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Maximum Entropy (MaxEnt) modelling approach for predicting potential climate suitable locations of popular banana varieties in India: I. Poovan (AAB)

N. Sivaraj, K. Rameash and B. Sarath Babu

[1]*ICAR-National Bureau of Plant Genetic Resources, Regional Station, Hyderabad 500 030, Telangana State*

Abstract

Maximum Entropy modelling approach for predicting the potential climate suitable region for the sustainable cultivation of Poovan banana variety described in this article for the present and future climate (2050) scenario.

KEY WORDS: Poovan variety, banana, GIS, MaxEnt modelling

I. INTRODUCTION

The Banana is the world's most popular fruit and a staple crop for more than 400 million people. India ranks first in terms of area and production, growing in about 4, 90,700 ha with an annual production of 168, 13,500 mt sharing about 17% of global production. Among the states in India, Tamil Nadu, Karnataka and Maharashtra possesses major share in area and production of banana in the country. Poovan variety (AAB) is one of the leading commercial banana cultivars grown perennially throughout the country. Poovan has region specific ecotypes viz., *Palayankodan* (Kerala), *Karpura Chakkarakeli* (Andhra Pradesh). Tamil Nadu is the leading producer of Poovan cultivar owing to its climatic and marginal soil condition. Poovan is also commercially cultivated for leaf industry throughout Tamil Nadu and in certain parts of Kerala. It produces medium sized bunch (weighing around 25 kg) with 12 hands yielding more than 200 fruits of medium size. Fruit possess thin skin which peels off easily. It is slightly acidic, firm and has typical sour-sweet aroma. Crop duration is between 11 and 14 months. Fruits turn to attractive golden yellow on ripening. The bunch is having closely packed fruits with good keeping quality and resistant to fruit cracking is its plus points. Considering its importance, an attempt has been made to map the climate suitability regions in India for the sustainable cultivation of *Poovan* banana variety in the climate change regime. We have used Maximum Entropy modelling for delineating the potential regions for the cultivation of *Poovan*, a popular banana variety.

II. MATERIALS AND METHODS

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 *Poovan* growing regions in India viz., Arunachal Pradesh, Meghalaya, Tripura, Mizoram, Jharkhand, Andamans, Kerala, Karnataka and Tamil Nadu. 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 *Poovan* variety 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].

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 tobuild a predictive model. We have used this technique to identify suitable locations to grow red banana in the changed climate regime.

Figure 1 represents the MaxEnt modelling probability matching locations suitable for *Poovan* banana cultivation in India based on the presence points. The high probability value range of 0.5 to 1.0 for likely potential regions for cultivation occurs in Parts of Tamil Nadu, Kerala, Karnataka, Andhra Pradesh, Arunachal Pradesh, Assam, Meghalaya, Tripura, Mizoram, Bihar, Jharkhand, Uttarakhand, Nagaland, West Bengal and Odisha. Warmer colours in the map indicate the better predicted conditions for *Poovan* banana cultivation.

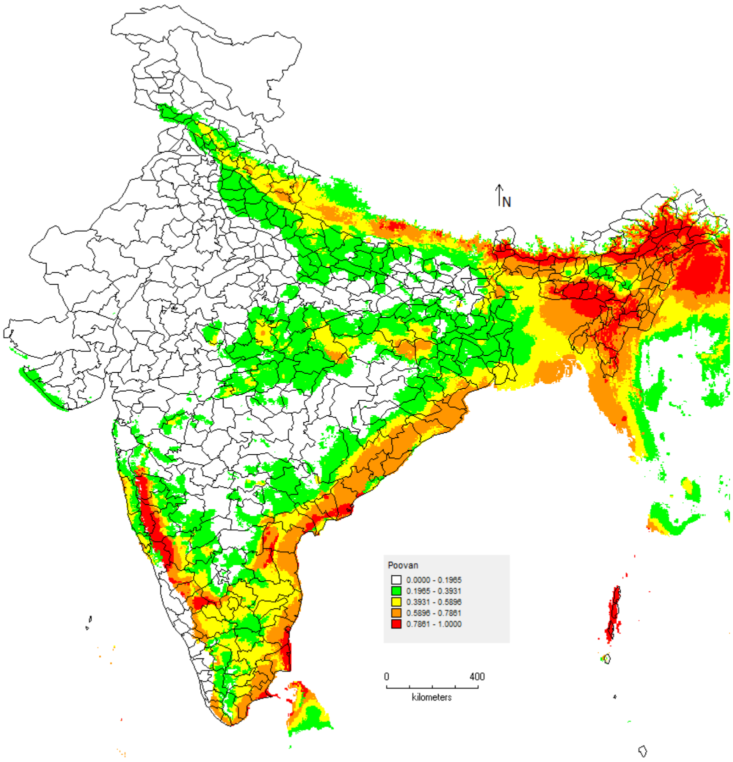

Fig.1. MaxEnt model generated for Poovan banana variety using current climate data

Fig.2 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.3 shows the results of the jackknife test of variable importance. The environmental variable with highest gain when used in isolation is bio13, 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.

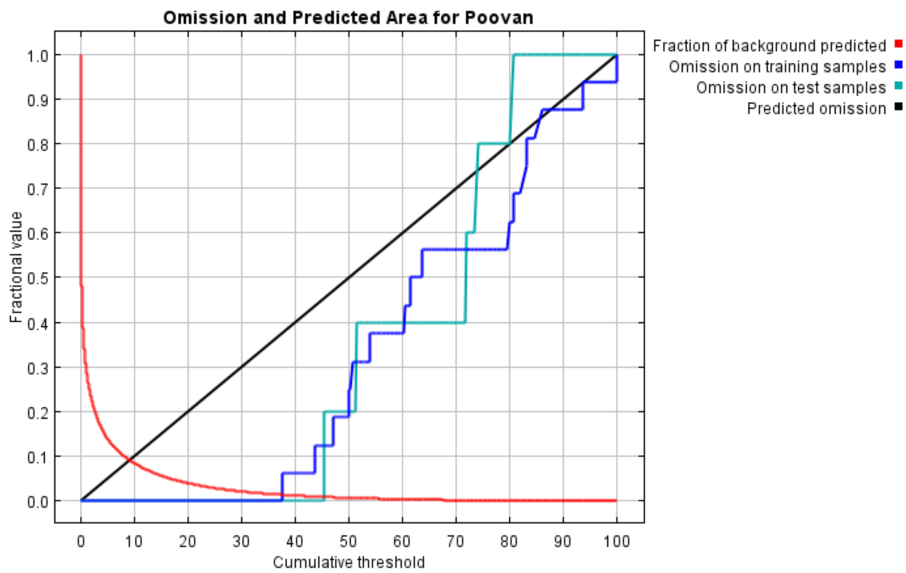

Fig.2. Omission and predicted area for Poovan variety in the MaxEnt model

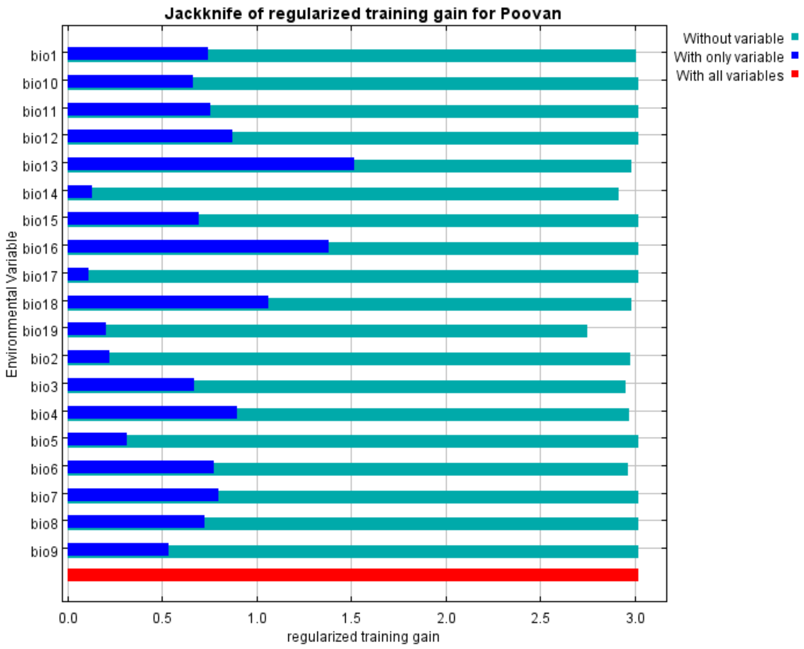

Fig.3. Result of Jackknife test performed on *Poovan* banana variety

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 *Poovan* banana variety

Variable	Percent contribution	Permutation importance
Precipitation of wettest month (bio13)	35.6	4.7
Precipitation of coldest quarter (bio19)	12.8	15.7
Isothermality (bio3)	10.9	13.3
Precipitation seasonality (bio15)	10.7	0
Mean temperature of wettest quarter (bio18)	7.4	0.5
Minimum temperature of the coldest month (bio6)	5.5	2.3
Precipitation of wettest quarter (bio16)	4.7	0
Precipitation of driest month (bio14)	3.5	4.6
Min Temperature of coldest quarter (bio11)	2.9	0
Mean diurnal range (bio2)	2.9	4
Temperature seasonality (bio4)	1.7	54.5
Mean Temperature of Driest Quarter (bio9)	0.8	0
Annual mean temperature (bio1)	0.5	0.1
Mean temperature of the wettest quarter (bio8)	0.1	0.1
Mean Temperature of Warmest Quarter (bio10)	0	0.1
Annual Precipitation (bio12)	0	0
Precipitation of driest quarter (bio17)	0	0
Max temperature of warmest month (bio5)	0	0
Temperature annual range (bio7)	0	0

Fig. 4 represents the MaxEnt model for red banana generated for future climatic conditions (2050). The model indicates that potential climate suitable regions could be available in 2050 for the cultivation of *Poovan* banana variety in the states of Tamil Nadu, Western Ghats region (Kerala & Karnataka), Parts of North Eastern States, Uttarakhand, Himachal Pradesh, Andhra Pradesh, Odisha and West Bengal. However, Bihar and Jharkhand would be wiped out from cultivation of this Poovan variety in 2050 as these areas are falling under low probability. It is advised that alternative crops suitable for that period's climatic conditions should be taken up for cultivation.

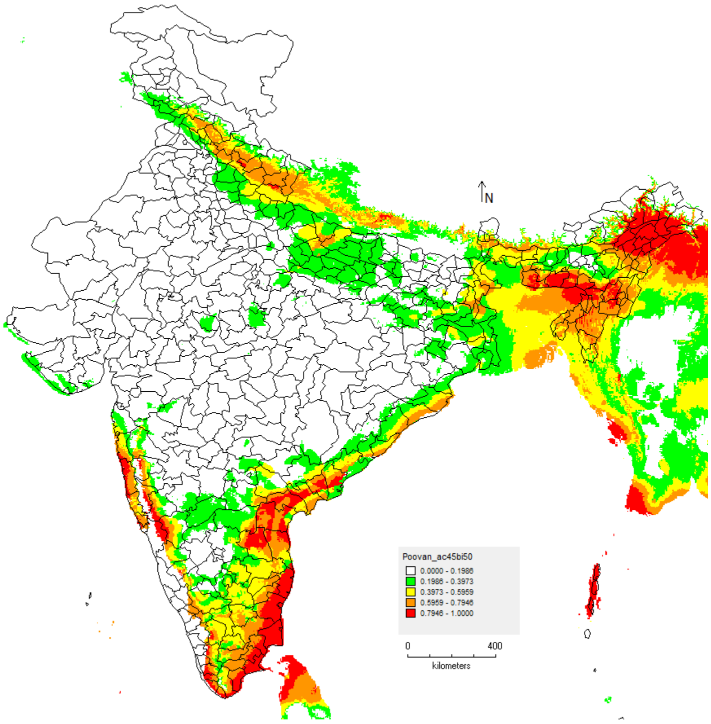

Fig.4. MaxEnt model generated for *Poovan* variety using future climate (year 2050)

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[3] [1]. 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 [2]. 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 [11,12,13,14,15-31]. 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][3]. However, we have attempted to identify suitable locations for sustainable *Poovan* banana variety cultivation in our country in the changed climatic regime.

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