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Mapping the Climate Suitability Using Maximum Entropy Modelling Approach for Red banana Cultivation in India.

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Abstract

Ecological niche modelling or Predictive habitat for cultivation framework for Red Banana (AAA), an important prized variety occurring in Tamil Nadu, Kerala, Karnataka, Gujarat, Chattisgarh state has been analyzed using Maximum Entropy method for present and future climatic conditions. The generated MaxEnt model indicated that the entire coastal belt of Tamil Nadu, Western Ghats region, Parts of Gujarat, Chattisgarh, Odisha, Andhra Pradesh, Bihar would be the ideal climate suitable locations for the cultivation of red banana variety in 2050. In-situ, on-farm conservation and other genetic resources management of Red banana variety could be taken up accordingly, in future in the identified areas in the light of climate change.

Keywords: AAA, Red Banana, DIVA-GIS, MaxEnt modelling

I. INTRODUCTION

Bananas are among the most widely consumed fruits in the world. India is the largest producer of banana among world countries contributing to 18% of world production with an average production of over 24.9 million tonnes in 2012. Red bananas, also known as *Sevvazhai* (Tamil),*Chovazha*, *Kappa pazham* (Malayalam), *Chandra bale* (Karnataka), *Lal velchi* (Bihar) are a highly prized variety of banana with reddish-purple skin. The colour of the pseudo-stem, petiole, midrib and fruit rind is purplish red. It is a robust plant with bunches weighing 20-30 kg under good management practices. When ripe, raw red bananas have a flesh that is cream to light pink in color. Fruits are sweet, orange yellow coloured and with a pleasant aroma sweeter and softer than the yellow Cavendish varieties. Commercial cultivation is popular in Kanyakumari, Tirunelveli districts of Tamil Nadu and parts of other states *viz*., Kerala, Karnataka, Gujarat, Chattisgarh, Bihar and Andhra Pradesh. To mitigate the challenges of vagaries in climate, an attempt has been made to map the climate suitability of red bananas using Maximum Entropy method. It is hoped that the generated models would be highly useful in managing red banana genetic resources in the country.

II. METHODOLOGY

MaxEnt 3.3.3k software (www.cs.princeton.edu/~schapire) was used as it requires only presence records and its efficacy has been well documented [1,2,3]. Presence records (geographical coordinates) were drawn from red banana growing regions in India (Fig.1). For the MaxEnt model, 19 bioclimatic variables [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); bio19 (Precipitation of coldest quarter)] with the 2.5 arc' resolution were available from the Worldclim website (www. worldclim.org), which was used to describe the climate suitable regions for red banana in India. This database comprises many derived variables based on long-term temperature and rainfall that are often used for species niche modelling. Twelve candidate variables were selected by use of correlation tests to eliminate highly correlated variables and by assessment of their ecological relevance, given current knowledge of the target species. MaxEnt was used to evaluate the habitat suitability of red banana based on its current range. Because species distribution models do not perform well if the climate in the target area is very different from the native and invaded ranges, a multivariate environmental similarity surface (MESS) was performed to determine the degree of model extrapolation in the areas of interest. DIVA-GIS version 7.5 [4] was used to generate maps by importing ASCI output files from MaxEnt. The Jacknife analysis was performed to indicate the most illuminating variables. The accuracy and performance of species distribution model was evaluated using threshold-independent receiver operation characteristic (ROC) analysis [2,3] and threshold dependent binomial test of omission [3]. The area under the (AUC) ranges between 0 and 1. Models with an AUC value higher than 0.75 are acceptable ROC curve models [5]. Omission rates in optimal models are less than 0.05 [6].

Fig.1. Red banana presence records used in the present study

Climate data for Future conditions were obtained from http://www.worldclim.org that was downscaled global climate model (GCM) data from CMIP5 (IPPC Fifth Assessment). The ACCESS1-0 climate model developed by CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia) in collaboration with BOM (Bureau of Meteorology, Australia) was used for the analysis at a special resolution of 2.5-minute (of a longitude/latitude degree) that is about 4.5 km at the equator. The greenhouse gas scenario was kept as RCP 4.5 (representative concentration pathway) for the year 2050 (average for 2041-2060). The RCPs are consistent with a wide range of possible changes in future anthropogenic (i.e., human) greenhouse gas (GHG) emissions. RCP 4.5 assumes that global annual GHG emissions (measured in CO2-equivalents) peak around 2040, then with emissions declining substantially thereafter.

III. RESULTS AND DISCUSSION

Species distribution modelling techniques produce maps of the potential distribution of species[7]. MaxEnt [2,3] is a predictive biogeography programme that uses a maximum entropy algorithmto match known locality points for a species to potential localities, based on theirenvironmental characteristics. It is a useful technique as it does not require absence records to build a predictive model. We have used this technique to identify suitable locations to grow red banana in the changed climate regime.

Figure 2 represents the MaxEnt modelling probability matching locations suitable for red banana cultivation in India based on the presence points. The high probability value range of 0.79 to 1.0 for likely potential regions for cultivation occurs in Tamil Nadu, Kerala, Karnataka, Maharashtra, Gujarat, Goa, Andhra Pradesh, Chattisgarh and Odisha. Warmer colours in the map indicate the better predicted conditions for red banana cultivation.

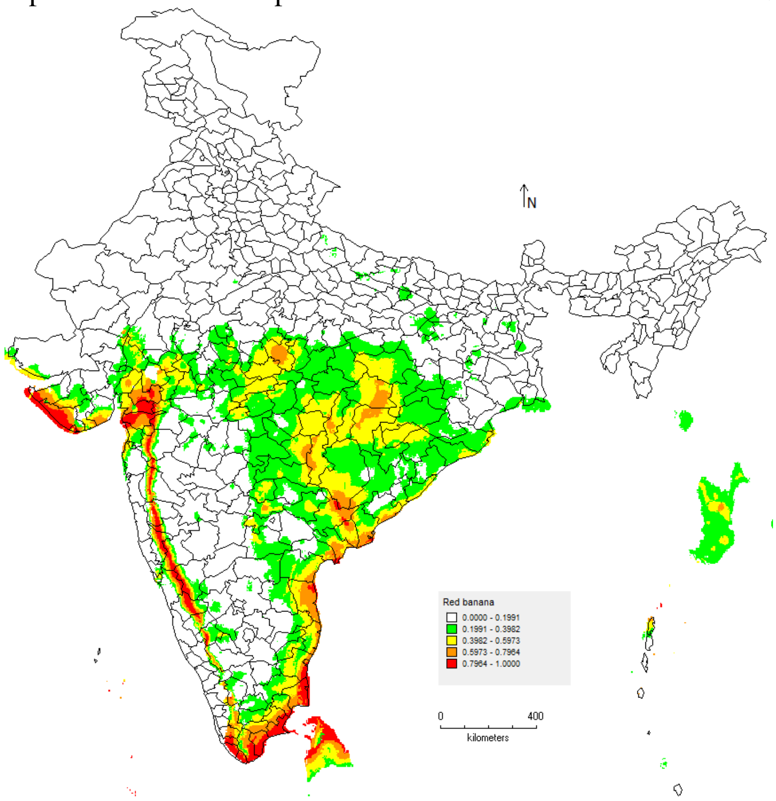

Fig.2. MaxEnt model generated for red banana using current climate data

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. Fig.4 shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio6, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is bio19, which therefore appears to have the most information that isn't present in the other variables.

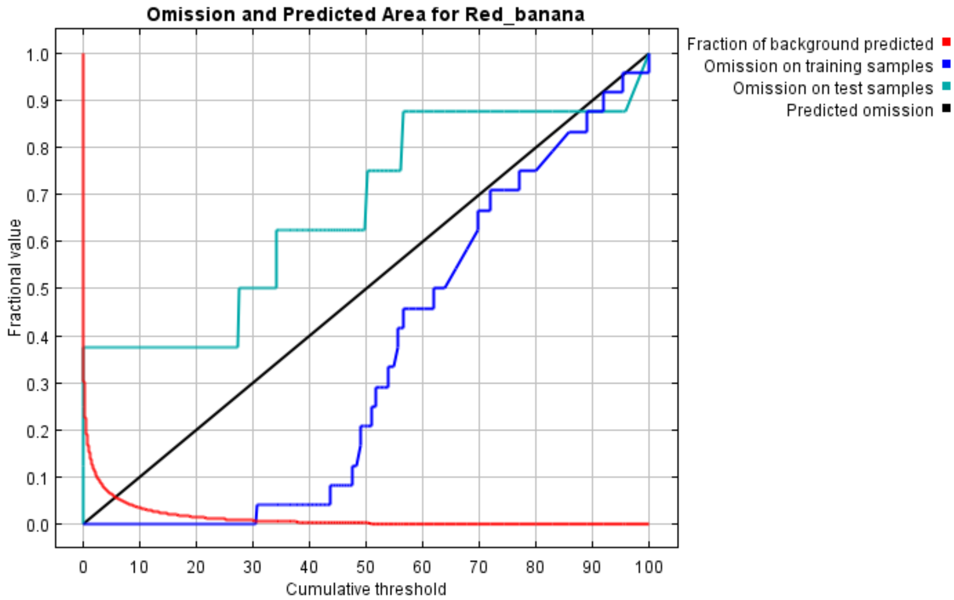

Fig.3. Omission and predicted area for Red Banana in the MaxEnt model

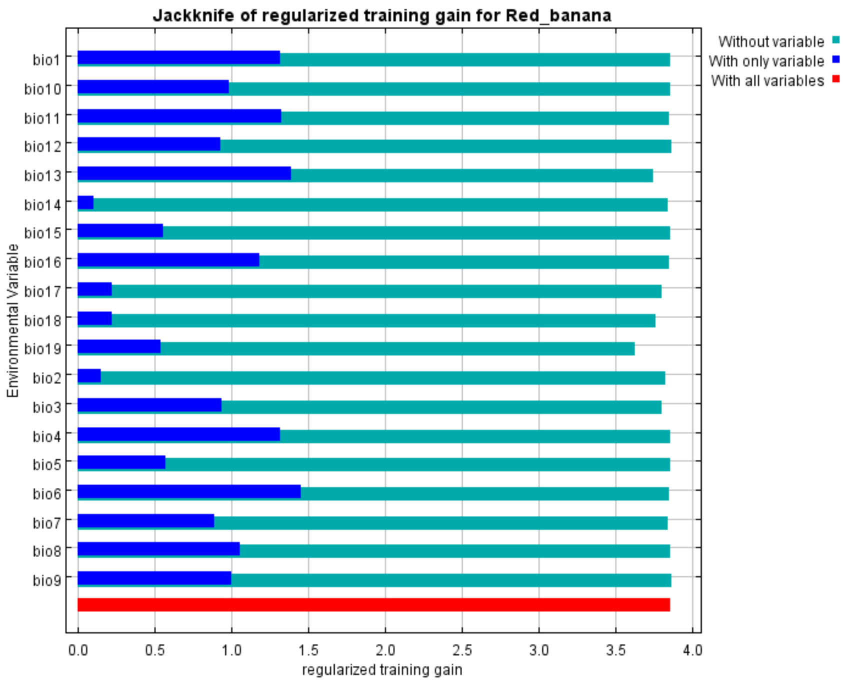

Fig.4. Result of Jackknife test performed on Red banana

Table 1 gives estimates of relative contributions of the environmental variables to the Maxent 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 reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Table 1. Estimates of relative contributions of environmental variables to the Maxent model on on Virupakshi hill banana variety.

Variable	Percent contribution	Permutation importance
Precipitation of wettest month (bio13)	29.1	12.4
Min Temperature of coldest quarter (bio11)	15.8	43.5
Isothermality (bio3)	15.6	4.3
Minimum temperature of the coldest month (bio6)	11.9	0
Precipitation of coldest quarter (bio19)	6.2	0.7
Mean temperature of wettest quarter (bio18)	5.2	2.4
Precipitation of driest quarter (bio17)	3.8	0.4
Precipitation seasonality (bio15)	3.2	0.1
Annual mean temperature (bio1)	2.9	0
Temperature annual range (bio7)	2.8	0.4
Mean diurnal range (bio2)	1.7	0.5
Precipitation of driest month (bio14)	0.7	0.2
Temperature seasonality (bio4)	0.4	34.4
Precipitation of wettest quarter (bio16)	0.3	0.1
Annual Precipitation (bio12)	0.3	0.3
Mean temperature of the wettest quarter (bio8)	0.1	0.3
Max temperature of warmest month (bio5)	0	0
Mean Temperature of Driest Quarter (bio9)	0	0
Mean Temperature of Warmest Quarter (bio10)	0	0

Fig. 5 represents the MaxEnt model for red banana generated for future climatic conditions (2050). The model indicates that more potential climate suitable regions could be available in 2050 when compared to present climatic scenario for the cultivation of red banana. Entire coastal belt of Tamil Nadu, Western Ghats region, Parts of Gujarat, Chattisgarh, Odisha, Andhra Pradesh, Bihar would be the climate suitable locations for the cultivation of highly prized red banana variety.

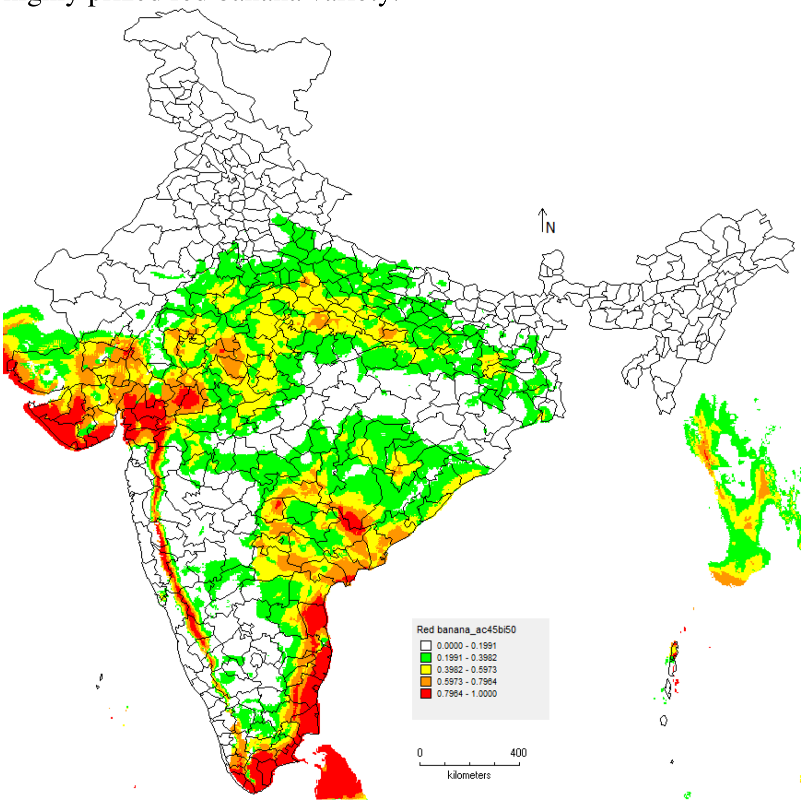

Fig.5. MaxEnt model generated for red banana using future climate (year 2050)

MaxEnt integrates species occurrences with background data (i.e., randomly selected points) from spatial environmental variables representing different environmental gradients in the study area and generates probability of species' presence [3]. It identifies areas that have conditions most similar to species' current known occurrences and ranks them from 0 (unsuitable or most dissimilar) to 1 (most suitable or most similar). MaxEnt generates a set of feature classes (*i.e*., linear [L], quadratic [Q], product [P], threshold [T], and hinge [H]) using environmental variables. It uses a regularization multiplier (RM) to reduce the number of parameters and thus automatically controls the model complexity (Phillips and Dudik 2008, Elith *et al*. 2011). The default RM value is 1; a smaller value of RM (1) may potentially overfit the model and produce more restricted distribution whereas a higher value (>1) would result in simpler models with less discriminating power and broader species potential distribution [3]. Therefore, tuning of MaxEnt model settings has been suggested for selecting an optimal model to enhance predictions [9, 10].

The maximum entropy modelling technique has been successfully used to model potential plant and insect pests distributions for purposes such as monitoring invasive species and disease vectors and their likely spread due to climate change by many researchers in the recent past (11,12,13-31]. Reddy *et al*., [32, 33] used MaxEnt for identifying suitable regions for cultivation of roselle and *Basella alba* respectively in the country to combat climate change that may affect the crop growing conditions. It executes well on small sample sizes [34], which indicates that the multiplicative methods used in MaxEnt give better predictions than the discriminative methods employed by other techniques [1,2,8]. However, we have attempted to identify suitable locations for sustainable red banana cultivation country in the changed climatic regime.

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