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Prediction of environmental suitability for invasion of *Mikania micrantha* in India by species distribution modelling

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Abstract

Environmental niche modelling was used to assess the invasion of *Mikania micrantha* H.B.K, an extremely fast growing, perennial vine and one of the world's most notorious invaders. It has spread in many parts of India, especially south-west and north-eastern states and caused severe damage to tree crops and agroforestry plantations in moist tropical zones. Using known occurrence points, the environmental suitability for the risk of invasion of *M. micrantha* in India was predicted using three species distribution models (BioClim, GARP and MaxEnt). From the three models, BioClim and GARP showed higher accuracy whereas MaxEnt showed comparatively lower accuracy. The Jackknife evaluation result indicated that Bio 13 (Precipitation of wettest period) and Bio 3 (Isothermality) were having high percentage of contribution for spread of *M. micrantha*. This species showed most significant ($p \leq 0.001$) difference in distribution frequency along the altitudinal gradient and climatic zone. Thus, it is reasonable to expect a decline in the frequency of occurrence with an increase in altitude.

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Introduction

Ecological niche modelling (alternatively known as Species Distribution Modelling or Predictive Habitat Distribution Modelling) is a mathematical tool which combines observations of species occurrence or abundance with environmental estimates (Pulliam, 2000; Peterson, 2001; Phillips *et al*., 2006; Elith *et al*., 2006). Species Distribution Models have (SDMs) emerged from the efforts to determine relationships between species and their environment (Austin, 2002; Robertson *et al*., 2004; Guisan and Thuiller, 2005). They are used to predict climate change impacts, study biogeography, assist in reserve selection, improve species management and assist development of solutions to problems relating to conservation biology (Guisan and Zimmermann, 2000). In addition to this, these models allow interpolation among limited number of species occurrences and climatic data. This approach uses geo-referenced primary occurrence data for species, in combination with digital maps representing environmental parameters to build models characterizing ecological requirements of species (Rajasri *et al*., 2011). Then such conditions are located on landscapes and maps are created to indicate distributional potential of the species (Peterson *et al*., 2001; Pearson and Dawson, 2003; Thuiller *et al*., 2003). SDMs have been used to assess the invasion potential of species into new habitats (Beerling *et al*., 1995; Peterson 2003; Thuiller *et al*., 2005) or to explore niche stability and niche modelling issues during invasion (Broennimann *et al*., 2007; Fizpatrick *et al*., 2007; Beaumont *et al*., 2009). On the contrary, SDMs are generally not preferred at predicting invasions, as species often shift niche, have different levels of competition, are not at equilibrium with their environment (expanding range) or are not near their physiological tolerance limits in original environments (Thompson *et al*., 2011).

An early detection of new areas of potential invasion and new foci of spread would allow implementation of intervention methods at an early stage of invasion with a potential to pre-empt severe problems.

Mikania micrantha H.B.K (also known as Mile-a-minute / climbing hemp weed / Chinese creeper), is an extremely fast growing, perennial vine and one of the world's most notorious invaders (Cronk and Fuller, 1995). This weed invaded India in the early 1940s, after being imported from tropical America as a ground cover for tea plantations and is known to occur in many states of India (Ramachandran and Soosairaj, 2008; Reddy and Raju, 2009; Chaterjee *et al*., 2009). *M. micrantha* is widely distributed throughout the tropical forest zones (tropical rain forests and tropical moist deciduous forests) of the Western Ghats and the north-eastern Himalayas (Fig. 1). The literature survey revealed that the weed occurs in all the four major land use patterns namely disturbed open areas/newly opened up areas, agroforestry, forest plantations, home gardens and forest edges (Sankaran and Sreenivasan, 2001; Ramachandran and Soosairaj, 2008; Tripathi *et al*, 2011; Banerjee, 2012) . This weed is an early successional colonizer under slash burn agricultural fallows in north-east India and it also adapted to fire cycle where fire is used as a management tool in clearing unwanted vegetation. The species spreads through seeds and also through ramets (Ramet is a vegetative propagule. A node on stolon having two leaves and few roots is capable of regenerating as a new individual plant when they are detached or broken away from the parent plant) by either wind, water and through transportation (Swamy and Ramakrishnan, 1987). In Tamil Nadu, and elsewhere in India, dispersal is mainly through water, especially along the river banks/river island (Ramachandran and Soosairaj, 2008), along roadside and water channels. However, spread is minimal but consistent. Therefore, it is important to predict spread or invasion of *Mikania* into newer environment and to formulate or design appropriate weed management strategies. In this context, the present study becomes relevant by evaluating three SDMs (BIOCLIM, GARP and MaxEnt) in predicting the spread of *M. micrantha* in India.

Materials and Methods

Species occurrence and environmental data : The occurrence points of *M. micrantha* were considered based on the field and literature surveys (Fig. 1). The spread of plant was recorded according to the habitat in which it occured (i.e., disturbed open forest area/agroforesty/plantation crops/home garden).

The environmental variables used for all the three modelling algorithms were bioclimatic and some geographic variables. Bioclimatic variables are derived from monthly temperature and rainfall values, in order to generate more biologically meaningful variables. The bioclimatic variables represent annual trends (e.g. mean annual temperature, annual precipitation), seasonality (e.g. annual range in temperature and precipitation) and extreme or limiting environmental factors (e.g. temperature of the coldest and warmest month, precipitation of wet and dry quarters). For variables and their code, refer to Table 1. These variables were obtained from globally interpolated datasets (source: http://www.worldclim.org and http://www.eros.usgs.gov) which are presumed to be relevant to plant existence (Pearson and Dawson, 2003; Hijmans *et al*., 2005; Irfan-ullah *et al*., 2007). Analyses were conducted at the 1 x 1 km pixels spatial resolution of the environmental data sets. Slopes, altitudes, global land covers and tree covers were the geographic variables used for modelling (Source: http://www.spatial-analyst.net/wiki/?title=Global_datasets and http://www. worldclim.org).

Model development and validation : BIOCLIM is one of the earliest modelling techniques, based on climatic envelop. For each given environmental variables the algorithm finds mean and standard deviation (assuming normal distribution) associated with occurrence points. Each variable has its own envelope represented by the interval

$$[M - CO^{*} StDev, M + C^{*} StDev]$$

where 'M' is the mean; 'CO' is the cut off input parameter; and 'StDev' is the standard deviation. Besides the envelope, each environmental variable has additional upper and lower limits taken from the maximum and minimum values related to the set of occurrence points (Busby, 1991).

GARP, genetic algorithm for ruleset prediction is an ecological niche modelling method based on genetic algorithm. The model predicts suitable environmental conditions under which the species should be able to maintain population. For input, GARP uses a set of point localities, where the species is known to occur and a set of geographical layers that might limit the species' capabilities to survive. This model is a random set of mathematical rules which can be read as limiting environmental conditions (Stockwell and Peterson, 1999). In the present study, default values available in Open-modeller *i.e.,* commission threshold = 50% of distribution models, omission threshold = 20% of the models with least omission error and resample value = 2,500.

The maximum entropy (MaxEnt) approach estimates target probability distribution of the species by finding the probability distribution of maximum entropy (i.e., that is most spread out or closest to uniform with reference to a set of environmental variables). Default values of different parameters, maximum iterations = 500, convergence threshold = 0.00001 and 50% of data points were used as a random test percentage in the present study (Peterson, 2001; Phillips *et al*., 2004).

The sensitivity values were calculated using confusion matrix. A curve which maximizes sensitivity against low false positive fraction values is considered a good model which was evaluated using area under the curve (AUC). Cross-validated AUC values were summarized to present overall model performance by taking mean AUC values of all model accuracies. AUC ranged from 0.0 to1.0. A model providing excellent prediction has an AUC higher than 0.9, a fair model has an AUC between 0.7 and 0.9, and a model with AUC below 0.7 is considered poor (Swets, 1988). The *Jackknife* procedure was used to assess the importance and percentage of contribution of the variables. The final potential species distribution map had a range of values from 0 to 1, which were regrouped into three classes of potential habitats viz., 'high potential' (>0.6), 'medium potential' (0.2–0.4) and 'low potential' (<0.2). Models outputs are also validated by ground truth verification in and around the occurrence points of Tamil Nadu, where high probability *of M. micrantha* invasion showed in output maps.

Analysis of heterogeneity of habitat of *M. micrantha* : The G-test was used to determine heterogeneity in the distribution frequency of *M. micrantha*, and estimated its adaptability to the expected new environment using the relationships shown by G value and G_{adj} value and determined its selectivity on the physical environment. The numbers of observations in each category were compared with the expected counts, which were calculated using theoretical expectation (Sokal and Rohlf, 1994).

Results and Discussion

Invasive species are a current focus of interest to ecologists, conservationists and natural resource managers due to their rapid spread, threat to local biodiversity and damage to ecosystems. Rapid increase in invasive species like *Mikania* is posing great threat to native biodiversity in India and elsewhere in the tropical world (Swamy and Ramakrishnan 1987). The study predicted precisely the potential habitat suitability distribution by using niche/habitat suitability models *i.e.,* Maxent, GARP, BIOCLIM. Prediction was well in accordance with locations where species presence was known.

Model outputs varied with the modelling techniques used and they indicated that, GARP predicted the largest area (73.8%) under potential distribution when compared to BIOCLIM (34.73%) and MaxEnt (37.14%) (Table 2). Both GARP and MaxEnt showed wide range of distribution from low probability to high probability occurrence throughout India, whereas BIOCLIM output was restricted to south-western, southern, eastern, north-eastern and central regions of India. The present study suggested that BIOCLIM and GARP algorithms were good and better than MaxEnt in predicting the spread of *M. micrantha* in India. On the contrary, it was suggested that MaxEnt was better than GARP in predicting the potential geographical distribution of *M. micrantha* in China (Zhang *et al.*, 2011). BIOCLIM and GARP models showed a good performance with AUC value of 0.98 and 0.97, with low omission error in the present study (Table. 2).While, Zhang *et al.*, (2011) reported 0.91 for GARP and 0.97 for MaxEnt model. AUC measures model performance that ranges from 0 to 1. A model performs well when AUC is large. Usually, AUC values >0.9 indicate high accuracy, values of 0.70 – 0.9 indicate good accuracy, and values 0.5 (random) to 0.7 indicate low accuracy. A higher accuracy and low omission rate is necessary condition to accept it as a good model (Anderson *et al.*, 2003). The models for species with broad geographic ranges and environmental tolerances tend to be less accurate than those for species with smaller geographic ranges and limited environmental tolerances (Manel *et al.*, 2001; Thuiller *et al.*, 2005; Elith *et al.*, 2006). On the contrary it was said that the spatial autocorrelation in distribution of species occurrences and environmental variables may also influence SDM accuracy (Raes and Steege, 2007).The *Jackknife* evaluation results indicated that the presence of Bio 13 (Precipitation of wettest period) showed highest gain and absence of Bio 3 (Isothermality) declined the gain (Fig. 1). This clearly showed that high precipitation and isothermal lines had a bearing on the distribution and future spread of *M. micrantha*. This is in agreement with the results obtained by Zhang *et al.* (2011). The relationship between distribution of *M. micrantha* and other physical factors such as altitude, land cover, relative humidity and climatic zone are shown in Table 3. The results suggested the most significant ($p \le 0.001$) difference in distribution frequency along an altitude (G_{adj} value = 30.94) and climatic zone (G_{adj} value = 28.23) and least significant ($p \le 0.025$) difference through land cover (G_{adj} value = 10.17). Whereas no significant ($p \ge 0.05$) difference was found in the distribution frequency with relative humidity (G_{adj} value = 3.43). The highest distribution frequency of

Table 1: Environmental variables used in the model development

Variables	Details
Bio1	Annual mean temperature
Bio2	Mean diurnal temperature range [mean of monthly (max temp–min temp)]
Bio3	Isothermality (P2/P7) (×100)
Bio4	Temperature seasonality (standard deviation×100)
Bio7	Temperature annual range (P5–P6)
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
Bio15	Precipitation seasonality (coefficient of variation)
Bio16	Precipitation of wettest quarter
Bio17	Precipitation of driest quarter
Bio18	Precipitation of warmest quarter
Bio19	Precipitation of coldest quarter
Slope	Slope value from global digital elevation model
Altitude	Elevation above sea level (m)
Land cover	Global land cover map
Tree cover	Percent tree cover

Table 2 : Comparative details of the modelling outputs

Parameters	Bioclim	GARP	MaxEnt
Accuracy (%)	100	100	100
AUC value	0.98	0.97	0.83
Omission error	0	0	0
Total distribution (%of the total area)	34.73	73.77	37.14

M. micrantha was found in low altitudes (0-400 m) and in the climatic zone of tropical wet areas. In other words, the distribution frequency of *Mikania* decreased with an increase in altitude. Day *et al*. (2012) developed a Climex model using the native range distribution of *M.micrantha* consisting of 685 localities in 22 countries in America from Mexico to Argentina in the south and Ecuadar to the west and found that except very high altitude areas (above 1300m asl) in Papua New Guinia. However, Zhang *et al.* (2011) reported no influence of altitude and seasonal variation in rainfall on the distribution of this weed in China. The limitations to predict potential invasion by using niche models could be the species interactions which are not considered in the above modelling process (Bourg *et al*., 2005; Raxworthy *et al*., 2007; Pascual and Saurez, 2008). The factors that make a

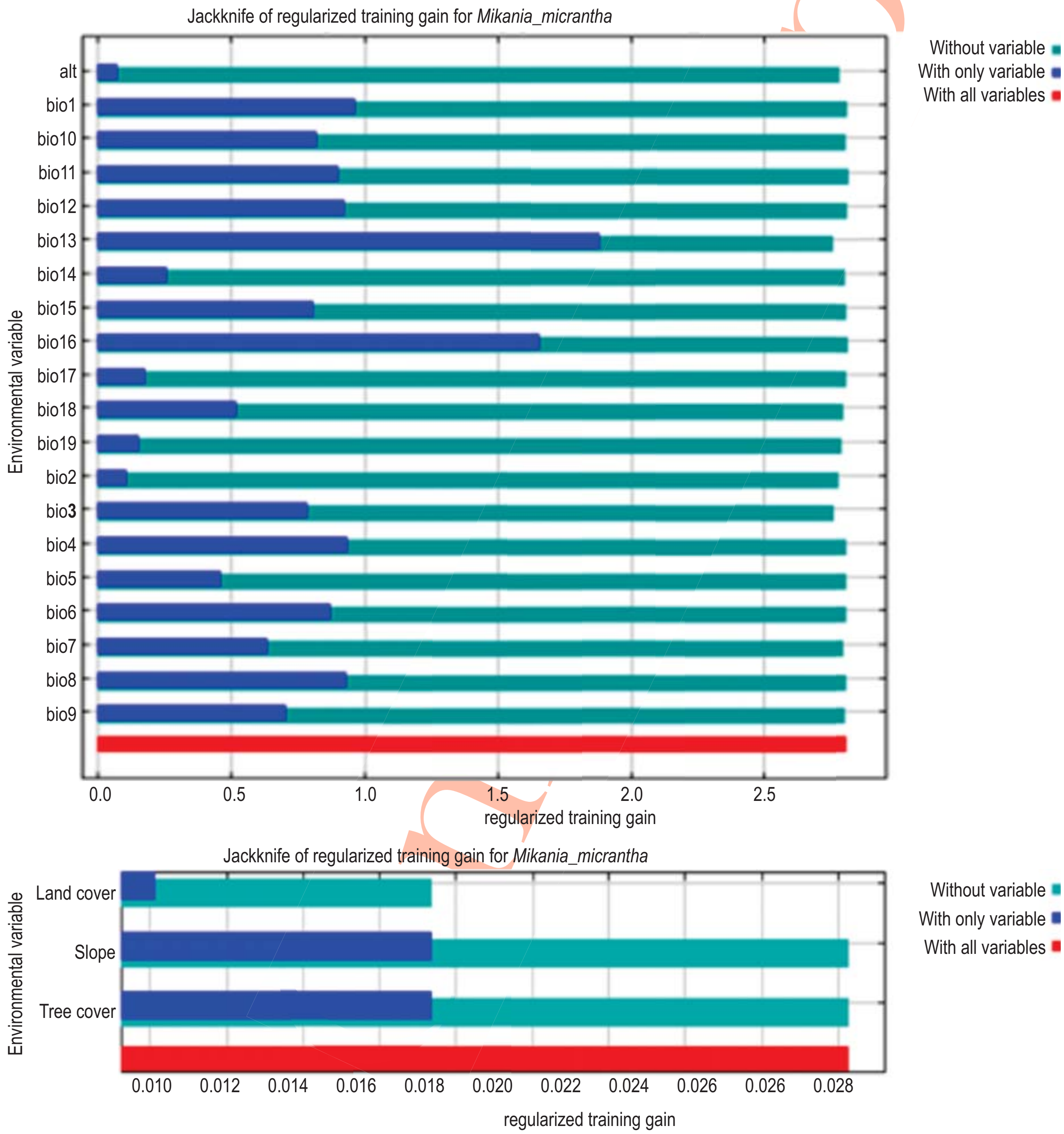

Fig. 1 : *Jackknife* test for evaluating relative importance of environmental variables for *M. micrantha* in India. (Note: For details of environmental variables refer Table 1)

Table 3 : Distribution frequency of *M. micrantha*

Altitude	Frequency (%)	Land cover[a]	Frequency (%)	Relative humidity	Frequency (%)	Climatic zone[b]	Frequency (%)
0-400	59.26	1	25.92	0-40	40.74	1	59.26
400-800	25.92	2	22.22	40-80	59.26	2	22.22
800-1000	14.82	3	37.04			3	18.52
		4	14.82				
x^2	**32.1**	x^2	**10.29**	x^2	**3.43**	x^2	**30.46**
Gadj Value	**30.94******	Gadj Value	**10.17***	Gadj Value	**3.43**	Gadj Value	**28.23*****

a Land Cover: 1) Tree cover, broad leave, evergreen type; 2) Tree cover, broad leave, deciduous close; 3) Cultivated and Managed areas; 4) Water bodies; b Climatic zone: 1) Tropical wet; 2) Semi Arid; 3) Tropical wet and dry; *, **and *** refer to $p \le 0.05$, $p \le 0.01$ and $p \le 0.001$, respectively. No asterisk means "not significant"

species invasive are clearly more complex than just niche considerations (Thuiller *et al*., 2005).

Potential distribution maps showed the probable areas of spread of *M. micrantha* in India. High probability areas are in the south-eastern, southern, north-eastern, eastern and central region of India, around the occurrence points. This indicated that suitability of the region for further spread of the species could be in habitats like agricultural areas, coast land, natural forest, planted forest, riparian zones, disturbed shrub lands, urban areas and wetlands. Further, ground verification of model predicted results is essential to confirm the accuracy. Therefore, the model predicted results were cross checked on the ground during field survey in Tamil Nadu. *M. micrantha* was found to occur at Kodhayar, Palani and Karur as shown in the output maps of niche modelling. This occurrence was not reported earlier/ prior to this study. Further, research is needed to enhance model accuracy in order to make predictions more reliable by increasing species specific habitat occurrence points and associated plant traits.

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