RESEARCH ARTICLE

MODELLING POTENTIAL SPREAD OF OIL PALM BAGWORM, *METISA PLANA* (LEPIDOPTERA: PSYCHIDAE) IN INDIA WITH MAXENT APPROACH

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Abstract: Oil palm bagworm, *Metisa plana* (Lepidoptera: Psychidae) is a serious insect pest of oil palm, *Elaeis guineensis* Jacq. in India. The pest is reported to cause severe defoliation on oil palm in oil palm gardens located in Andhra Pradesh, India. Hence, ecological niche modelling study was attempted to identify climate suitable locations for the pest spread in India as area under oil palm cultivation is expanding. Geographical coordinates of 37 pest presence sites, world climate grid files, nineteen bioclimatic variables, MaxEnt software, DIVA-GIS were used for the construction of ecological niche model of *M. plana*. The model indicated potential geographical locations (districts) in seven states *viz*., Andhra Pradesh, Karnataka, West Bengal, Kerala, Odisha, Telangana and Tamil Nadu for the spread of pest in India. One of the interesting predictions emerging from this study is that the pest is not likely to spread to North Eastern states of India and Eastern States, Andaman and Nicobar Islands, Gujarat, Goa, Maharashtra and Chhattisgarh. The predictions of potential distribution of the pest arrived at in this study should help in developing strategies for monitoring and managing this defoliator of oil palm.

Keywords: Bagworm, *Metisa plana*, DIVA-GIS, MaxEnt model, Oil palm, India

INTRODUCTION

Oil palm (*Elaeis guineensis* Jacquin: Arecaceae) is known to be the highest edible oil yielding perennial crop, capable of yielding 4–5 MT of palm oil and 0.4– 0.5 MT palm kernel oil with good planting material, irrigation and proper management (Anonymous, 2018b). Looking at its potentiality, Government of India has been expanding area under oil palm in order to bridge the gap between consumption and domestic production of edible oil. Potential area of 1.93 m ha spread over 18 states has been identified for the expansion of oil palm cultivation in the country as a part of oil palm promotion policy of Government of India. Currently, it is grown in an area of 0.32 million ha. in 15 Indian states under both rain fed and irrigated conditions. In recent years, it is observed that the insect pests and diseases incidence and their damage are in increasing trend. Among the insect pests, defoliators are important pests of oil palm throughout the world causing heavy yield losses (Chung *et al*., 1995; Zeddam *et al*., 2003; Martínez *et al*., 2009; Cheong *et al*., 2010; Ho *et al*., 2011; Martinez *et al*., 2013). Bagworm, *M. plana* (Lepidoptera: Psychidae) is one of serious and dominant defoliators of oil palm, *Elaies guineensis* Jacq. in India (Kalidas *et al*., 2002) as well as in other oil palm growing countries. Complete life cycle of *M. plana* ranges from 80 to 113 days and in controlled environment, it is 103. 5 days (Kok *et al*., 2011). The early-stage caterpillars scarify the abaxial surfaces of leaves resulting in necrotic areas and later instars chew the entire leaf tissue, forming holes and notches in the palm leaves. There is progressive necrosis and eventual skeletonization and drying of fronds. Normally they attack the middle and older fronds of the palms. Untreated infestation of *M. plana* can lead to devasting losses in oil palm industry mainly due to the potential of causing a complete skeletonization and eventual death of oil palm fronds. This will jeopardize the ability of palms to carry out photosynthetic activities that will support the growth of the palms and reduce the efficiency of palms to produce optimum yield. The effects of defoliation on performance in the palms were investigated by manual defoliation to simulate pest infestation. A loss in the harvest up to 40.0% is caused due to 50.0% defoliation, if limited only to the upper half of the canopy, i.e., all palmate leaves in the upper half of the canopy destroyed (Wood *et al*., 1974). Even a lower damage such as 10.0–13.0% can also cause a similar yield loss. In Sumatra and Honduras, reduction of 10.0–25.0% and 22.0–36.0% respectively in yield was recorded due to defoliators (Sipayung *et al*., 1989). Defoliation by insects reduces palm oil production from 5.0 to 30.0 t/ha/year (Giblin Davis and Howard 1989). In Sabah, Malaysia, reduction of 27.0 t of FFB (Fresh Fruit Bunches) occurred during the 30 months following the defoliation of 60.0% by *Setora nitens* (Syed and Saleh, 1998). Defoliation of the top layer of the canopy is very detrimental, and the plant may need up to 2 years to rebuild the canopy (Young 1977; Corley 1983; Henson 1990; Darus and Basri 2000). Canopy defoliation reduces plant size and biomass (Young, 1977; Henson ,1991; Dufrene and Saugier, 1993; Corley and Donough 1995). *M. plana* is inflicting serious damage in West Godavari, Krishna and East Godavari districts and in few areas of Nellore District of Andhra Pradesh, India. It is a common pest of coconut, oil palm and cocoa. The pest population is gradually increasing in the coastal districts of Andhra Pradesh and became endemic in some locations.

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Taking into account the high potential of severe economic losses that could be caused by *M. plana*, rigourous control methods and mitigation systems should be properly planned and executed. The success in doing so is to ensure that necessary steps are to be carried out at the precise times and locations. In order to achieve this, the ecological knowledge of *M. plana* especially spatial and temporal domain, should be well understood. Ecological aspects such as weather play an important role in the lavishness of bagworms outbreak owing to its adverse influence on insect behaviour.

Currently, the effort of understanding weather aspects affecting the insect pest outbreaks, along with their control practices are still leaning towards the conventional approaches that are highly dependent on in situ data collection which can be most of the times ineffective. Exploitation of modern technology such as MAXENT, DIVA GIS and GPS will essentially benefit agricultural industry. Unlike, the conventional approaches, information on the triggering factors of insect pest outbreaks, such as temperature, rainfall and vegetative conditions can be obtained through these technologies in rapid, harmless and cost-effective manner. Keeping in view of expansion of oil palm area and damage potential of *M. plana*, it is imperative to predict its potential new distribution and abundance in order to adapt by developing and supporting farmers with adequate pest management strategies to reduce greater crop and quality losses. In this sense, models are important analytical tools for understanding the risk of establishment and expansion of the pest spatially. In this study, it is attempted to predict the potential geographical distribution of *M. plana* using its current distribution and data on a range of environmental parameters using maximum entropy approach.

MATERIALS AND METHODS

In the present ecological niche modelling study, it is analysed the potential spread of Oil palm bagworm, *M. plana*, an important oil palm defoliator of interest in the region and in the light of climate change using the Maximum Entropy (MaxEnt) approach (http:// www.cs.princeton.edu/~schapire/ MaxEnt). The geographical coordinates recorded using the Global Positioning System (Garmin 12 GPS) for the pest during pest surveys programme, diagnostic field visits and obtained from CPC databases (Crop Protection Compendium, https://www.cabi.org/cpc/) were used as presence points for the species. A total of 37 presence points recorded from Bhadradri Kothagudem district of Telangana State and East Godavari, West Godavari and Krishna districts of Andhra Pradesh and six obtained from CPC databases were used for the analysis. For the current climate of India, we used monthly data from the WorldClim (http://www.worldclim.org) database sourced from global weather stations. The bioclimatic variables, including annual mean temperature, mean diurnal range, maximum temperature of warmest month, minimum temperature of coldest month, annual precipitation, and precipitation of the wettest and driest months were downloaded from the WorldClim dataset-(freely available at http://www.worldclim.org). The WorldClim data provides interpolated global climate surfaces using latitude, longitude and elevation as independent variables and represents long term (1950-2000) monthly means of maximum, minimum, mean temperatures and total rainfall as generic 2.5 arc-min grids. Environmental layers used (all continuous) in the modelling were: bio1 (Annual mean temperature); bio2 (Mean diurnal range); bio3 (Isothermality); bio4 (Temperature seasonality); bio5 (Max. temperature of warmest month); bio6 (Min. temperature of coldest month); bio7 (Temperature annual range); bio8 (Mean temperature of wettest quarter); bio9 (Mean temperature of driest quarter); bio10 (Mean temperature of warmest quarter); bio11 (Mean temperature of coldest quarter); bio12 (Annual precipitation); bio13 (Precipitation of wettest month); bio14 (Precipitation of driest month); bio15 (Precipitation seasonality); bio16 (Precipitation of wettest quarter); bio17 (Precipitation of driest quarter); bio18 (Precipitation of warmest quarter); and bio19 (Precipitation of coldest quarter). The model included the regularization values linear/quadratic/product:0.365, categorical value: 0.250, threshold:1.760 and hinge:0.500. Twenty four presence record used for training and seven for testing. Maximum number of background points (10024) used to determine the Maxent distribution. A logistic output for constructing the predictive models was selected as it is the easiest to comprehend, giving a value between 0 and 1 as the probability of occurrence of grass species (Phillips and Dudik, 2008). Jackknife analyses and mean area-under-curve (AUC) plots were created using MaxEnt. AUC is commonly used as a test of the overall performance of the model (Elith *et al*., 2006) and it remains a handy indication of the usefulness of a model (Elith *et al*., 2006 and 2011). A value of 1.00 is an exact agreement with the model, while a value of 0.50 represents a random fit. Jackknife analysis indicates which variable has the greatest stimulus on the model and the overall success of the model. DIVA-GIS software version 7.5, a freely downloadable software from http://www.diva-gis.org was used to generate the potential distribution map with input ASCI file obtained in MAXENT analysis (maximum entropy method).

RESULTS AND DISCUSSION

Early understanding of potential spread insect pest occurrence and early detection of outbreaks and via geospatial technology can potentially, reduces labour time and cost, limit environmental pollution and reduce the potential of a devastating impact of insect pest outbreaks by controlling them before they spread. The Ecological Niche Model generated for the current climatic grids using the Maximum entropy approach are provided in Fig. 1. The potential districts identified for new geographic distribution and establishment of *M. plana* in India are Chittor, Ananthapur, Guntur, Nellore, Visakhapatnam, Prakasham, Vizianagaram, Srikakulam districts apart from East Godavari, Krishna and West Godavari (already present) in Andhra Pradesh; Dakshin Kanada, Kollar, Tumkur and Bellary districts in Karnataka; North Hugli, 24 Paragnas and Mednapur South of West Bengal; Trissur, Palakkad and Malapupuram districts of Kerala; Puri district in Odisha; Chengalpattu, North Arcot and Thiruvannamalai districts in Tamil Nadu; and Khammam, Bhadradrigudem (already present), Nalgonda and Warangal districts in Telangana state, India based on the model generated in the present study. Various Committees constituted by Department of Agriculture, Cooperation and Farmers Welfare (DAC and FW), Government of India have identified 19.33 lakh ha area suitable for oil palm cultivation in the country. Among them potential States were Andhra Pradesh, Arunachal Pradesh, Assam, Chhattisgarh, Gujarat, Karnataka, Kerala, Mizoram, Odisha, Telangana, Tamil Nadu, Goa, Tripura, Maharashtra, West Bengal and Nagaland. One of the interesting predictions emerging from this study is that the pest is not likely to spread to North Eastern states of India (having a potential area of 2.18 lakh ha) and Eastern States, Andaman and Nicobar Islands, Gujarat (having potential area of 2.6 lakh ha.), Goa, Maharashtra (having 1.8 lakh ha.), Chhattisgarh (having 0.5 lakh ha) etc. In fact, observations made during field visits to North Eastern states, and Andaman and Nicobar Islands also indicated that the results are qualitatively upheld by the absence this pest in those regions. Among the major oil palm producing states in India, Andhra Pradesh has the largest acreage (1.63 lakh ha.) and has maximum suitable environment for *M. plana* according to the present study. Hence, to prevent further introductions and expansions to predicted areas, appropriate management efforts should be focussed. In oil palm area expansion programme, site suitability is an important factor to determine the productivity of the crop, in this regard, map of potential geographical distribution of *M. plana* will be useful to determine areas which will have the greatest success for growing the crop.

Table 1 gives estimates of relative contributions of the environmental variables to the MAXENT models of current and future climatic conditions in predicting the potential distribution of *M. plana*. Bioclimatic variables *viz*., Annual mean temperature (bio1), mean temperature of warmest quarter (bio10), precipitation of driest month (bio14), precipitation of coldest quarter (bio19), precipitation of warmest quarter (bio18), mean temperature of wettest quarter (bio8), mean temperature of coldest quarter (bio11), mean temperature of driest quarter (bio9) and isothermality (bio3) contributed maximum to the current climate model with percent values of 39.1, 24.2, 8.1, 7.6, 5.7, 4.3, 3.2, 2.5 and 2.0 respectively. Interestingly, the bioclimatic variables such as temperature seasonality (bio 4) and maximum temperature of warmest month (bio 5) have no specific contribution in building up of the model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is re-evaluated on the permuted data, and the resulting drop in training AUC is shown in the Table 1, normalized to percentages. As with the variable Jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated. Fig.3. shows the results of the Jackknife test of variable importance generated using MAXENT model. It is appropriate to examine the importance of a single environment variable in prediction process. The environmental variable with highest gain when used in isolation is bio1, which therefore appears to have the most useful information by itself in affecting the spread of *M. plana*. The environmental variable that decreases the gain the most when it is omitted is bio18, which therefore appears to have the most information that is not present in the other variables. The MAXENT model expressed regularized training gain is 4.750 for current climate, while training AUC is 0.999 and unregularized training gain is 5.449 respectively. Fig. 3 shows the omission rate and predicted area as a function of the cumulative threshold. The omission rate is calculated both on the training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold.

Figures 4 (A, B, C, D) are the response curves which show that how each environmental variable affects the MaxEnt prediction for current climate model influenced by environmental variables Bio1, Bio10, Bio14 and Bio19. The response curve is an important result of the model output and indicates the relationship between species and environment. The curves show how the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. The response curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together. In contrast to the above marginal response curves, Fig. 4 (E, F, G, H) each of the following curves represents a different model, namely, a MaxEnt model created using only the corresponding variable. These plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other variables.

Maximum entropy (MAXENT) is considered as the most accurate model, performing extremely well in predicting occurrences in relation to other common approaches (Elith *et al*., 2006; Hijmans and Graham, 2006), especially with incomplete information. MAXENT is a niche modelling method that has been developed involving species distribution information based only on known presences and was selected to model potential current and future distribution of a crop. It has been successfully used by many researchers earlier to predict distributions such as sugarcane woolly aphid, *Ceratovacuna lanigera* (Ganeshaiah *et al*., 2003) macro fungi (Wollan *et al*., 2008); forests (Carnaval and Moritz, 2008), rare plants (Williams *et al*., 2009), stony corals (Tittensor *et al*., 2009); seaweeds (Verbruggen *et al*., 2009); sorghum (Sivaraj *et al*., 2016); *Spodoptera frugiperda* on maize (Baloch *et al*., 2020) and many other species (Elith *et al*., 2006). Several articles describe its use in ecological modelling and explain the various parameters and measures involved (Phillips *et al*., 2004, 2006 and 2008; Elith *et al*., 2011). MaxEnt is the most adapted model used for coffee and mango (Eitzinger *et al*., 2013). In information theory, entropy is randomness or unpredictability, meaning that the portion that is not explained by the probability distribution has no remaining information with respect to the distribution of the prior data. In one of the previous studies, it was found the temperature played significant role in the occurrence of *A. meyriki* infesting oil palm (Saravanan *et al*., 2020). Temperature is the main environmental factor that affects the growth, development and distribution of insects. Also, reproduction of insects is greatly affected by the external temperature, so that reproduction is reduced whenever the temperature is too high or too low. Use of Ecological Niche Models to assess the distribution of *M. plana* for current regions in Indian climate was the primary focus of the study. This study utilized the geo-referenced occurrence locations and climatic grid data for the collection sites and analysed information about environmental conditions at the current locations of *M. plana* on oil palm to predict the probability of suitable conditions existing for the pest at other locations of the country. The predictions of potential distribution of the pest arrived at in this study should help in developing strategies for monitoring and managing this defoliator of oil palm. Further, the modelling tools used in this study can be of great help in tackling several invasive pests and diseases. More importantly, such predictions would facilitate better preparedness to fight the outbreak of pests and diseases in crops.

Table 1. Estimates of relative contributions of the environmental variables to the MAXENT model for *M. plana*

Variable	Percent contribution	Permutation importance
Annual mean temperature (bio1)	39.1	67.1
Mean temperature of warmest quarter (bio10)	24.2	12
Precipitation of driest month (bio14)	8.1	0.4
Precipitation of coldest quarter (bio19)	7.6	0.4
Precipitation of warmest quarter (bio18)	5.7	0
Mean temperature of wettest quarter (bio8)	4.3	0
Mean temperature of coldest quarter (bio11)	3.2	0.1
Mean temperature of driest quarter (bio 9)	2.5	0.1
Isothermality (bio 3)	2	0
Precipitation of driest quarter (bio17)	1.3	0.1
Mean diurnal range (bio 2)	1.2	19.5
Precipitation of wettest month (bio13)	0.3	0
Precipitation of wettest quarter (bio16)	0.3	0
Temperature annual range (bio7)	0.1	0.2
Annual precipitation (bio12)	0.1	0
Minimum temperature of coldest month (bio6)	0.1	0
Precipitation seasonality (bio15)	0.1	0.1
Temperature seasonality (bio 4)	0	0
Maximum temperature of warmest month (bio 5)	0	0

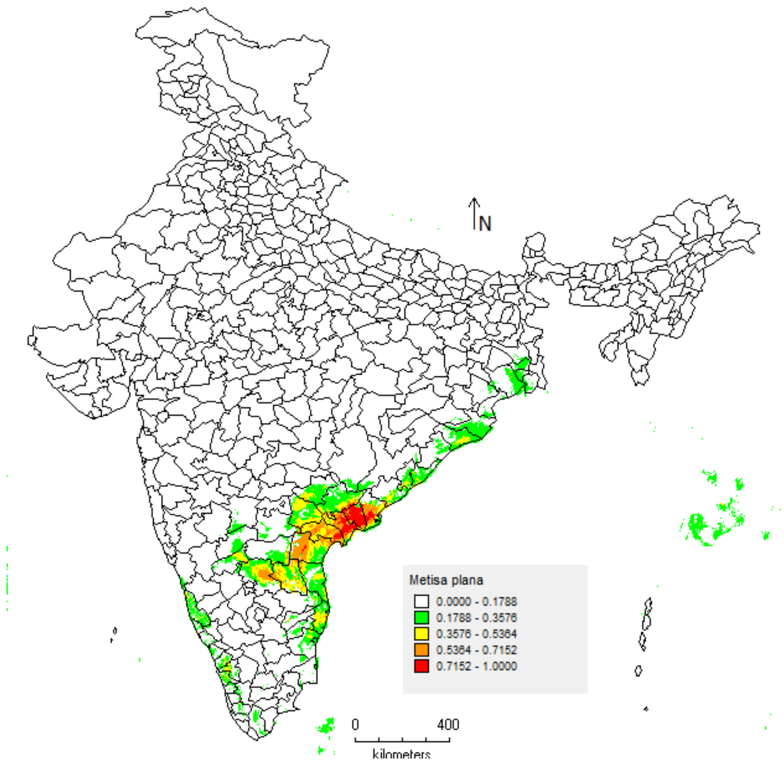


Figure 1. Ecological Niche Model generated for *M. plana*

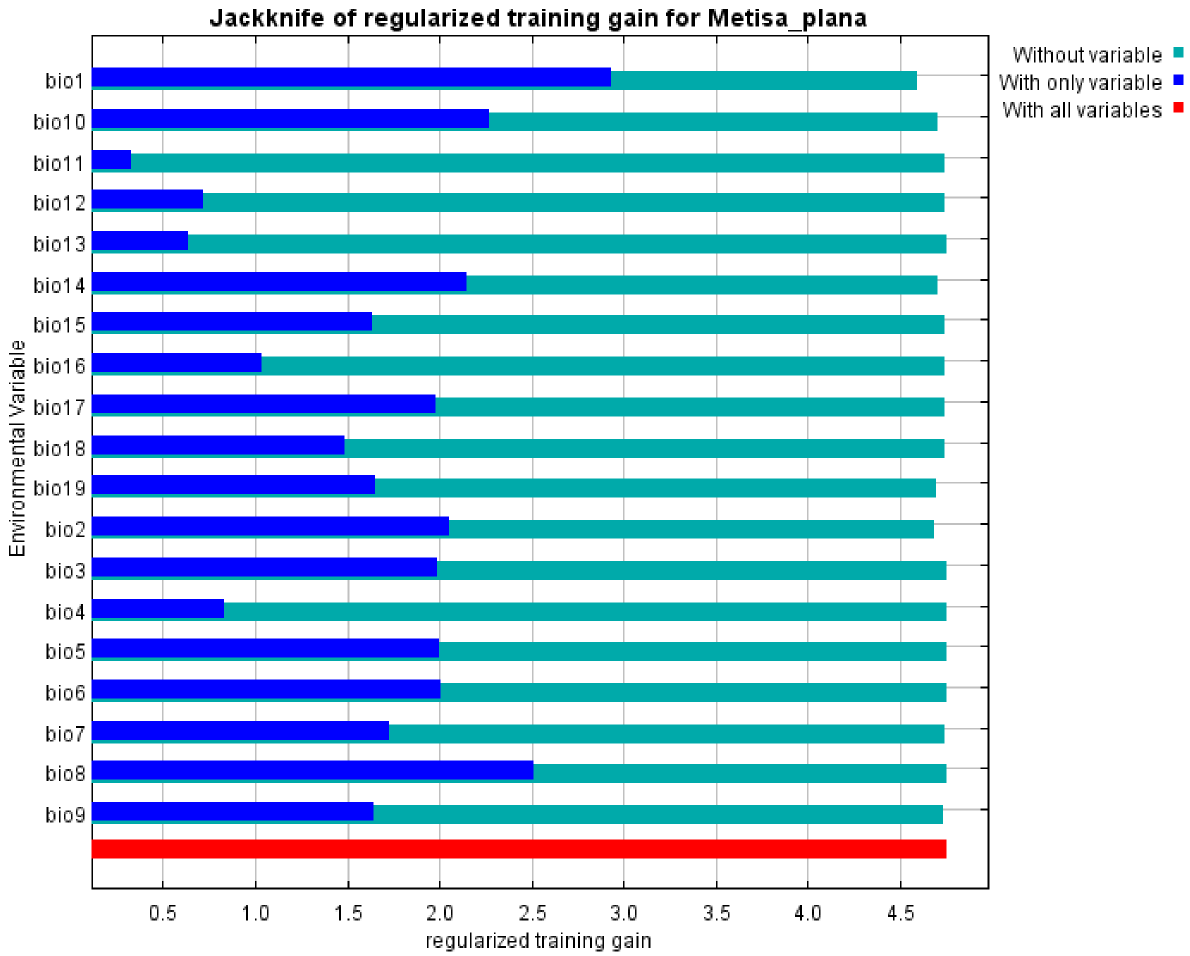


Figure 2. Jackknife of regularized training gain for *M. plana*

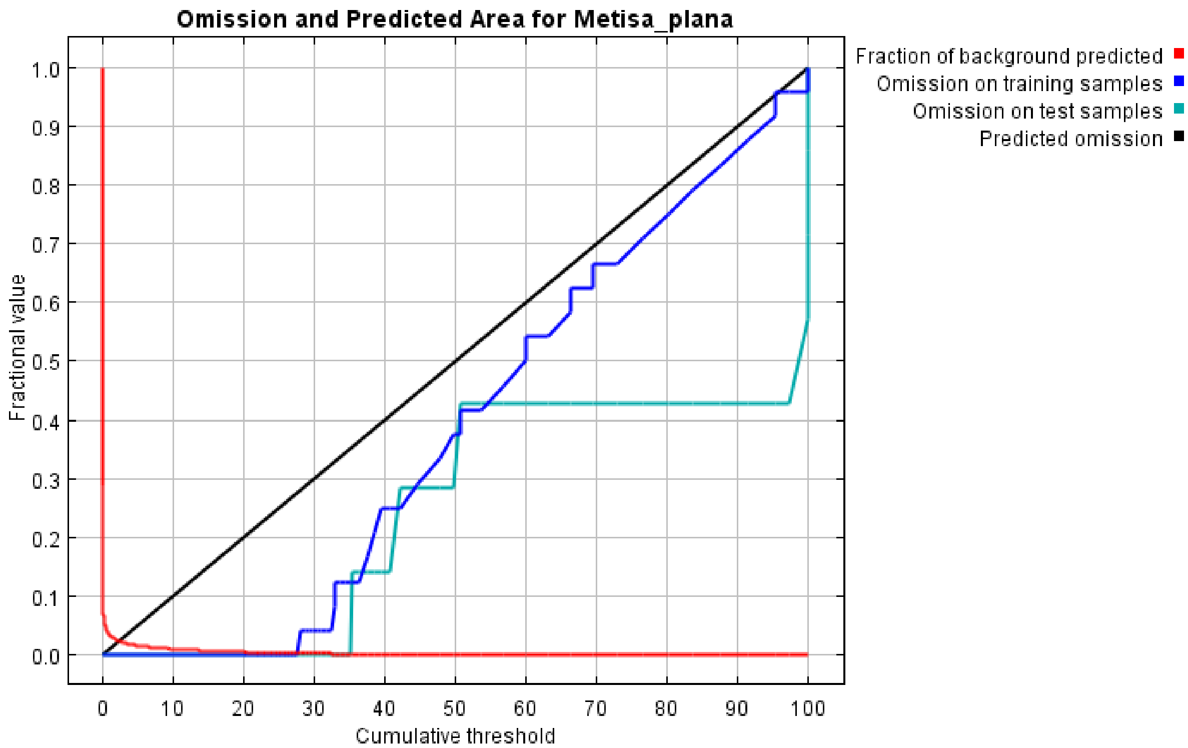
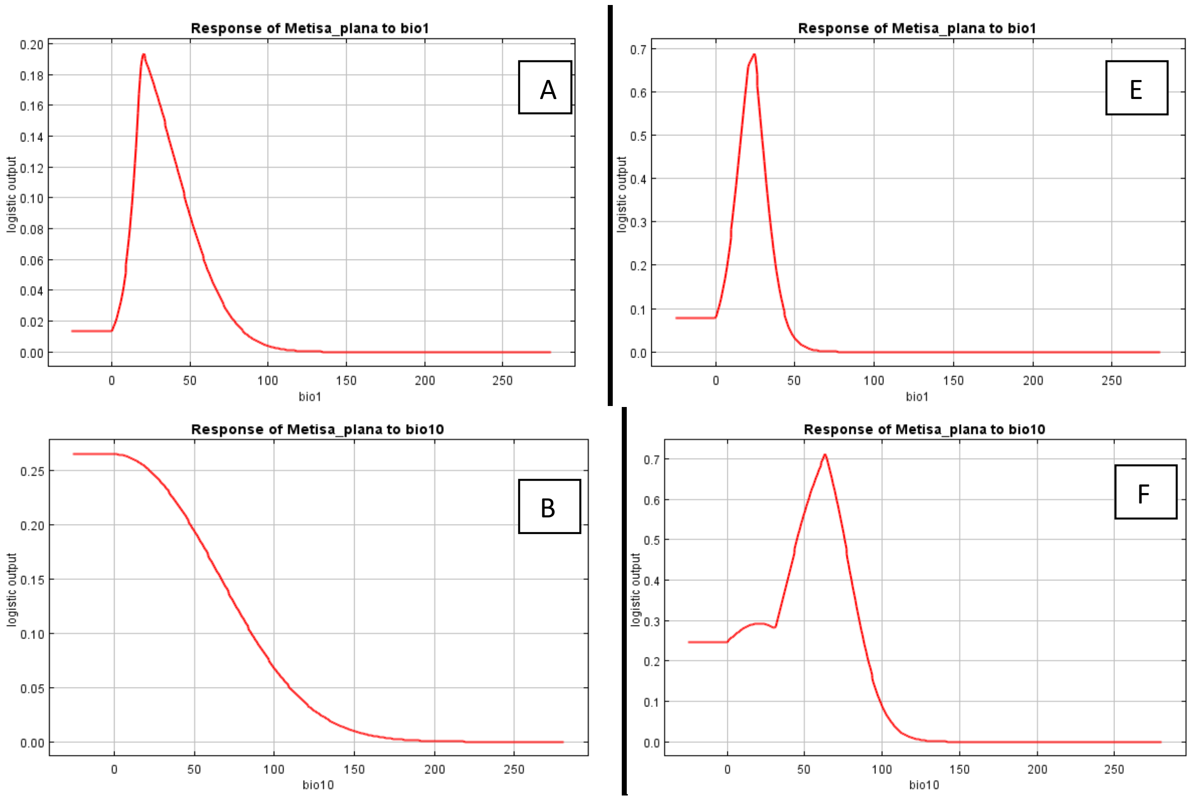


Figure 3. Omission and Predicted Area for *M. plana*



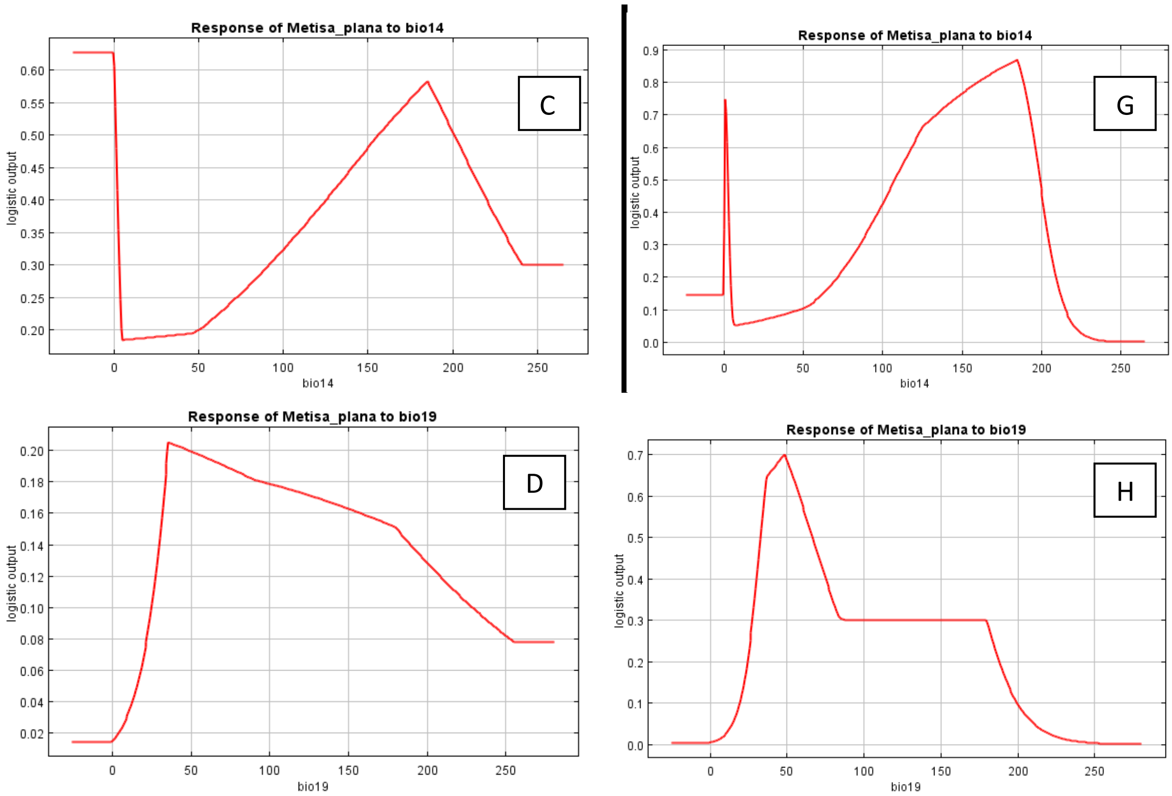


Figure 4. Response curves for bioclimatic variables having high influence on the MAXENT Model on *M. plana* for current climate (A, B, C, D) and dependencies induced by correlations (E, F, G, H)

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