Predicting the invasion potential of indigenous restricted mango fruit borer, *Citripestis eutraphera* (Lepidoptera: Pyralidae) in India based on MaxEnt modelling

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The mango fruit borer, *Citripestis eutraphera* (Meyrick), originally confined to the Andaman Islands, is a recent invasion in mainland India. With changes in climatic conditions, the pest is likely to spread in other major mango-growing regions of the country and can pose serious threats to mango production. In this backdrop, the present study examines the impact of climate change to develop spatio-temporal distribution of invasive *C. eutraphera* in India using the maximum entropy (MaxEnt) modelling approach. Integration of point data on current occurrence of pest and corresponding bioclimatic variables in MaxEnt were used to define the potential distribution in India and mapped using spatial analysis tool in ArcGIS. The model framework performed well as indicated by high area under the curve (0.97) value. Jackknife test for estimating predictive power of the variables indicated that 'isothermality' and 'temperature seasonality' significantly affected *C. eutraphera* distribution. It was found that mango-growing pockets in the southwestern parts of Gujarat, as well as parts of Kerala and Tamil Nadu were moderately to highly suitable for *C. eutraphera* distribution in 2050 and 2070. The results of this study could be an important guide for selecting monitoring and surveillance sites and designing integrated pest management policies in the context of climate change against this invasive pest of mango.

Keywords: Climate change, mango, invasive pest, species distribution models.

INVASIVE foreign species, an animal or plant species when introduced into a new area can be a serious threat to human and animal health, livelihoods, agricultural biosecurity and ecosystem sustainability, and also to the biodiversity of native species[1,2]. In India, growing global trade has boosted the rate of invasion of new pests in the recent past[3,4] and previous research has underlined that climate change will influence the expansion and exacerbate the impacts of invasive pests in their new ranges[1,5,6]. The most recent classical example of intra-national invasion of insect pests from the Andaman and Nicobar Islands to mainland India is the mango fruit borer, *Citripestis eutraphera* (Meyrick) (Lepidoptera: Pyralidae, Phycitinae)[7].

According to records, C. *eutraphera* was restricted to the Andaman Islands on local endemic mango species, *Mangifera andamanica* L. belonging to the family Anacardiaceae[8]. Later, this species also became a major pest on cashew (*Anacardium occidentale*) from the Andaman Islands[9]. Geographically it is also present in Java, Indonesia and Australia[10]. It also appeared in Bangladesh as a minor pest on mango[11]. This species recently invaded and spread to mainland India and infested mango, *Mangifera indica* L., in Karnataka, Tamil Nadu, Kerala and Gujarat[7,12]. It also infested seedlings and grafts of cashew, *Anacardium occidentale* L. in Kerala[12]. The reported host plants of *C. eutraphera* are *M. indica*, *M. andamanica*, *A. occidentale*, *Mangifera caesia* Jack (Anacardiaceae), *Dipterocarpus baudii* Korth., *D. chartaceus* Symington (Dipterocarpaceae) and *Parkia javanica* Merr. (Fabaceae)[13]. The larvae causes damage to mango and cashew fruits through boring and feeding inside the soft piths of young fruits. Larvae also bore through the shoot and fruit stalk of *M. indica*[14]. Larval infestation on young fruits causes premature fruit dropping[7]. The pest has the capability of damaging radicle, fruits, stem and leaves, which enhances its invasion capacity on mango and cashew. Recorded infestation levels on mango fruits ranged from 2.46% to 64.00% in India during the 2013–2015 fruiting period in the surveyed region of Karnataka and Tamil Nadu[4,7]. All these evidences suggest that the insect has certainly become a potential pest of mango, the main fruit crop of India.

Establishment into new areas, distribution and population dynamics of any invasive insect is highly dependent on location-specific climatic factors like seasonal variations in moisture, temperature and humidity. Determination of

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habitat suitability for pest under changing climatic conditions using forecast modelling could facilitate development of better strategies for the management of invasive species and restrict their spread to new areas[15]. Such modelling studies will provide an evolutionary and ecological approach to understand species invasions[15].

Integration of species distribution models (SDMs) and ecological niche models (ENMs) is a more appropriate approach to predict potential distribution and spread of pests on the basis of occurrence records and corresponding climatic and other environmental variables[16,17]. Recently, mapping the potential distribution of agriculturally important insect pests using computer-aided MaxEnt (maximum entropy modelling) tool that applies ENM/SDM integrated approach is extensively being used[18–20]. The present study used ENM-based approach in MaxEnt to predict the invasion potential of *C. eutraphera* in India under various climate change scenarios through delineation of the bioclimatic variables governing its geographical spread and abundance. Information generated in this study could facilitate mango growers for better preparedness against the possible establishments of *C. eutraphera* by undertaking effective pest management strategies well in advance.

Materials and methods

Location-specific geocoded (i.e. latitude and longitude) data on the occurrence of *C. eutraphera* were compiled from the published literature[4,7–9,12], survey and surveillance of mango pests under the 'ICAR-National Innovations in Climate Resilient Agriculture' (ICAR-NICRA) project during 2011–2017. The latitude and longitude for the selected points were referenced using information published earlier and global positioning system (GPS) during the survey of mango pests. In the present study, data on 40 records were collected for predicting the spatial and temporal distribution of *C. eutraphera* over the Indian subcontinent.

WorldClim database (ver. 1.4; http://www.worldclim.org/) was used to obtain data on current climatic conditions of 19 'bioclimatic' variables[21]. These data are available at 2.5 arc min (approx. ~4.6 km resolution at the equator) spatial resolution. The required data of the Indian region were extracted from world data by masking the India boundary in ArcGIS™ (ver. 10.4) environment. The data on 'bioclimatic' variables included temperature (minimum, maximum, average monthly, average quarterly, average annual) and rainfall recorded for the period 1960–1990.

Multicollinearity has been found to have a significant effect on relationships between species and environment, and can hamper the analysis[20]. In the present study, we used ENMTools (ver. 1.0) to assess multicollinearity among the bioclimatic variables[22]. Pairwise comparisons were made for all 19 bioclimatic variables and highly correlated variables were removed using Pearson's correlation statistic. When two variables had a value of Pearson's coefficient $|r| \geq 0.85$, only the one with higher relative importance and higher predictive power expressed in terms of per cent contribution and jackknife training gain for determining *C. eutraphera* distribution was selected for model development[20]. Based on importance, only 10 environmental variables were further processed: annual mean temperature (BIO1), mean monthly diurnal range (BIO2), isothermality (BIO3), temperature seasonality (BIO4), annual precipitation (BIO12), precipitation of wettest (BIO13) and driest (BIO14) month; precipitation seasonality (BIO15) and precipitation of warmest (BIO18) and coldest (BIO19) quarter. Details of these bioclimatic variables are available in Hijmans *et al.*[21].

Future climatic data at a spatial resolution of 2.5 arc min, as downloaded from Worldclim (ver. 1.4), were used to predict the potential future distribution of *C. eutraphera* in India. Two future representative concentration pathways (RCP 2.6 and RCP 8.5) were selected in this study as against four RCPs proposed in the Fifth Assessment of the Intergovernmental Panel for Climate Change (CMIP5)[23]. These two scenarios were selected so as to reduce the extremity in climatic variations. Future climate data for the years 2050 and 2070 pertaining to these two scenarios were downscaled from Hadley Global Environment Model 2-Atmosphere Ocean (HADGEM2-AO) global climate model. Year 2050 represents the average for the years from 2041 to 2060, while 2070 represents average for the years from 2061 to 2080. These data provided the best representation for future climate scenarios. Two climate-change scenarios (RCPs) and two time limits (2050 and 2070) resulted in four different scenario combinations for future predictions.

In the present study, potential invasion risk and geographic distribution of *C. eutraphera* were mapped using MaxEnt model[24]. Selection of MaxEnt was feasible due

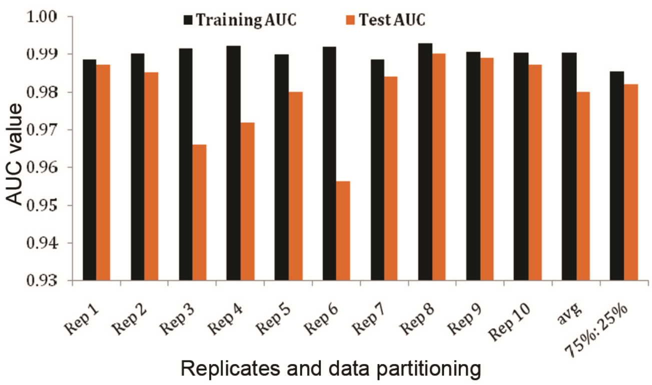

Figure 1. Evaluation statistics from test and training Area Under the Curve (AUC) values of ten-fold cross-model run validation and from random data partitioning. Black represents training AUC and orange represents test AUC.

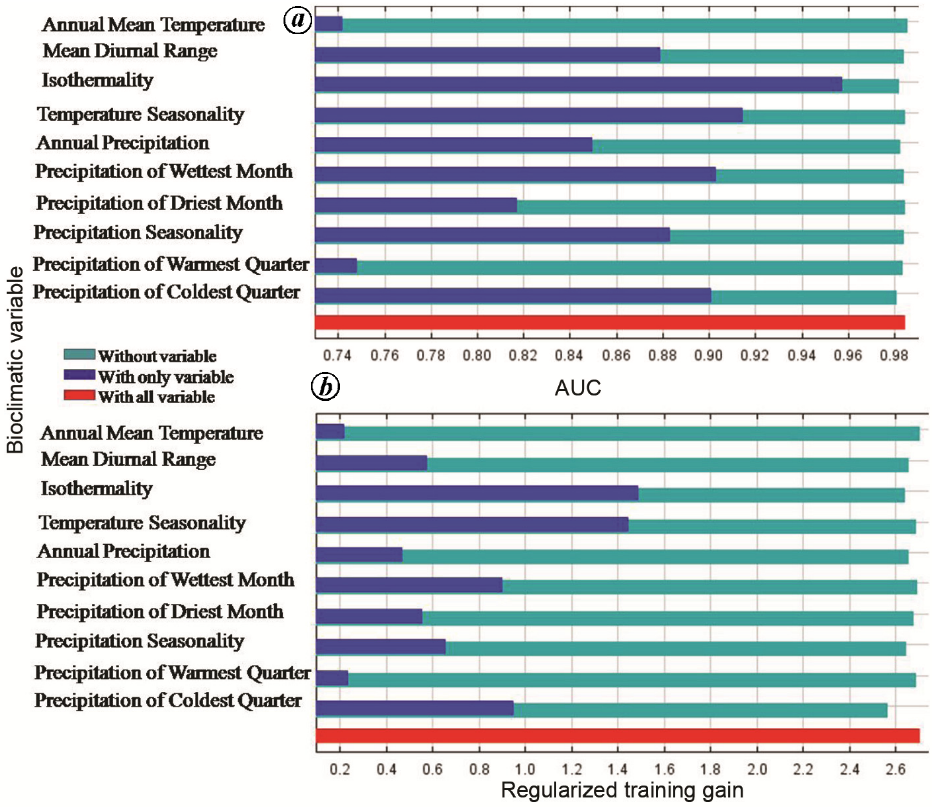

Figure 2. Relative importance of bioclimatic variables based on results of jackknife tests in the development of MaxEnt. Graphics show variable contributions to (***a***) AUC (area under the Receiver Operating Characteristic (ROC) curve) and (***b***) regularized training gain. Values shown are averages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

to requirement of 'presence only' data which could be effective at low number of occurrence data[25,26]. The MaxEnt approach first develops the probability distribution function for species occurrence using 'presence only' database. It then generates environmental conditions for random locations on the basis of maximum entropy distribution of species[24]. After testing of different parameters in MaxEnt, we found that default settings yielded the best model for *C. eutraphera* distribution in India. Less number of samples used in this study led to selection of linear, quadratic, product, threshold and hinge features of modelling. Other settings such as convergence threshold, maximum iterations and maximum number of background points with values 10^{-5}, 5000 and 10,000 respectively, were used to run the model. Variable selection in model development was done on the basis of jackknife test of relative importance of variables.

The model performance was assessed on the basis of area under the curve (AUC) of Receiver Operating Characteristic (ROC)[27] and Akaike Information Criterion (AIC) according to Peterson *et al.*[28]. The interrelationship between bioclimatic variables and predicted probability of the presence of *C. eutraphera* was presented using response curves. The modelling errors arising from random splitting of data into testing and training subsets were minimized using tenfold cross-validation. The model was also run by randomly dividing sample data into two quasi-independent subsets, i.e. training data (75%) and test data (25%)[19]. The output from the final MaxEnt model was projected onto a spatial map for the selected climate scenarios (RCP2.6 and RCP8.5) to visualize current and future habitat suitability for *C. eutraphera*. Spatial mapping was carried out in ArcGIS to produce suitability maps under current and future climatic scenarios.

Results

Model performance and impact of bioclimatic variables

Higher mean training AUC value of 0.99 (range 0.98–0.99) and test AUC value of 0.98 (range 0.95–0.99; Figure 1) indicated that the model MaxEnt performed well in predicting the potential distribution of *C. eutraphera*. The final model included only 10 variables after multicollinearity assessment among 19 bioclimatic variables. The most important variable for *C. eutraphera* prediction was temperature seasonality (BIO4; 29.8%), followed by isothermality (BIO3; 26.5%) and precipitation

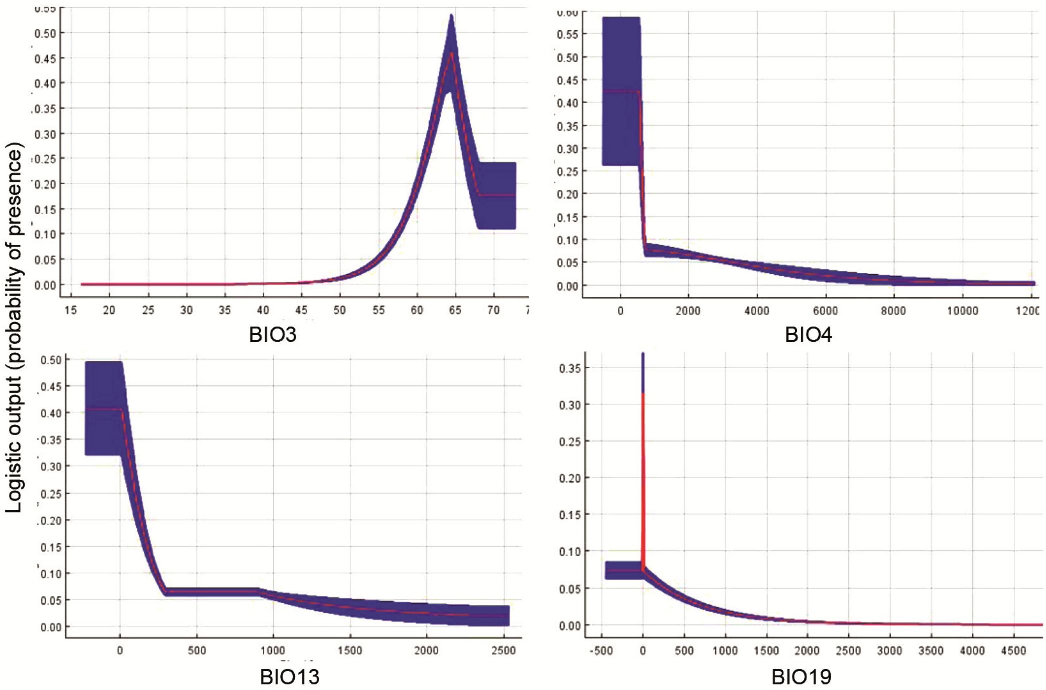

Figure 3. Relationships between top bioclimatic variables and probability of presence of *C. eutraphera* in India. Red curves show the mean response and blue margins are ± SD calculated over 10 replicates.

Table 1. Relative contribution of different bioclimatic variables to MaxEnt model for *C. eutraphera*

Bioclimatic variables	Per cent contribution
Temperature seasonality (Bio4; °C)	29.8
Isothermality (Bio3; °C)	26.5
Precipitation of coldest quarter (Bio19; mm)	22.76
Mean diurnal range (Bio2; °C)	6.05
Precipitation seasonality (Bio15; mm)	3.82
Precipitation of wettest month (Bio13; mm)	3.59

of coldest quarter (BIO19; 22.8%; Table 1 and Figure 2). These three variables could explain 79.21% of the model contribution. The remaining seven variables contributed <10% each to the model. The omission of BIO19 (precipitation of coldest quarter) as the prime explanatory variable reduced the model gain significantly, highlighting its relative importance to other 10 selected bioclimatic variables in determining potential distribution of the pest. Based on individual response curves for different bioclimatic variables, probability of *C. eutraphera* presence decreased with increasing mean diurnal temperature (BIO2) up to 10°C, but increased between 10°C and 12°C (Figure 3). The predicted probability of *C. eutraphera* was negatively correlated with precipitation in the wettest month (BIO13), while positively correlated with precipitation seasonality (BIO15; Figure 3). Overall, it appeared that seasonality of thermal regime and precipitation were the major factors in determining the probability of *C. eutraphera* distribution.

Current and future predicted distribution patterns

Figure 4 presents the potential distribution of *C. eutraphera* in India under current climatic conditions and occurrence data. Predictions showed that the native region, Andaman and Nicobar (A&N) Islands are as highly suitable areas for occurrence of *C. eutraphera*. The southwestern parts of Gujarat (major mango-growing belt), parts of Kerala and Tamil Nadu were predicted to have highly suitable environmental conditions for pest invasion and establishment. Mango-growing belts of Maharashtra, Karnataka, Kerala and Tamil Nadu were also predicted with moderate to high risk of invasion by the pest under current climatic conditions. The coastal mango-growing areas of Indian mainland are particularly predicted with high risk of *C. eutraphera* invasion due to better adaptability of the pest species to coastal climate as against very low to nil risk in the plains.

The model predicted highest risk of *C. eutraphera* invasion and spread in Gujarat by 2050 under RCP2.6 and RCP8.5 climate scenarios, as against currently only few suitable areas in the state (Figures 5 and 6). The potentially suitable area for *C. eutraphera* habitat is predicted to reduce by 2070 all over the country, whereas by 2050 it will decline in parts of Karnataka, Kerala and Tamil Nadu (Figures 5 and 6). Presently, these regions face *C. eutraphera* infestation, but the model predictions showed them under a low risk class by 2050 and 2070 under both (RCP2.6 and RCP8.5) scenarios (Figures 7 and 8). The model predictions for present and future climate scenarios

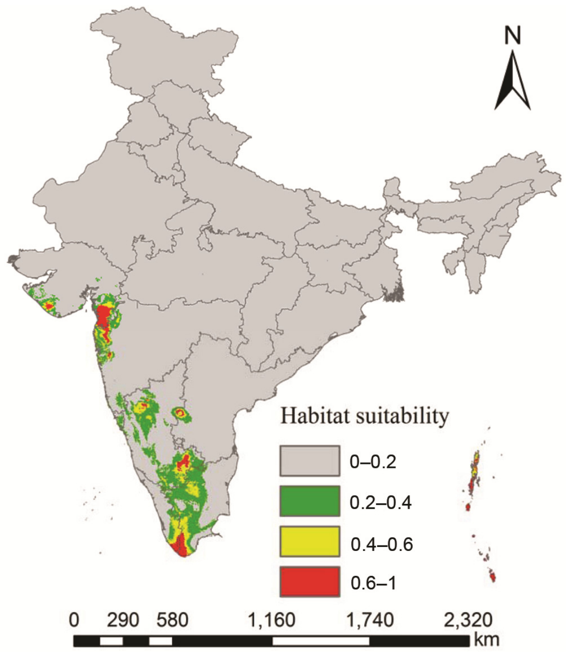

Figure 4. Potential distribution map of *C. eutraphera* in India based on current environmental variables. Grey, Unsuitable habitat area; green, Low habitat suitability area; orange, Moderate habitat suitability area and red, High habitat suitability area.

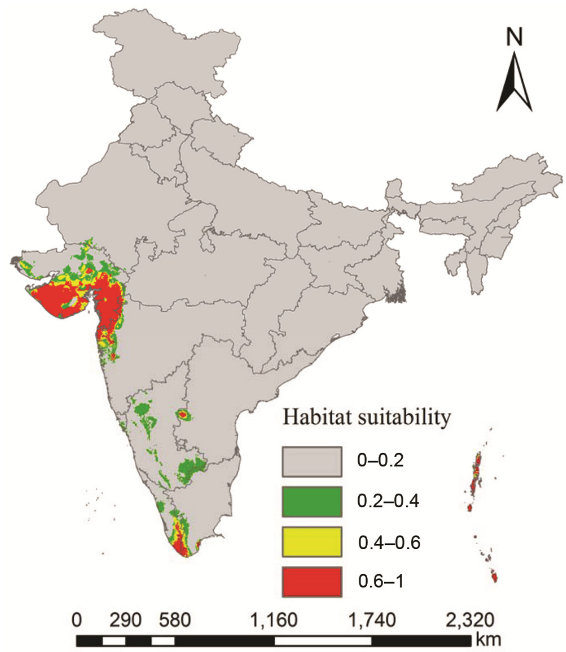

Figure 6. Future distribution models map of *C. eutraphera* in India under climate change scenario RCP 8.5–2050. Colour codes same as in Figure 4.

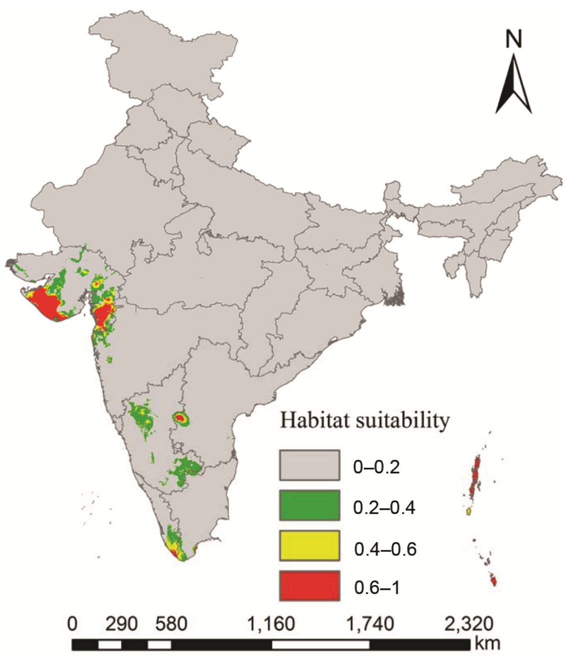

Figure 5. Future distribution models map of *C. eutraphera* in India under climate change scenarios RCP 2.6–2050. Colour codes same as in Figure 4.

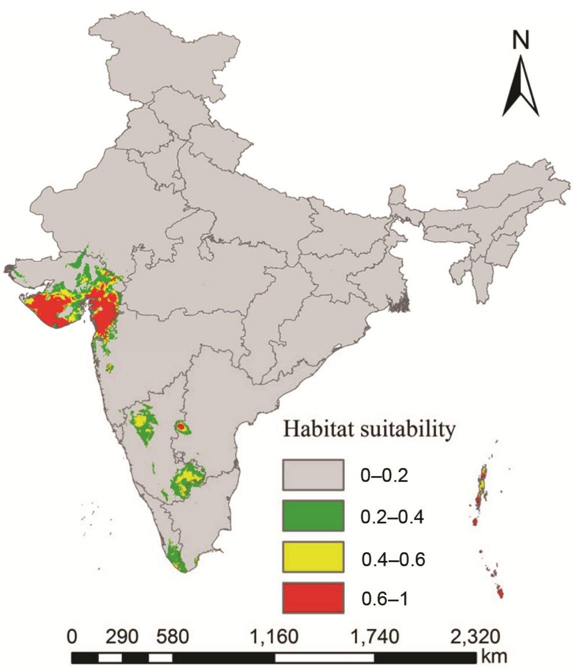

Figure 7. Future distribution models map of *C. eutraphera* in India under climate change scenario RCP 2.6-2070. Colour codes same as in Figure 4.

revealed a high risk in the A&N Islands, native region of *C. eutraphera*.

Discussion

MaxEnt modelling used in the present study has advantages over other climate suitability process-based modelling, e.g. CLIMEX model, due to its inclusion of biotic interactions of host species with their occurrence locations[29]. The model was successfully validated and found to be feasible in predicting high and medium risk in currently documented invasion occurrences of *C. eutraphera*. The maps presented in this study can be used to design future surveys with improved details. With limited occurrence points of *C. eutraphera* in India, the model identified several suitable areas in the coastal regions, indicating further scope for establishment of this species in other regions of the country. Seasonality of thermal regimes and precipitation conditions were major factors to determine *C. eutraphera* distribution, highlighting the fact that changing climatic regimes would severely impact the future distribution of *C. eutraphera* in India. Optimum temperature (>10°C) and precipitation seasonality had positive influence, whereas precipitation in the wettest month and low temperature (<10°C) had negative effect on *C. eutraphera* distribution. The results showed that low (<10°C) and high (>40°C) temperature regimes were not suitable for *C. eutraphera.* Similar optimal conditions were also suitable for mango fruit development and ripening[30,31].

The model predicted some mango-growing pockets as highly suitable areas for *C. eutraphera* invasion in new regions. Interestingly, maps suggested that the southwestern parts of Gujarat, parts of Kerala and Tamil Nadu were suitable habitats for this pest in current and future climatic conditions, where mango witnessed huge economic loss due to this species[7,12]. Presently, pest establishment has been reported from only a few sites in these areas. This calls for enforcement of strict legislation on quarantines which will restrict further spread of this species to other parts of country, as also suggested in earlier reports on *C. eutraphera*[4,7]. Decline in suitability in Karnataka, Kerala and Tamil Nadu in future climatic conditions may be due to unfavourable biological circumstances resulting from natural enemies, physical barriers and local adaption[21]. Predictions also supported that the increased invasion potential under future climatic conditions may negatively impact mango production in other parts of the country.

Although prediction accuracy of the model in the present study was excellent, some natural biotic aspects like availability of host plants, parasitoids and predators have not been considered, which limits species distribution through interspecific interactions[32]. Absence of *C. eutraphera* from geographical areas with environmental conditions favourable for its occurrence may be due to lack of invasion in those particular areas or presence of geographical barriers preventing the species from occupied areas[19]. Another limitation of the present study is the temporal mismatch between occurrence records of *C. eutraphera* and climatic data. This is due to absence of most recent climatic data layers. The present study included bioclimatic variables only from 1960 to 1990 (ref. 22). Future comprehensive modelling studies on assessing the impact of climate change on *C. eutraphera* should focus on new sets of bioclimatic variables obtained using the recent climatic datasets. Thus, for better precision of entropy modelling, in addition to recent bioclimatic variables, other important variables such as interspecific interactions, host-plant species distributions (mango, cashew nut, etc.), host phenology variables related to specific species (e.g. fruiting in host species), geographic barriers and dispersal ability should also be considered[17,33].

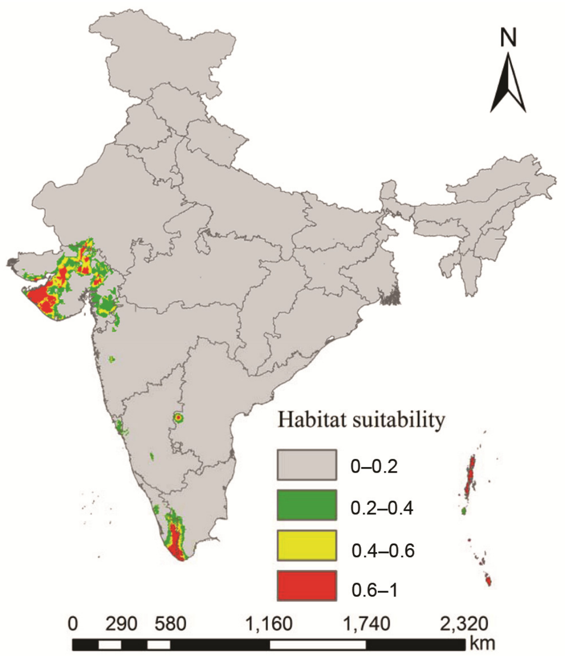

Figure 8. Future distribution models map of *C. eutraphera* in India under climate change scenarios RCP 8.5-2070. Colour codes same as in Figure 4.

Conclusion

Thus in the present study we have examined the model distribution and predicted nation-wide invasion risk of the pest *C. eutraphera* using MaxEnt modelling in the Indian subcontinent. The maps showing potential distribution of *C. eutraphera* will be useful for designing pest management policies for eradication of pests from established areas and also serve as an important tool in understanding the impact of changing climatic conditions on distribution and activity of *C. eutraphera*. Results also provide in-depth knowledge about influence of various climatic parameters affecting occurrence and distribution of *C. eutraphera* in India, which will be useful for combating the possible outbreaks of this pest well in advance. The spatio-temporal variability maps presented in this study will be useful in developing strategies for monitoring of this species, which in turn will enable assessment of establishment risk in the presently unaffected mango-growing regions.

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