Journal of Agrometeorology

ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 24(3) : 269-275 (September 2022)

https://journal.agrimetassociation.org/index.php/jam

Research Paper

Maximum entropy modelling for predicting the potential distribution of invasive rugose spiraling whitefly, *Aleurodicus rugioperculatus* in India

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ABSTRACT

The potential distribution of invasive rugose spiraling whitefly, *Aleurodicus rugioperculatus* Martin (Hemiptera: Aleyrodidae) was predicted under present (2020) and future climate change emission scenarios in 2050 and 2070 under four representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5) using maximum entropy (MaxEnt) niche modelling. The study revealed that the most dominant climatic factors i.e annual mean temperature, mean diurnal range, precipitation seasonality and iso-thermality with 23.2, 21.4,17.5 and 16.4% respectively were significantly influenced the potential distribution and establishment of rugose spiraling whitefly. Eastern coastal parts of Tamil Nadu, North-Eastern parts of Andhra Pradesh, Eastern coastal belts of Odisha, North-Western coastal belts of Kerala, South-Western coastal parts of Karnataka and Western coastal belts of Maharashtra and Gujarat were predicted the highest habitat suitability places/ regions. The present study data would help to formulate control measures for monitoring, surveillance and early pest warning of rugose spiraling whitefly and combating outbreaks well in advance in newer geographical locations.

Keywords: Climate change; rugose spiralling whitefly; species distribution models

Biological invasions are significantly impact the native ecosystem, biodiversity, and the economy; however, the possible factors contributing to successful invasion remain elusive, resulting to the severe ecological damage and economic loss. An increase in the volume, diversity and frequent movement of plants and their byproducts for the trade across the globe has led to the quick dissemination of invasive species and those closely associated with plants, such as scales, mealybugs and whiteflies (Wosula *et al.* 2018). Further, climate changes such as extreme climatic events could enhance invasive processes from initial introduction, establishment and spread to other potential geographical regions (Diez *et al.* 2012). Rugose spiraling whitefly is a highly invasive, voracious sap sucker, high reproduction, excretion of excessive honey-dew and adapted to warmer climates. It has become a major pest on coconut, oil palm, banana, guava and many other host plants in India and causing substantial damage in more than 30 host plants (Selvaraj *et al.* 2019). Due to variation in the agro-climatic conditions of different regions, the arthropods show varying trends in their incidence also in nature and extent of damage to the crop (Elango *et al*., 2021).

Determination of habitat suitability for the growth and development of invasive species under changing climatic conditions using a forecast model could facilitate better management strategies and contain their spread to new geographical regions (Kumar *et al.* 2015). Integration of ecological niche models (ENM) with species distribution models are the most appropriate approaches to predict the potential distribution and spread of various pests based on occurrence points and corresponding climatic variables (Bentlage *et al.* 2013). Chattopadhyay (2021) stated that the management of weather and climate risks in agriculture has become an important issue due to climate change. Mapping the potential distribution of agriculturally important insect pests using computer-aided MaxEnt (maximum entropy modelling) is ideal tool in a habitat suitability model. The model perform based on the ecological niche principle that use species distribution data, extensively being used for pest risk zoning of invasive species (Wang *et al.* 2020). Therefore, the present study was proposed to predict the potential geographical distribution of invasive rugose spiraling whitefly under present (2020) and futuristic (2050 & 2070) climate change scenarios through ecological niche models-based approach.

Article info - DOI: https://doi.org/10.54386/jam.v24i3.1729
Received: 27 April 2022; Accepted: 12 July 2022; Published online: 31 August 2022

MATERIALS AND METHODS

Occurrence data of rugose spiraling whitefly

Data on geographic coordinates (i.e., latitude and longitude) of current pest occurrence is the primary requirement for ecological niche modelling. For this study, occurrence data of rugose spiraling whitefly were collected during the roving surveys between August 2016 and March, 2021 in different states of India and few from published literatures (Patel *et al.* 2020). Geographic coordinates for each occurrence point were compiled using the global positioning system (GPS) during the survey, and duplicate, neighbouring occurrence points were removed as per the requirements of MaxEnt model. Finally, 83 valid occurrence points were used in the study to predict the potential distribution of rugose spiraling whitefly under different climate change scenarios.

Environmental layers

Data for 19 'bioclimatic' variables for current climatic conditions (1970-2000) were collected from the World Clim database, version 1.4 (http://www.worldclim.org/) at a spatial resolution of 2.5 min. Further, data were processed as per the requirement of the study using ecological niche modelling (ENM) software version 1.4.4 (Warren *et al.* 2011). Multi-collinearity among the bioclimatic variables which hinder the species environmental relationships was assessed. Pearson correlation coefficient was used to classify and remove highly correlated variables in each pair-wise comparison of 19 bioclimatic variables. When two variables had a value of Pearson's coefficient $|r|\geq 0.80$, only one variable from pair considering its biological importance for rugose spiraling whitefly distribution and their predictive power (*i.e.* per cent contribution and Jackknife gain) was selected for model development. Finally, twelve bioclimatic variables *viz.,* BIO1 (annual mean temperature), BIO2 (mean diurnal range), BIO3 (iso-thermality (BIO2/BIO7) (*100)), BIO5 (maximum temperature of the warmest month), BIO6 (minimum temperature of the coldest month), BIO8 (mean temperature of the wettest quarter), BIO10 (mean temperature of the warmest quarter), BIO12 (annual precipitation), BIO14 (precipitation of driest month), BIO15 (precipitation seasonality), BIO18 (precipitation of the warmest quarter) and BIO19 (precipitation of the coldest quarter) were selected based on importance and processed for modelling. The future climate projection data were downloaded from the World Climate Database, version 1.4 (http://www.worldclim.org/) at a spatial resolution of 2.5 arc minutes on a global scale to predict the potential distribution of rugose spiraling whitefly in India in future climatic conditions. Statistically downscaled and bias-corrected future climate data were obtained from Climate Change Agriculture and Food Security (CCAFS) (http://www.ccafs-climate.org), at a spatial resolution of 2.5. The Global Climate Model (GCM) of Geophysical Fluid Dynamics Laboratory (GFDL) that represents simulations for four representative concentration pathways (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) from the Fifth Assessment of the Intergovernmental Panel for Climate Change (CMIP5) was selected for representing the future climatic scenario by the year 2050 and 2070. Each scenario represents the radiative force estimated for future climate based on the predicted greenhouse gas emissions.

MaxEnt (Maximum entropy species modelling) (Version 3.3.3k) was employed to predict the potential habitat distribution of rugose spiraling whitefly under current and future climate change scenarios (Phillips *et al.* 2006). MaxEnt model can estimate the probable potential distribution of species occurrence and randomly generated background points of environmental conditions by finding the maximum entropy distribution of species. The model settings were employed as convergence threshold (10−5), maximum iterations (5000) and a maximum number of background points (10000) to run the model. Based on background data, MaxEnt model can compare the environmental characteristics of presence records.

Model development, validation and visualization

The performance of the model was assessed using the area under the curve (AUC) of the receiver operating characteristic (ROC). The AUC value ranges from 0 to 1, which with values >0.9 indicating excellent performance (Peterson *et al*. 2011). Response curves were used to study the relationships between bioclimatic variables and the predicted probability of the presence of rugose spiraling whitefly. Errors arising from the random splitting of data were minimized using tenfold cross-validation. The model was run with two quasi-independent subsets, *i.e.* training data (75%) and test data (25%) by randomly dividing sample data. Spatial mapping was carried out in Diva-GIS 7.3 software to produce suitability maps for each selected climate scenario (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) to visualize current and future habitat suitability for rugose spiraling whitefly. Habitat suitability on the map of rugose spiraling whitefly was divided into five levels as high habitat suitability area (0.75–1.0), optimum habitat suitability (0.56–0.75), moderate habitat suitability (0.37–0.56), low habitat suitability (0.18–0.36) and unsuitable habitat (0.0–0.18).

RESULTS AND DISCUSSION

Potential distribution of rugose spiraling whitefly

The most important bioclimatic variables for *Aleurodicus rugioperculatus* in India were temperature related variables such as annual mean temperature (23.2%), mean diurnal range (21.4%), iso-thermality (16.4%). Among the precipitation related variables, precipitation seasonality (17.5%) and annual precipitation (11.6%) had the highest contribution to the model (Table 1). In the Jackknife test, the mean temperature of the warmest quarter was found as a crucial variable with the highest values of training gain, test gain and area under the curve in the model (Fig. 1 & 2). Prabhulinga *et al.* (2017) predicted that the two major contributing climatic variables *i.e* the mean temperature of warmest quarter (BIO10) and precipitation seasonality (BIO15) contributes 32% and 23.7%, respectively for the potential distribution of *Bemisia tabaci* in North India. Similarly, Ramos *et al.* (2018) predicted the annual mean temperature (BIO1), precipitation seasonality (BIO15), mean annual precipitation (BIO12), precipitation of driest month (BIO14), mean diurnal range in temperature (BIO2) and temperature annual range (BIO7) are most contributing bioclimatic variables for the distribution of *B. tabaci* in Brazil. In Kenya, Mudereri *et al.* (2020) predicted that precipitation of the wettest month (BIO13), precipitation of the coldest quarter (BIO19), and annual temperature range (BIO7) were the most significant bioclimatic variables affecting the distribution of *B. tabaci*.

Table 1: Percent contribution of bioclimatic variables to distribution modelling of rugose spiralling whitefly *Aleurodicus rugioperculatus* in India

Bioclimatic variables	Present scenario (2020)	Future scenario (2050)				Future scenario (2070)			
		RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Annual Mean Temperature (BIO1)	23.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mean Diurnal Range (BIO2)	21.4	24.4	24	27.5	25.3	25	21.8	27.3	24.5
Isothermality (BIO3)	16.4	14.9	12.4	13.3	12.7	14.8	12.4	12.6	8.7
Minimum Temperature of Coldest Month (BIO6)	4.2	24.7	23.4	22.9	22.7	24.3	23.2	24.3	24.4
Annual Precipitation (BIO12)	11.6	8.0	9.5	7.5	8.3	2.5	11.7	7.7	0.0
Precipitation Seasonality (BIO15)	17.5	23.2	25.6	25.3	25.2	20.6	23.9	23.7	24.5
Precipitation of Wettest Quarter (BIO16)	0.0	0.0	0.0	0.0	0.0	8.0	0.0	0.0	10.7

RCP-representative concentration pathways; BIO-Bioclimatic variables.

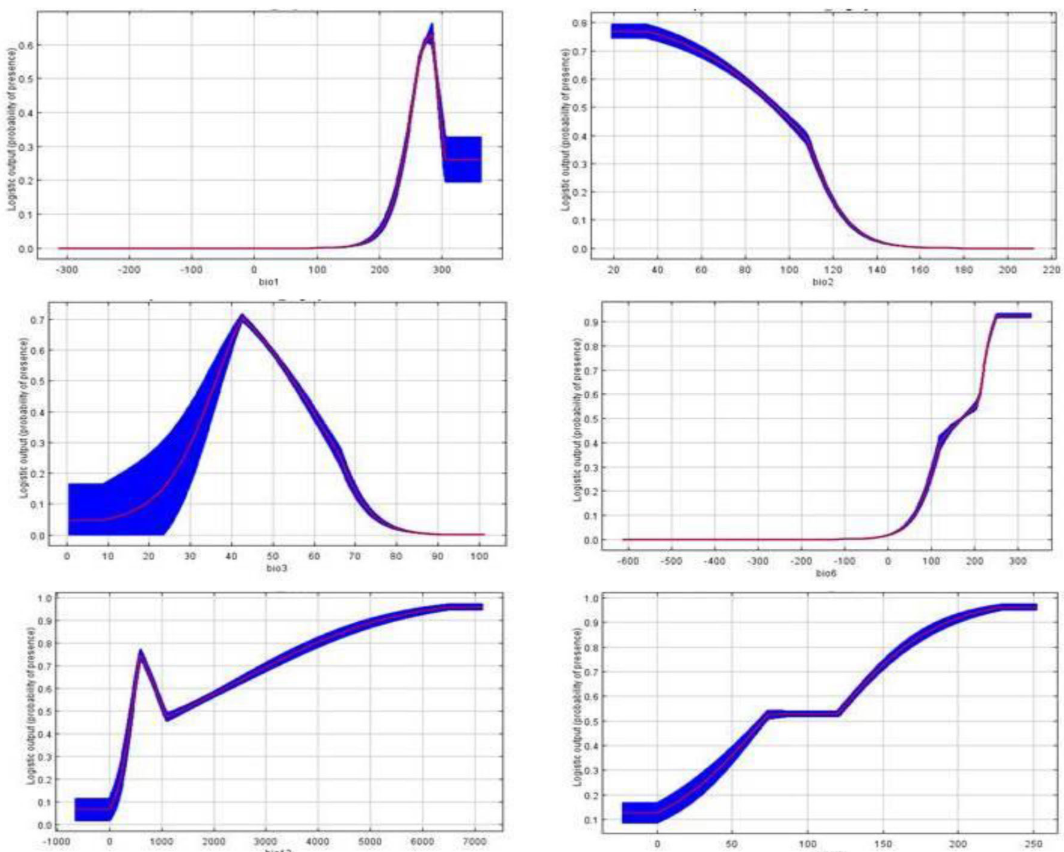

Fig. 1 : Relationship between six strongest environmental predictors and rugose spiralling whitefly probability of presence. Value shown are averages of 10 replicate runs

In the present study, MaxEnt model has predicted the highest suitability areas for rugose spiraling whitefly in Eastern coastal parts of Tamil Nadu, North-Eastern parts of Andhra Pradesh, Eastern coastal belt of Odisha, North-Western coastal belts of Kerala, South-Western coastal parts of Karnataka and Western coastal belts of Maharashtra and Gujarat. Moderate suitability areas for pest occurrence was predicted in southern parts of Tamil Nadu, Northern parts of Kerala, Western parts and central parts of Karnataka, Western coastal regions of Maharashtra and coastal regions of South Gujarat, South-Eastern parts of Andhra Pradesh, Odisha and Southern parts of West Bengal (Fig. 3).

Ecological niche models perform based on the quantitative relationship between bioclimatic variables and species occurrences are used to predict areas of possible introduction, establishment and spread (Kumar *et al.* 2014b). Correlative models are widely used tools for assessing the risk of establishing various species including, insects, aquatic organisms, plants, human diseases, vertebrates and pathogens (Galdino *et al.* 2016). The model developed for rugose spiraling whitefly distribution was mainly determined by the temperature related bioclimatic variables like yearly mean temperature, mean diurnal range, iso-thermality, minimum temperature of the coldest month and precipitation related bioclimatic variables like annual precipitation, precipitation

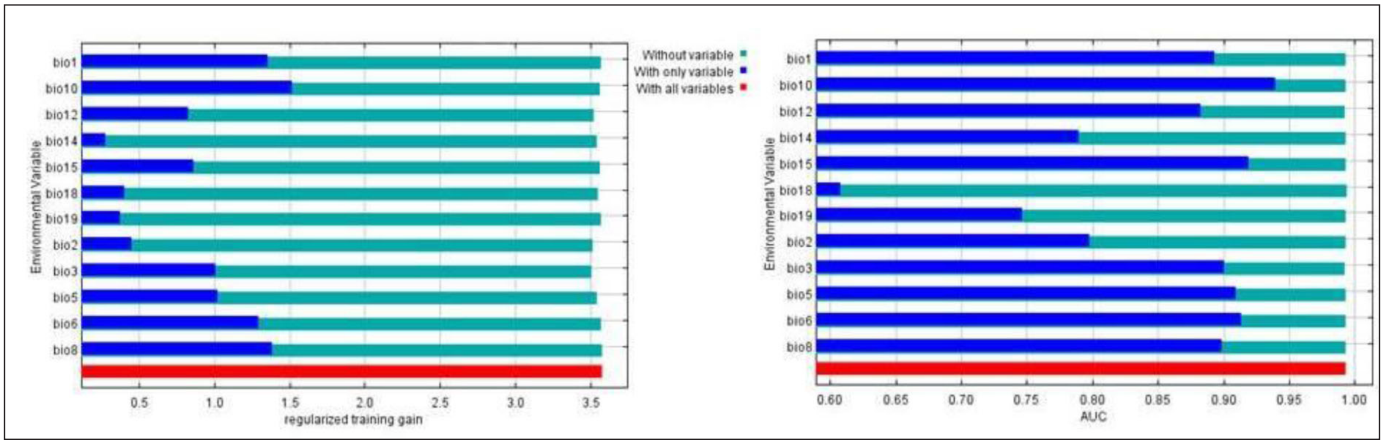

Fig. 2 : Relative importance of the environmental variables based on the Jackknife test. The figure shows each environmental variable's contribution to 'training gain' and 'AUC' both are measures of model's predictive ability. Values shown are averages of 10 replicate runs

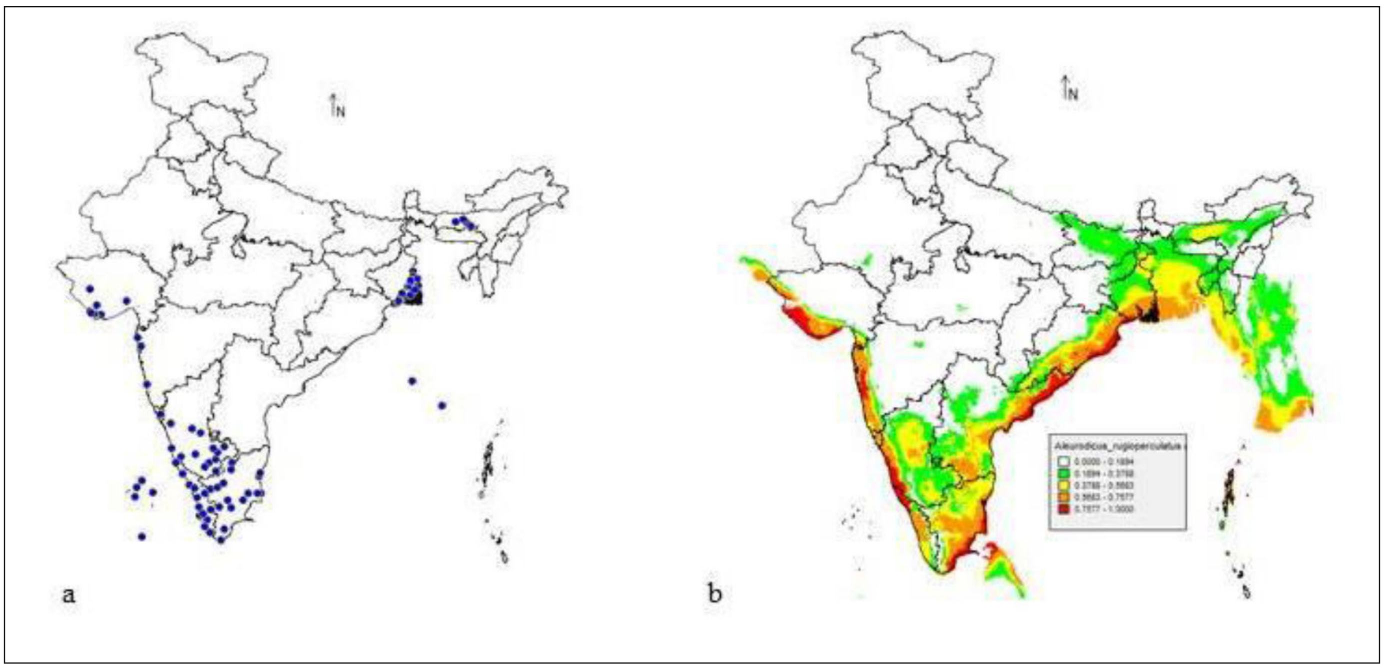

Fig. 3 : Occurence records used in the study to predict the potential distribution of rugose spiralling whitefly (a) and their distribution under present scenario (2020) in India

of the coldest quarter and precipitation seasonality. These results provide a valuable theoretical basis for risk assessments and control of rugose spiraling whitefly. The decline in morning and evening relative humidity up to 7% compared to the previous year (2015), and rise in temperature over 2^{o}C during summer might be another pre-disposing factor for the increase in rugose spiraling whitefly population and quick dispersal in a short period. Chakravarthy *et al.* (2017) observed that the prevailing warm weather conditions, 28-31^{0}C temperature with 40-50% relative humidity and deficient rain favoured rugose spiraling whitefly. At the time of this study, very little is known about the developmental biology of *A. rugioperculatus,* near related species such as spiraling whitefly, *Aleurodicus dispersus* were observed to have a developmental range of 12-32^{o}C and high mortality at suboptimal temperatures.

Impact of climate change on future potential distribution of rugose spiraling whitefly

The potential distribution of rugose spiraling whitefly was predicted at different future climate change scenario (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) of 2050. In all RCP's model was predicted with the AUC of 0.993 to 0.994. The highest relative contributions of the environmental variables to the predicted model were with a minimum temperature of the coldest month (22.7-24.7%), mean diurnal range (24.0-27.5%), precipitation seasonality (23.2-25.6 %) iso-thermality (12.7-14.9%) and annual precipitation (7.5-9.5%) (Table 1). The distribution of the pest in the 2050 scenario is similar to the present (year, 2020) climate prediction. However, highly suitable areas for pest occurrence was found in coastal parts

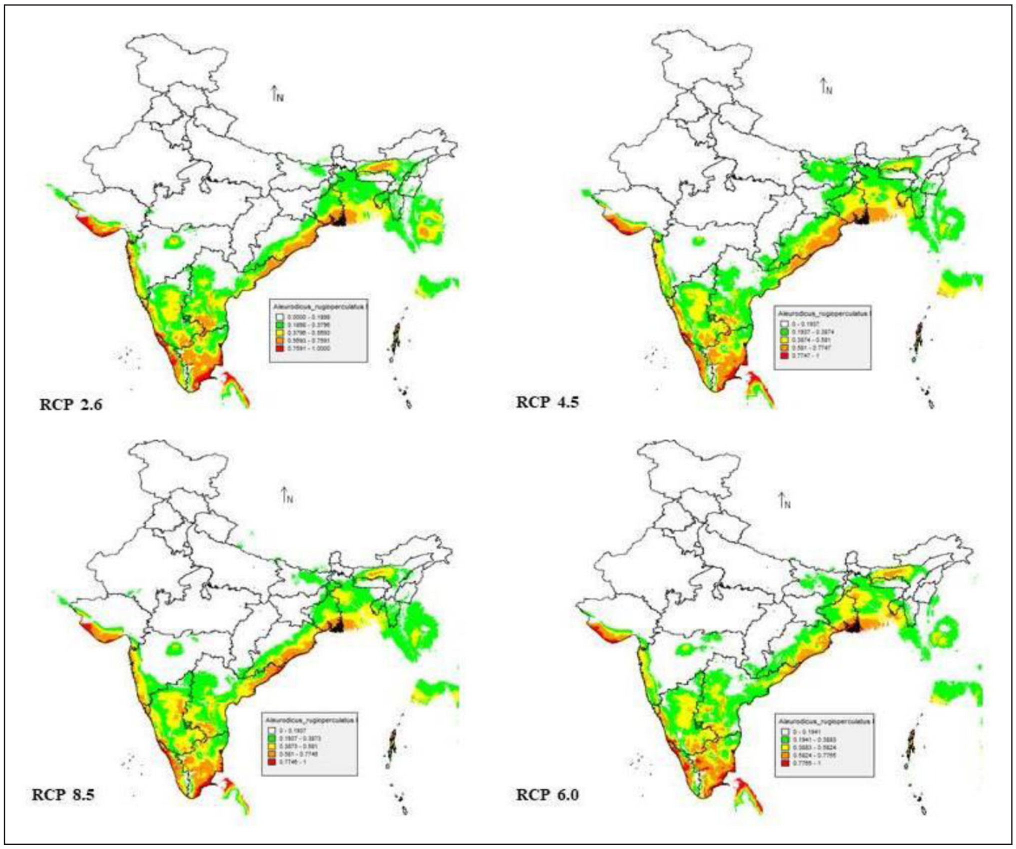

Fig. 4 : Predicted potential distributions of rugose spiralling whitefly in India under 2050 scenario

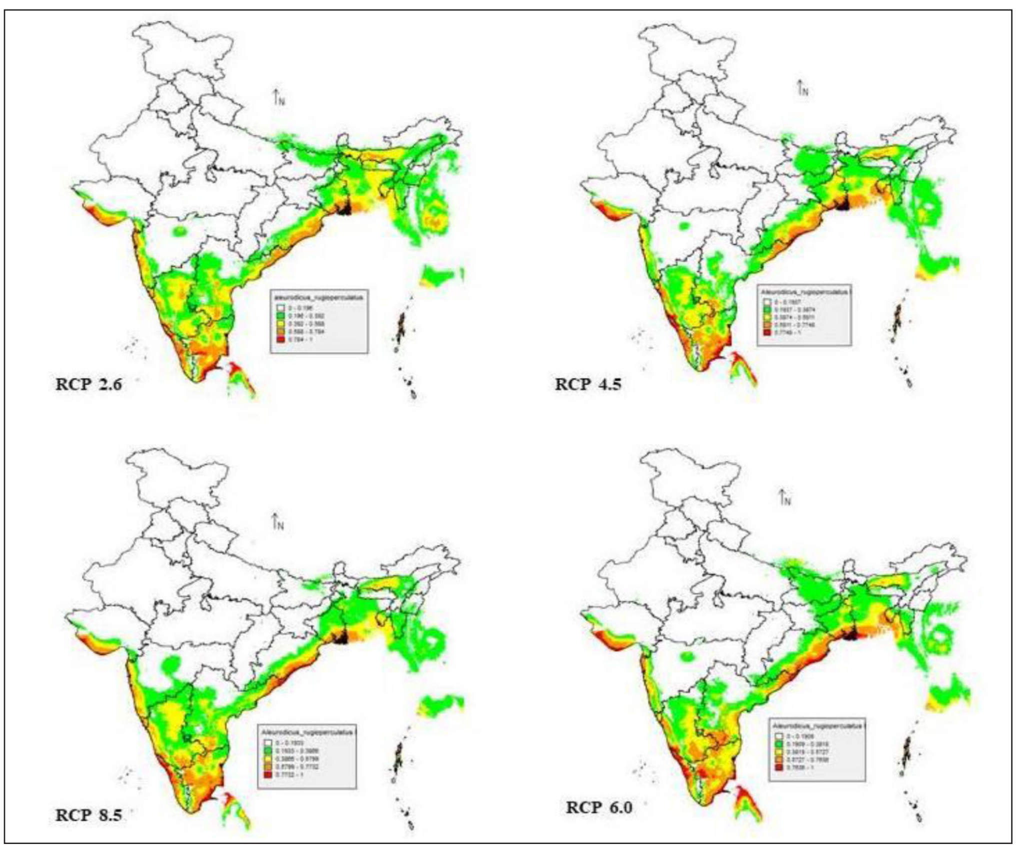

Fig. 5 : Predicted potential distributions of rugose spiralling whitefly in India under 2070 scenario

of Tamil Nadu, Kerala, Karnataka and Gujarat (Fig. 4), and low to moderate suitability areas of the prediction is similar to that of the present scenario prediction (year, 2020). In the 2070 future climate scenario, the model was predicted with AUC of 0.992 to 0.993. Across all the RCP's, environmental variables which contributes maximum to the model were with a minimum temperature of the coldest month (23.2-24.4%), mean daily range (21.8-27.3%), precipitation seasonality (20.6-24.5%) and iso-thermality (8.7-14.8%). The contribution of annual precipitation to the model was in RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 were 2.5, 11.7 and 7.7%, 0.0%, respectively. Interestingly, the future climate scenario of 2070 in RCP 2.6 and RCP 8.5 environmental variable precipitation seasonality had 8 and 10.7% contribution to the model (Table 1). In the 2070, scenario across all the RCPs the prediction trend is more or less similar to the 2050 scenario. However, high suitability areas for pest occurrence were predicted in parts of Odisha and Andhra Pradesh (Fig. 5).

The distributions of the pest in climate scenarios in the present study are in more considerable agreement with the distribution report of the pest based on the field survey by Sundararaj and Selvaraj (2017). Mondal *et al*. (2020) attributed the possible reason for the establishment and the spread of rugose spiraling whitefly due to the import of agricultural materials from the new world suitable climatic conditions (tropical warm and humid climate) of the Indian subcontinent. In the present study, the pest distribution model prediction showed that most of India's coastal regions and southern parts had maximum habitat suitability areas for the introduction and colonization of rugose spiraling whitefly. Rugose spiraling whitefly is widely distributed in the coastal regions is predicted due to the prevalence of congenial weather factors and the availability of coconut palms. Selvaraj *et al.* (2019) reported intensive coconut cultivation and transportation of infested seedling might be the possible region for its spread in entire South Indian states. The study further speculates the availability of a wide range of host plants in large areas and favourable weather conditions could be a reason for its distribution and spread (Sundararaj *et al.* 2021). Only one previous study by Chakravarthy *et al.* (2017) predicted that South West coastal regions of India *viz.,* Kerala, Karnataka, Goa, Maharashtra and extended up to Maharashtra-Gujarat border is highly favourable for distribution and establishment using CLIMEX model concerning climatic factors. Besides, few isolated regions in Andhra Pradesh, Odisha, Bihar, Uttar Pradesh, Chhattisgarh, and West Bengal also found favourable climatic conditions for establishing rugose spiraling whitefly.

MaxEnt model only provides estimates of relative suitability regardless of how the background sample is specified. However, several calibrations can be made, significantly influencing the model performance and, consequently, its accuracy (Kumar *et al.* 2015). These calibrations include selecting background points and extent, the value of regularization multiplier and selection of feature types (Phillips *et al.* 2006). Considering these potential pitfalls in the modelling process, utmost care was taken in the present model during calibration, thus generating predictive models consistent with the current known distribution of the species. It can be observed in the quality of response curves and good validation results.

CONCLUSION

Under future climate change scenarios, increased habitat suitability for rugose spiraling whitefly and expansion of its distribution in to newer geographical region in India may be noticed. Further, highly suitable area may turn in to excellent suitable area for the colonization of rugose spiraling whitefly under future climate change scenarios. This study provides deeper more profound insight into the potential distribution of rugose spiraling whitefly using a MaxEnt model. The habitat suitability map developed from the study will be useful for monitoring, developing forewarning strategies and formulating pest management policies for the rugose spiraling whitefly in coconut and many other crop plants. The present results could be an important guide to understand the potential changes in distribution and activity of rugose spiraling whitefly in response to current–future climate change scenarios**.**

ACKNOWLEDGEMENTS

The authors thank the Director, ICAR-NBAIR, Bengaluru for providing facilities to carry out the research and The Chairman, Coconut Development Board, Kochi for financial support through research grant.

Conflict of Interest Statement: The author (s) declares (s) that there is no conflict of interest.

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