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Maximum entropy modelling for predicting the potential distribution of cotton whitefly *Bemisia tabaci* (Gennadius) in North India

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Abstract

To comprehend the reasons for the cotton Whitefly *Bemisia tabaci* outbreak in north India, a computer based ecological niche modelling, MAXENT approach was attempted to predict the potential distribution, suitable habitat and the favourable environmental factors. The analysis showed that the climatic variables *viz.*, mean temperature of warmest quarter (Bio10) and Precipitation seasonality (Bio15) contributes 32 and 23.7 per cent with 79 and 1.2 per cent permutation importance respectively for potential distribution of whitefly. These are the two major climatic contributors were responsible for the potential distribution of the pest in cotton growing states viz., Punjab, Haryana and Rajasthan of north India in 2016. The study was conducted during 2016 cotton cropping season (April-October). The assessment of the pest risk by the MaxEnt analysis provided the information for the pest management decision making; which helps to develop the cost effective pest management strategies and to prevent the spread of domestic quarantine CLCuD by controlling the vector by suitable integrated pest management strategies.

Keywords: Whitefly; MaxEnt; WorldClim

1. Introduction

Cotton whitefly, *Bemisia tabaci* (Gennadius) is a phloem feeder on various important agricultural and horticultural crops worldwide [1, 11, 17]. The development and spread of the pest largely depends on the climatic conditions prevailing in the cropping area. The pest grows rapidly in hot and humid weather condition [12]. In 2015, northern India major cotton growing states like Punjab, Haryana and Rajasthan grossly affected by the Whitefly. The pest outbreak caused heavy loss to the tune of 1.23 million bales worth of 0.4 b USD [12]. Generally, the habitat marks a significant impact on the abundance and distribution of the species. So, the prediction of species distributions is central to the various applications in ecology, evolution and conservation science [5] and forecasting [8, 9, 19]. To predict the species distribution many ecologists and conservation biologists used to study relationships between environmental parameters and species richness [16]. There are many computer based ecological niche modelling techniques are available in the public domain, which needs species' occurrence data, environmental data layers of high spatial resolution as inputs [23]. Among many species distribution models (SDM) used, the maximum entropy (MaxEnt) model is the most acceptable and widely used one. There are many cases where MaxEnt application was used example; by using the district-level occurrences data predicted the invasion potential of an exotic insect pest cotton mealybug *Phenacoccus solenopsis* (Tinsley) in India [21]. In Italy [15] predicted the climatic variables responsible for the distribution or colonization of emerging plant pathogen *Xylella fastidiosa* a xylem-limited Gram-negative bacterium. He predicted low altitude (0–150 m a.s.l.), precipitations in the driest month < 10 mm, in the wettest month ranging between 80–110 mm and during the warmest quarter < 60 mm; mean temperature of coldest quarter ≥ 8°C; intensive agriculture. In Tunisia by using MaxEnt ecological niche modelling tool [2] predicted the factors responsible for an epidemic and very complex disease cutaneous leishmaniasis caused by *Leishmania major*, the rainfall and temperature contributed the most as predictors and the highest suitability for species occurrence in the central and south eastern part of Tunisian. There were seven variables, such as annual mean temperature, altitude, precipitation seasonality, precipitation of coldest quarter, the distance to the nearest river, temperature seasonality, and precipitation during the driest month variable contributed significantly for the prediction of distribution of endangered medicinal plant riparian species

Homonoia riparia (*H. riparia*) Lour in China [24]. The mean temperature of coldest quarter with highest gain value was the most important environmental variable determining the potential geographic distribution of cotton mealybug, *Phenacoccus solenopsis* by using MaxEnt algorithm [7]. Potential distribution of the invasive coconut whitefly, *Aleurotrachelus atratus* in Mozambique estimated by MaxEnt analysis tool to identify areas suitable for the pest distribution, predicted the coastal area of Mozambique and areas around Manica province suitable for the pest [3].

The present study was conducted to predict the geographic distribution of the *Bemisia tabaci* by using ecological niche modelling and the suitable habitat for the pest and finally the significance of the environmental variable which influence the pest distribution.

2. Materials and methods

2.1 Study area

The present study survey was conducted in 8 cotton growing districts belong to three states of north India namely, Sirsa, Fatehabad and Hisar districts of Haryana, Hanumangarh, Sriganganagar of Rajasthan, Fazilka, Bhatinda and Mansa districts of Punjab during 2016.

2.2 Ecological niche modelling: (Statistical analysis section 2.2-2.4)

Jayne's in 1957 proposed maximum entropy, presently which is used for the ecological niche modelling [18]. It is a computer based algorithm estimates based on the species presence data and environmental layers and it doesn't require absence data. It performs better than other models [5, 6, 14]. The outcome of the analysis gives the probable criteria for distribution on the basis of partial knowledge and it is the least biased estimate possible on the given information. The most reasonable prediction of the model is the probability of the area suitable for the species present in a set of ecological condition. More the information or the data about the species reduces the uncertainty. And the software is freely downloadable at http://www.cs.princeton.edu/~schapire/MaxEnt/. The MaxEnt version 3.3.3k software was used for the analysis.

The four important possible predictions of the model: (1) the species exists where predicted to exist (true positive, TP); (2) the species does not exist where predicted to exist (false positive, FP); (3) the species exists where not predicted to exist (false negative, FN); (4) the species does not exist where not predicted to exist (true negative, TN). These indexes used for the evaluation of SDM performance are calculated based on true positive, false positive, true negative and false negative rates.

2.3 Predictor variable

Nineteen different climatic variable data layers obtained from the worldClim dataset [19] http://worldclim.org/version2. This world climate data is generated by an interpolation technique using altitude and monthly temperature and precipitation recorded from 1950-2000.

Table 1: List of Climatic Variables used in the study.

Abbreviation	Environmental variables	Standard Units	Source
BIO1	Annual Mean Temperature	°C	WorldClim
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))	°C	WorldClim
BIO3	Isothermality (BIO2/BIO7) (* 100)	°C	WorldClim
BIO4	Temperature Seasonality (standard deviation *100)	°C	WorldClim
BIO5	Max Temperature of Warmest Month	°C	WorldClim
BIO6	Min Temperature of Coldest Month	°C	WorldClim
BIO7	Temperature Annual Range (BIO5-BIO6	°C	WorldClim
BIO8	Mean Temperature of Wettest Quarter	°C	WorldClim
BIO9	Mean Temperature of Driest Quarter	°C	WorldClim
BIO10	Mean Temperature of Warmest Quarter	°C	WorldClim
BIO11	Mean Temperature of Coldest Quarter	°C	WorldClim
BIO12	Annual Precipitation	mm	WorldClim
BIO13	Precipitation of Wettest Month	mm	WorldClim
BIO14	Precipitation of Driest Month	mm	WorldClim
BIO15	Precipitation Seasonality (Coefficient of Variation)	mm	WorldClim
BIO16	Precipitation of Wettest Quarter	mm	WorldClim
BIO17	Precipitation of Driest Quarter	mm	WorldClim
BIO18	Precipitation of Warmest Quarter	mm	WorldClim
BIO19	Precipitation of Coldest Quarter	mm	WorldClim

These bioclimatic variables are derived from the monthly temperature and rainfall values. The bioclimatic variables represent annual trends, seasonality, and extreme or limiting environmental factors. These particular variables were chosen to represent the environment relevant to the distribution and survival of small arthropods [4]. The data selected from worldClim was in raster format with 2.5 arc min spatial resolution.

2.4 Evaluation of model performance

The MaxEnt software package employs AUC to appraise the model performance. AUC is one of the excellent indexes to evaluate the model performance. To assess the model performance the area under the curve (AUC) of the receiver operating characteristic (ROC) was used as a threshold independent performance criterion. A model with a less AUC value is less reliable model and model with a large area under the ROC curve indicates that the model is able to accurately predict presence and absence or the larger the AUC value, better is the model performance. The model performance is categorised by [22] is model is failing (0.5-0.6), poor (0.6-0.7), fair (0.7-0.8), good (0.8-0.9) and excellent (0.9-1). The model performance is better if the AUC is closer to 1.

3. Results and Discussion

The maximum entropy species distribution model predicted the potential habitat for the cotton whitefly *Bemisia tabaci* in north India. Whitefly develops rapidly in area where there is hot and humid condition exists (27 ºC and 71% RH) [13]. In north India most of the cotton growing districts had hot and humid weather condition which was most suitable for rapid growth and development of whitefly. It was similar to results of [13] and the potential distribution of the invasive coconut whitefly, *Aleurotrachelus atratus* in Mozambique, predicted the coastal area of Mozambique suitable for the pest [3]. After the analysis it was found that the two major contributing climatic variables for the potential distribution of cotton whitefly in north India which were, the mean temperature of warmest quarter (Bio10) and Precipitation seasonality (Bio15) contributes 32 and 23.7 per cent with 79 and 1.2 per cent permutation importance respectively. The contributing factors for different insect pest species are differ for example; the mean temperature of coldest quarter with highest gain value was the most important environmental variable determining the potential geographic distribution of cotton mealybug [7], Potential distribution of whitefly was predicted in Sirsa, Mansa, Bathinda, Faridkot, Sriganganagar and Fazilka districts of cotton growing regions of north India (Fig. 1a and 1b). These potential distribution areas are potential cotton growing area where application of inputs were very high like, use of heavy dose of fertilizers especially nitrogenous fertilizers, frequent sprays accompanied with high dose of insecticide and mixture of insecticides. Such disturbed ecosystem condition affected greatly on the abundance and diversity of natural enemies which in turn pave the way for pest outbreaks/resurgence etc.

Analysis of ROC showed that the value of training data set and test data set were 0.998 and 0.998 respectively (Fig. 2). The red line indicates the AUC value of training data and blue line indicates the AUC value of test data. The gaining AUC value obtained for the model predated is 0.998 and it falls in the range of 0.9-1 of sweets model performance is category which means the model performed was excellent.

The analysis of relative importance of 19 different environmental variables layers used in MaxEnt algorithm based on the Jackknife tests regularised training gain value. Max. temperature of warmest month (BIO5), mean temperature of wettest quarter (BIO8) and mean temperature of warmest quarter (BIO10) provided very high gains (>3) when used independently, which means temperature of warmest month, mean temperature of wettest quarter and mean temperature of warmest quarter contained more useful information than other variables used in the analysis. BIO1, BIO11, BIO15, BIO2, BIO3, and BIO6 had moderate gain when used independently, remaining variable had very less gain contained less information by themselves (Fig. 3). So the main environmental variables contributors for the prediction of whitefly distribution in north India were BIO5, BIO8 and BIO10.

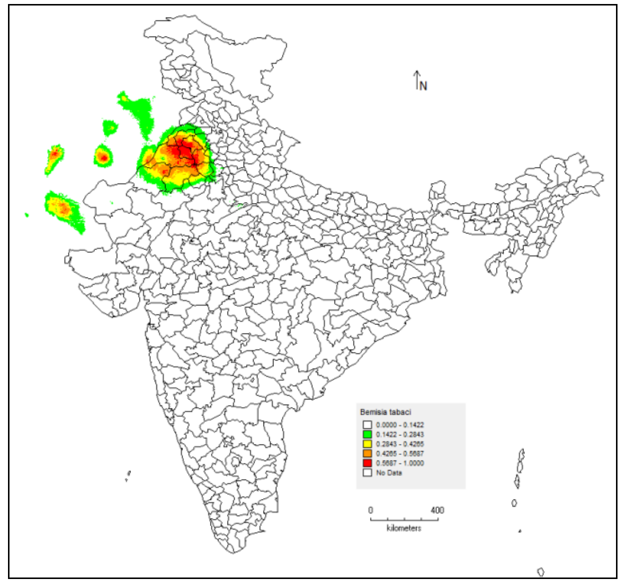

Fig (1a): Predicted potential distribution of whitefly in north India and parts of Pakistan.

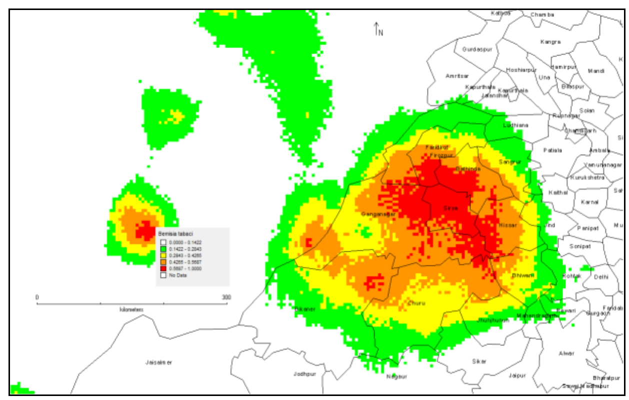

Fig (1b): Predicted potential distribution of whitefly in Punjab, Haryana and Rajasthan.

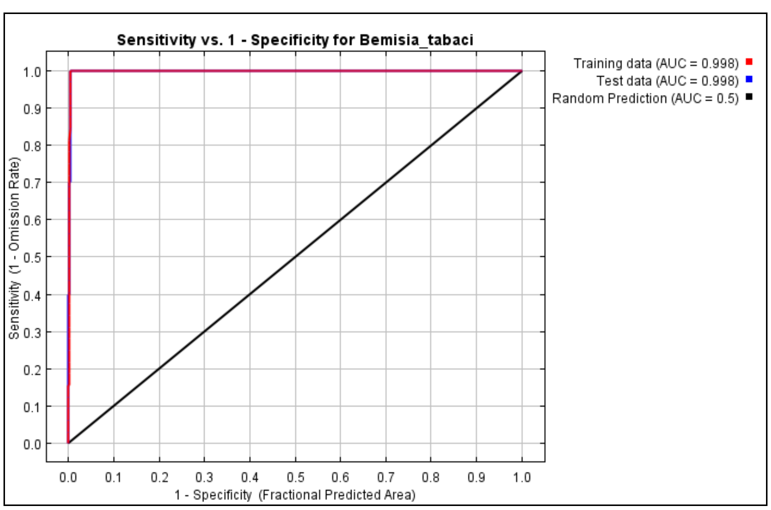

Fig 2: The AUC curves in whitefly habitat suitability model. (Redline is AUC training data, blue line is AUC test data and it is almost running in the redline fashion keen observation required to see the blues colour).

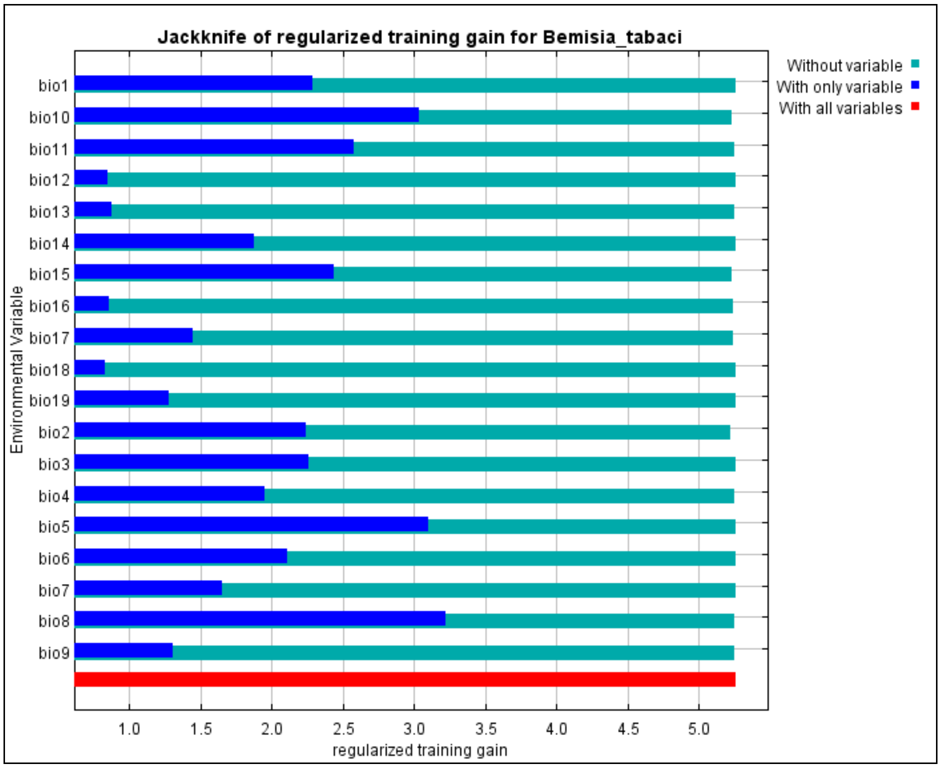

Fig 3: The relative importance of 19 environmental variable based on Jackknife tests in MaxEnt.

4. Conclusion

Whitefly develops rapidly in area where there is hot and humid (27 ºC and 71% RH) condition exists. Most of the cotton growing districts of north India had hot and humid weather condition which greatly favoured the growth and development of whitefly. And it was found that the mean temperature of warmest quarter (Bio10) and Precipitation seasonality (Bio15) are two major contributing climatic variables for the potential distribution of whitefly in north India. The climate change will bring this kind of epidemics/outbreaks in cropping system. So, nature should be protected for normal functioning of ecosystem.

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