COMPARISON OF BIOCLIMATIC, NDVI AND ELEVATION VARIABLES IN ASSESSING EXTENT OF COMMIPHORA WIGHTII (ARNT.) BHAND.

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ABSTRACT:

Commiphora wightii (Arnt.) Bhand., is an important medicinal plant of Indian Medicine System (IMS) since ancient time. It is used in different ailments of obesity, arthritis, rheumatism and high cholesterol. Due to overexploitation its natural populations declined to large extent. IUCN has put it under Data Deficient (DD) category due to lack of data on its extent of occurrence in nature. Hence, the study was carried out using MaxEnt distribution modelling algorithm to estimate its geographic distribution and to identify potential habitats for its reintroduction. For modelling employed 68 presence locality data, 19 bioclimatic variables, Normalize Difference Vegetation Index (NDVI) and elevation data. These were tested for multicollinearity and those variables having r-value less than 0.8 were selected for further analysis, which was carried out in two ways i) Bioclimatic variables and elevation; ii) NDVI and elevation. Area Under the Curve (AUC) in both analysis was above 0.9 for all variables, indicating very high accuracy of prediction. Variables governing distribution of *C. wightii* in the analysis using bioclimatic and elevation data set are precipitation seasonality (56.6%),annual precipitation (16.4%) and elevation (14.7%). Extent of occurrence of *C.wightii* predicted by model closely matched in the districts of Jaisalmer and Barmer. In the second analysis elevation (48.3%), NDVI of June (11.1%) and August (11.2%) contributed for NDVI and Elevation data set. NDVI of June corresponds to its leafing phase while NDVI of August to flowering phase. Area of its occurrence predicted for NDVI and elevation data set are Bikaner, Churu, Jhunjhunun some part of Jodhpur which are completely sandy, where *C. wightii* is totally absent. Extent of occurrence was also validated in ground survey. Potential areas for its reintroduction were identified as Jaisalmer and Barmer districts in Indian arid zone.

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1. INTRODUCTION

Habitat fragmentation, over exploitation, climate change and human activities are responsible for biodiversity degradation. Consequently, some 20% of plant species are now close to disappearance from planet earth (Brummitt & Bachman, 2010). In order to conserve these species understanding patterns of occurrence of these species is a prerequisite to prioritize habitats for reintroduction (Margules & Pressey, 2000). One of the most effective ways to know habitat suitability for reintroduction is to model existing habitats of occurrence so as to know areas of abundance, scarcity and absence. This enables conservation planning for rescue and recovery of threatened species with assured success under the challenging situations of degradation and climate change. (Gogol-Prokurat, 2011; Barik & Adhikari, 2011). Different environmental factors affecting species distribution are assessed by using Ecological Niche Modeling (ENM) (Guisan & Zimmermann, 2000; Elith et al., 2006, Adhikari et al., 2012). Ecological Niche is defined as a set of ecological conditions allowing a species to persist and produce offsprings (Grinnell, 1917). Modelling of these ecological conditions takes into account temperature, precipitation, soil, vegetation and land cover; much of it from Geographic Information System (GIS) databases (www.worldclim.org and www.diva-gis.org.). High resolution satellite imageries coupled with environmental variables and spatial datasets on climate and vegetation enhance models accuracy (Philips et al., 2006). Since ENM predicts occurrence of a species, it can be inter-alia used to extrapolate species distribution across landscape in time and space. Species distribution maps prepared using ENM have, therefore high level of statistical confidence and help to succinctly locate suitable areas for reintroduction of threatened species (Irfan-Ullah et al., 2006, Kumar & Stohlgren, 2009; Ray et al., 2011; Adhikari et al., 2012). But data on species distribution in many regions is not available and collecting such data involves huge cost and labor (Ottaviani et al., 2004). Predictive modeling of species' distributions specially ENM is being increasingly favoured by conservation managers to study biogeography, evolution, ecology, conservation, and invasive-species management (Peterson & Robins, 2003; Araujo et al., 2004).

These predictive models combine many GIS tools to generate maps of areas where the habitats are most similar to those where the species is actually found. Amongst the different models, generalized linear model (GLM) (Guisan et al., 2000), ecological niche factor analysis (ENFA) (Santos et al., 2006), genetic algorithm for rule-set production (GARP) (Sweeney et al., 2007). MaxEnt (maximum entropy algorithm modeling program) have been widely used in recent studies (Elith et al., 2006), in view of their useful predictions. Hence, in order to know trends in distribution of *C. wightii* and selecting areas and habitats for its reintroduction amongst large variety of agroclimates in Indian Arid Zone, ecological niche modeling to assess distribution of *C. wightii* in arid regions of India assumed importance and priority in view of its unconfirmed threat status. We describe below results of this investigation.

2. Materials and Methods

2.1 Study species and occurrence data

Commiphora wightii (Arn.) Bhandari, the 'guggal,' of the family Burseraceae, is a small shrub, characterized by a thick main stem with crooked knotty branches. It occurs in arid tracts of Rajasthan (Fig1). It has been categorized as threatened but International Union for Conservation of Nature (IUCN) has put it under data deficient (DD) category. Consequently, placing it in 'Data Deficient' category of IUCN requires detailed information on its spatial distribution and other related aspects. Species occurrence records were collected from previously published research papers, floras, herbarium records and during field work. During course of field work, it was observed that it occurs in low rainfall area i.e. mostly in arid area.

Figure 1. Study area for potential habitats of *C. wightii.*

2.2 MaxEnt model

MaxEnt, a general purpose model was employed as it assesses environmental layers based on the training data location and then selects the probability of occurrence of species in the whole study area (Buehler & Ungar, 2001). It is based on maximum entropy algorithm and can be downloaded from the website: http://www.cs.princeton.edu/~schapire/maxent/ (Phillips et al., 2006)

2.3 Environmental variables

Three types of environmental variables viz. bioclimatic variables, NDVI and elevation were used in this study (Table 1). Nineteen bioclimatic variables (Hijmans et al., 2005) with 1 km resolution, were downloaded from World climate website (http://www.worldclim.org.). This has a set of climate layers representing bioclimatic variables, derived from monthly temperatures and rainfall recorded worldwide (Graham & Hijmans, 2006). The multicollinearity test was conducted by using Pearson Correlation Coefficient to examine the cross-correlation and variables with cross- correlation coefficient value of over 0.8 were excluded. Elevation (Digital Elevation Model-DEM) data were also obtained from the WorldClim website. The normalized difference vegetation index (NDVI) was used in the model as a measure of the amount of healthy green vegetation on the ground. NDVI was derived from SPOT vegetation sensor data. The NDVI data were processed to create 12 monthly mean composite NDVI images. All these variables are taken from mean value over 10 years from 2003 to 2013. The prediction year was 2013.

2.4 Modeling Procedure

We split the 68 occurrence point data into training data (75% of occurrence point data used for model prediction) and test data (25% occurrence point data used for model validation. Then we evaluated the resulting model with the Receiver Operating Curves (ROC) calculating the area under curve (AUC). The higher the AUC score, the better the model predicts presence/absence, indicating environmental variables that highly correlate with the predicted distribution of species, thus the prediction given by the model is of high quality. When the AUC values are <0.6, 0.6-0.7, 0.7-0.8, 0.8-0.9 or 0.9-1.0, the predictions are invalid, poor, fair, good or excellent, respectively (Swets 1988). We report an average AUC value from the ten test data sets.

Sr. No.	Code	Variable	Unit	Sr. No.	Code	Variable	Unit
1	Bio_1	Annual Mean Temp.	^{0}C	17	Bio _17	Precipitation of Driest Quarter	mm
2	Bio _2	Mean Diurnal Range	^{0}C	18	Bio _18	Precipitation of Warmest Quarter	mm
3	Bio _3	Isothermality (Bio2/Bio7)*100	-	19	Bio _19	Precipitation of Coldest Quarter	mm
4	Bio _4	Temp. Seasonality (Std. deviation*100)	-	20	Eu_1	NDVI January	-
5	Bio _5	Max Temp. of Warmest Month	^{0}C	21	Eu_2	NDVI February	-
6	Bio _6	Min Temp. of Warmest Month	^{0}C	22	Eu_3	NDVI March	-
7	Bio _8	Mean Temp. of Wettest Quarter	^{0}C	23	Eu_4	NDVI April	-
8	Bio _7	Temp. Annual Range (Bio5-Bio6)	^{0}C	24	Eu_5	NDVI May	-
9	Bio _9	Mean Temp. of Driest Quarter	^{0}C	25	Eu_6	NDVI June	-
10	Bio _10	Mean Temp. of Warmest Quarter	^{0}C	26	Eu_7	NDVI July	-
11	Bio _11	Mean Temp. of Coldest Quarter	^{0}C	27	Eu_8	NDVI August	-
12	Bio _12	Annual Precipitation	mm	28	Eu_9	NDVI September	-
13	Bio _13	Precipitation of Wettest Month	mm	29	Eu_10	NDVI October	-
14	Bio _14	Precipitation of Driest Month	mm	30	Eu_11	NDVI November	-
15	Bio _15	Precipitation Seasonality (Coefficient of variation)	-	31	Eu_12	NDVI December	-
16	Bio _16	Precipitation of Wettest Quarter	mm	32	h_DEM	Elevation	m

Table 1. List of NDVI, bioclimatic variables and elevation used in the model (Hijmans et al., 2005).

3. RESULTS AND DISCUSSION

3.1 MaxEnt Modeling Analysis

Of the 68 *C. wightii* record points 51 points were used to build the model (training points) and 17 points to test the model. Predicted potential habitats of *C. wightii* are shown in figs 2 and 3. MaxEnt's statistical evaluation of the model indicated that the model provided useful prediction. The AUC was above 0.9 for all variables indicating very high accuracy (Swets, 1988; Manel et al., 2001). The model that included all variables had the highest AUC. Relatively high AUC values (>0.8) for the testing points, were another indication of the predictive power of the model. Finally, MaxEnt tests the null hypothesis that the test points are predicting no better than a random prediction using various thresholds (Phillips et al., 2006). Further the MaxEnt model also allows for performing an internal jack-knife test to quantify the importance of the variables in influencing the distribution of *C. wightii* (Figs 4 and 5).

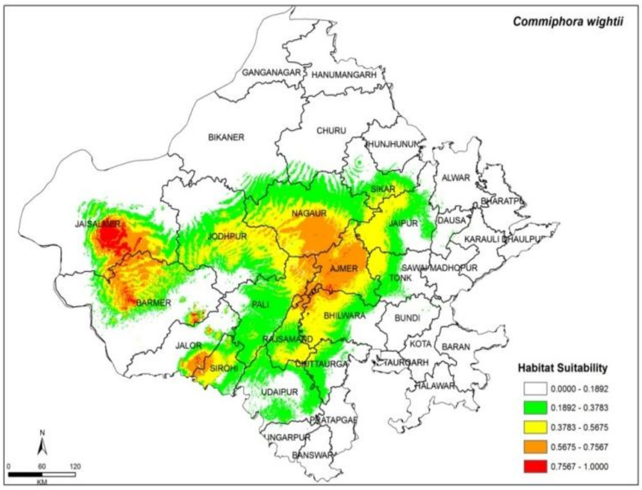

Figure 2. Predicted potential distribution of *C. wightii* for bioclimatic variables and elevation dataset.

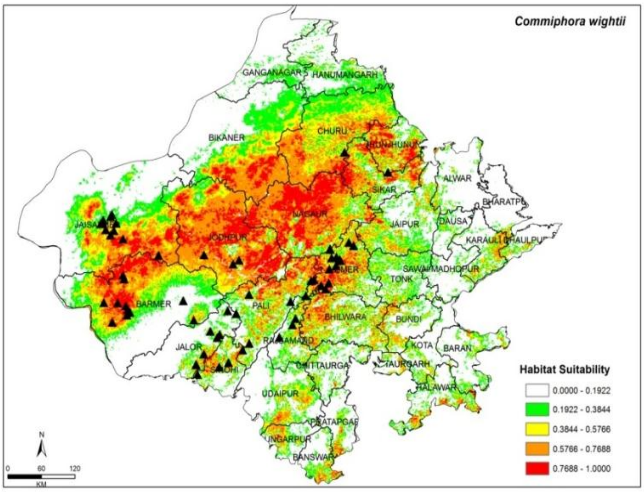

Figure 3. Predicted potential distribution of *C. wightii* for NDVI and elevation dataset.

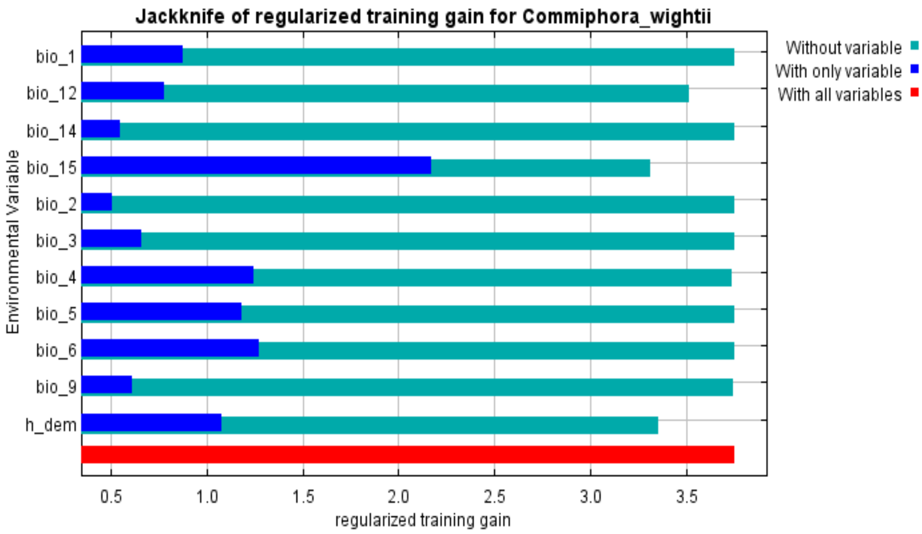

Figure 4. Jackknife test results for Bioclimatic variables and Elevation dataset.

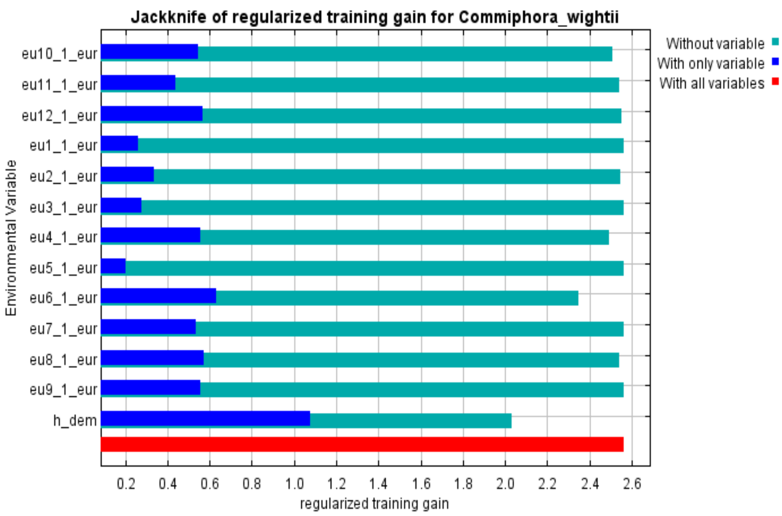

Figure 5. Jackknife test results for NDVI and Elevation dataset.

3.2 Contribution of the variables to the model

Variables which mostly contributed to the model are precipitation seasonality (coefficient of variation), precipitation of coldest quarter, elevation with 46.6%, 15.7% and 14.8% respectively for bioclimatic and elevation data set (Table 2). For NDVI and elevation dataset, elevation contributed 48.3% giving maximum gain, NDVI June (eu6_1_eur) and NDVI August (eu8_1_eur) contributing 11.1% and 11.2% respectively (Table 2). NDVI June is contributing more because new leaves emerge in June and flowers during August in *C.wightii*.

Based on above data coldest quarter with no precipitation receiving sites are the most favored areas for reintroduction of *C. wightii.* The habitats of *C.wightii* can withstand extreme variability in seasonal precipitation which is so common in arid parts of Rajasthan. Variability in seasonal rainfall in different districts of Rajasthan revealed that such districts are Jaisalmer and Barmer harbouring its habitats. These are also the areas having coldest quarter with no precipitation to enhance success in reintroduction of *C. wightii.*

Bioclimatic and elevation dataset			NDVI and elevation dataset		
Variable	**Percent contribution**	**Source/Reference**	**Variable**	**Percent contribution**	**Source/Reference**
Bio-15	56.6	WorldClim; Hijmans et al., 2005	h-DEM	48.3	Generated in GIS
Bio-12	16.4	WorldClim; Hijmans et al., 2005	Eu-6	11.1	WorldClim; Hijmans et al., 2005
h-DEM	14.7	Generated in GIS	Eu-8	11.2	WorldClim; Hijmans et al., 2005
Bio-6	6.2	WorldClim; Hijmans et al., 2005	Eu-4	10.8	WorldClim; Hijmans et al., 2005
Bio-5	3.1	WorldClim; Hijmans et al., 2005	Eu-12	10.4	WorldClim; Hijmans et al., 2005
Bio-4	2.4	WorldClim; Hijmans et al., 2005	Eu-10	5.5	WorldClim; Hijmans et al., 2005
Bio-9	0.5	WorldClim; Hijmans et al., 2005			
Bio-1	0.2	WorldClim; Hijmans et al., 2005			
Bio-2	0.1	WorldClim; Hijmans et al., 2005			
Bio-3	0	WorldClim; Hijmans et al., 2005			
Bio-14	0	WorldClim; Hijmans et al., 2005			

Table 2. Relative contribution of variables to the MaxEnt Model for different datasets.

3.3 Variables Performance and Ground Truthing

The predicted distribution naturally included most of the Aravallis hill ranges having rainfall up to 550 mm. Results of MaxEnt model using Bioclimatic variables and Elevation dataset are similar to what has been found in larger areas in the districts of Jaisalmer and Barmer, partially in Ajmer, Jalore, Sirohi, Nagaur and Pali (Fig.2). These results revealed that elevation is a major factor in determining the distribution of potential habitats of *C. wightii* in Rajasthan. Accordingly highly suitable habitats of *C. wightii* are reported up to ≈ 500 m elevations indicating that it is narrowly endemic (Irfan-Ullah et al., 2006), while mapping geographic distribution of *Agalia bourdillonii* using ENM in Western Ghats also concluded its narrowly endemic distribution that enabled them to identify key zones for additional protection. Narrowly endemic species have specific requirements which often make them vulnerable due to narrow ecological tolerances. That these environmental factors such as climate, geology and soil affect vegetation indices in time and space was also concluded by Soleimani et al., (2008). Since, vegetation is a reflex of sum total of all such environmental factors at a site, it is also amenable to quantification by using NDVI. In our study the layers NDVI June and NDVI August contributing the most to the Niche Model reflected period of leafing and flowering of the *C. wightii* (Fig 5). This makes NDVI an ideal surrogate variable representing the net results of complex environmental factors that determine the potential habitats of *C. wightii* but, potential areas predicted is mismatching. Predicted area was totally sandy which are not the habitats of *C. wightii*. This NDVI database has cumulative data of ten years and thus is a better option for landscape level modeling and prediction. Aim here was not to detect individual *C. wightii* plant for which field based hyperspectral data with resolution in terms of 50cm would be more suitable. The aim here was to use such variables which could model and predict likely zones for reintroduction of this species. And for this purpose, bioclimatic parameters and elevation are most preferred. Other variables like precipitation seasonality (bio_15) and precipitation of coldest quarter (bio_19) also have considerable predictive value with regard to distribution of *C. wightii*.

Ground truthing revealed that across all districts in western Rajasthan at gravelly soils of hills under both protected and unprotected conditions density of *C. wightii* was more than that in sandy soils of plains in all situations. This validates the modeling results that predicted its occurrence on mid elevation zone of upto 500m above mean sea level. Interestingly, low rainfall receiving districts i.e. Jaisalmer and Barmer (250 mm) had its higher density (10-12 plants per tenth ha) than those districts receiving more rain i.e. Ajmer and Sirohi (550 mm; 2-8 plants/ha) again confirming results of this model that it prefers low precipitation areas. Results of plant vigour i.e. height and canopy cover in low rainfall areas being better than that in higher rainfall areas (Table 3) further confirm these habitats to be most suitable for its sustainable growth. Thus both districts are highly correspondent with an actual occurrence in the study area.

Parameter	Jaisalmer & Barmer (Low Rainfall Areas)		Ajmer & Sirohi (High Rainfall Areas)	
	Gravelly	Sandy	Gravelly	Sandy
Height (cm) (Av./Range)	173.33 80-240	88.33 75-110	119.16 90-65	85 75-95
Canopy(m^2) (AV/Range)	3.71 1.46-4.9	1.27 1.14-1.51	1.68 0.99-2.11	1.33 0.78-1.11

Table 3. Ecological parameters of *C. wightii* in protected areas in low and high rainfall districts of Rajasthan.

Conclusion

We concluded from above study that

1. MaxEnt modeling based on bioclimatic variables and elevation together effectively determined habitat distribution and predicted habitats for reintroduction of *C. wightii*. NDVI has not given satisfactory results.
2. *C. wightii* preferentially occurs in mid elevational altitude ≈ 500 m.
3. *C.wightii* distribution prediction closely matched in the districts of Jaisalmer and Barmer; making them potential area of reintroduction.
4. Seasonal factors substantially contribute to its distribution. Hence, while planning its conservation/production areas, matching season for its optimum growth will result in sustainable plantations.

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