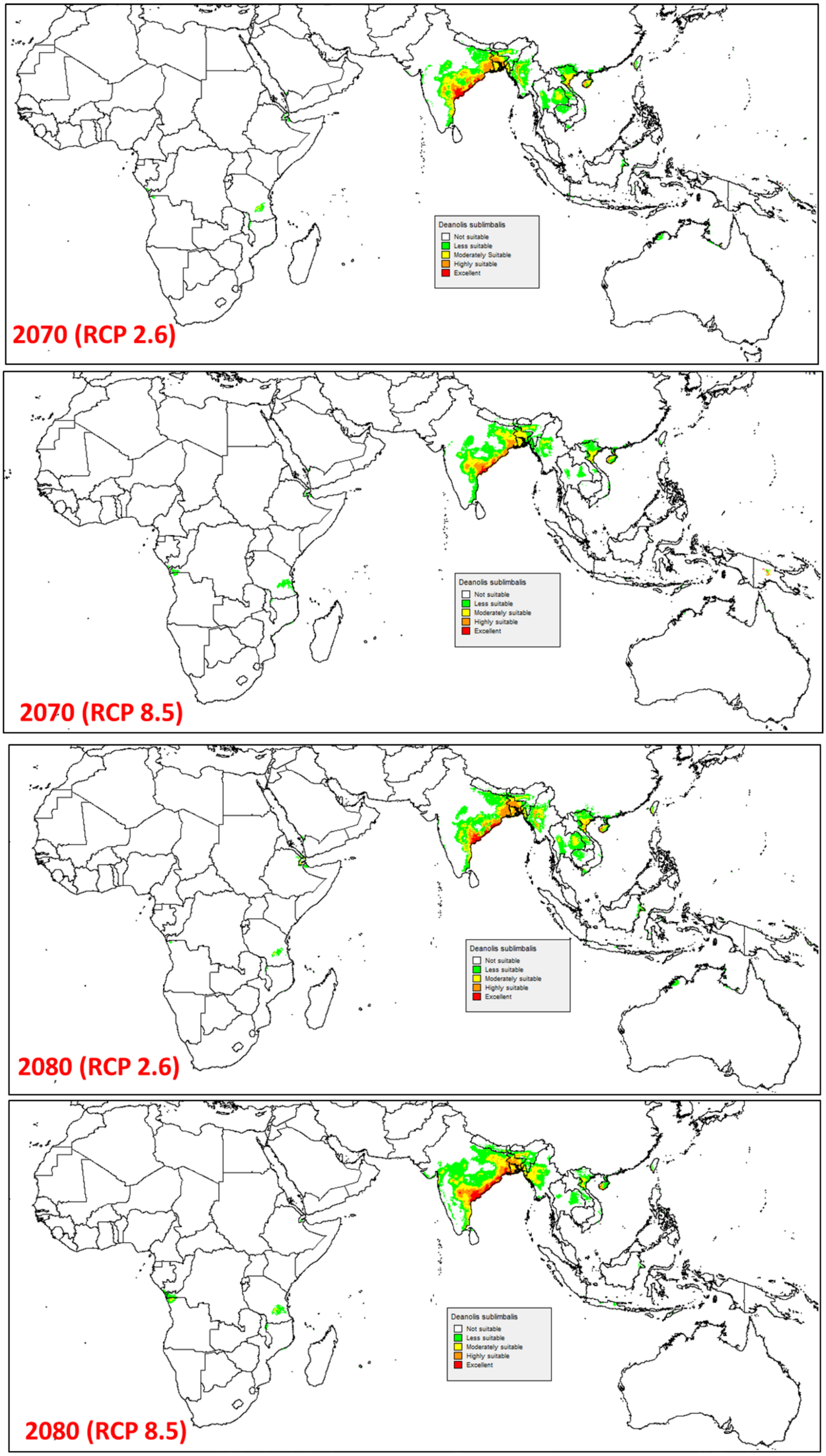

Fig. 8 Prediction of distribution of *D. sublimbalis* under future climate scenario of 2070 and 2080

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Authors' contribution GB and SC designed the study. KJPD, HSS, and SR conducted a field survey to collect the occurrence data of pests. GB and SC performed the analysis. All authors also read and approved the final manuscript.

Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Human and animals right statement The authors declare that no human participants and animals were involved in this study.

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