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Identification of High-Risk Agro-Ecological Regions using Species Distribution Modeling of Priority Invasive Species in Sri Lanka

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Mimosa pigra, Annona glabra, Lantana camara, Prosopis juliflora and *Parthenium histerophorus* are considered as priority invasive plants of Sri Lanka that cause considerable impact on agriculture and food security. The potential areas of these species are not available for land managers for timely control and management measures. This study modelled the suitable climate area for these invasive species under current climate scenarios using Maxent model. The resulting models were found to have good discrimination ability of presence and absence, with very high AUC values. The study identified highly responding variables for the model prediction of each species. Maxent predictions were overlaid on agro-ecological map of Sri Lanka and high-risk agro-ecological regions were identified for the five species considered. Resulting maps can be a vital tool for land managers to take information based decisions to control and manage invasive species.

Key Words: Invasive species, Maxent, Species distribution modeling

Introduction

Invasive species are a major threat to earth's biodiversity. An understanding of the current and potential distribution pattern of an invasive species is fundamental for managing invasive alien species (Taylor, 2012; Ward, 2007). Forecasting the potential areas of occupancy of invasive species is important to environmental planners for risk assessment and also to prepare long term management strategies (Taylor, 2012). Maxent (Phillips *et al*., 2006) is one of the accurate, increasingly popular and globally accepted machine-learning techniques (Graham and Hijmans, 2006; Ramirez-Villegas and Bueno-Cabrera, 2009) for presence-only data (Baldwin, 2009). Predicting and quantifying the actual or the potential areas of occupancy of invasive species facilitates environmental planners to take timely control, eradication or containment actions (Gormley *et al*., 2011) to manage the issue.

The aim of this study is to predict the potential distribution of five high priority invasive plants in Sri Lanka and identify agro ecological regions that could be under threat due to future invasion of these species.

Material and Methods

Study Species

Study focused on five priority invasive plant species in Sri Lanka *viz*., *Mimosa pigra, Annona glabra, Lantana camara, Prosopis juliflora* and *Parthenium histerophorus*. The ecological and economic damage caused by these species is significant for ecosystem health especially in production landscapes and protected areas.

Species Distribution Data

Field surveys of data collection were conducted at several locations of Sri Lanka. Occurrence data of species distribution was collected using random sampling. Primary data was sustained by geo-referenced secondary data which were collected from various reliable sources, such as study reports, expert consultations etc.

Environmental Data

Fine resolution (30 sec.), current bioclimatic data freely available at 'worldclim' database were selected for the study. All variables were plotted using 'get value' and 'hist' functions in R programme to visualize the range of values of each variable. Variables with higher value ranges comparatively were selected as the subset of variables for model run (Table 1). The selected variables were supplemented with 'yearly average aridity index' since this parameter showed a strong impact on the model prediction.

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Table 1. Selected parameters and their codes

Parameter	Code
Mean Diurnal Range (Mean of monthly (max temp - min temp))	bio_2
Isothermality (BIO2/BIO7) (* 100)	bio_3
Temperature Seasonality (standard deviation *100)	bio_4
Temperature Annual Range (BIO5-BIO6)	bio_7
Annual Precipitation	bio_12
Precipitation Seasonality (Coefficient of Variation)	bio_15
Yearly Average Aridity Index	ai_yr

Table 2. Contribution of environmental variables for *Mimosa pigra* model in Sri Lanka

Variable	Percent Contribution	Permutation Importance
ai_yr	53.4	59.4
bio_2	37.4	18.8
bio_4	6.8	18.1
bio_3	2.4	3.6
bio_7	0	0
bio_15	0	0
Bio_12	0	0

Running the Model in Maxent

Maximum Entropy Modeling version 3.3.3k was employed for the study (Phillips *et al*., 2009). Cumulative output format was selected instead of the default logistic output. Random test percentage was set to 25% enabling the model automatically set all presence points into training and test samples. Other relevant default settings of the maxent software were applied. Model was run for each species separately with the selected subset of variables. The discrimination capacities of these distributional models were determined by calculating the area under the receiver operating characteristic curve (AUC) criterion.

The areas of predictions were visualized for each species using 'minimum training presence' as the cut off level. Occurrences of each species were overlaid on the prediction image. Maxent prediction of each species was overlaid on agro-ecological map of Sri Lanka.

Results and Discussion

All models were found to have a high predictive power or good discrimination ability with high AUC_{test} values of 0.888, 0.989, 0.910, 0.821 and 0.998 for *M. pigra, A. glabra, L. camara, P. juliflora* and *P. histerophorus*, respectively (Fielding and Bell, 1997; Araujo *et al.*, 2005). AUC value is generally considered as a good statistical measure of evaluating the discrimination ability of species distribution models.

In *M. pigra* model, analysis of jackknife tests (Fig. 1) revealed that yearly average aridity index (ai_yr) which is an indicator for the degree of dryness significantly affected the model prediction. The percent contribution of each variable to the final model of *M. pigra* (Table 2) also showed significantly high contribution of aridity index. Therefore, suitable conditions for *M. pigra* will depend on the level of dryness caused by the evaporation or more combined effect associated with the variables.

Similarly, temperature seasonality (bio_4), isothermality (bio_3), Annual Precipitation (bio_12) and Isothermality (bio_3) contributes significantly in *A. glabra*, *L. camara*, *P. juliflora* and *P. histerophorus* models, respectively.

Areas predicted as suitable for *M. pigra, A. glabra, L. camara, P. juliflora and P. histerophorus* at minimum

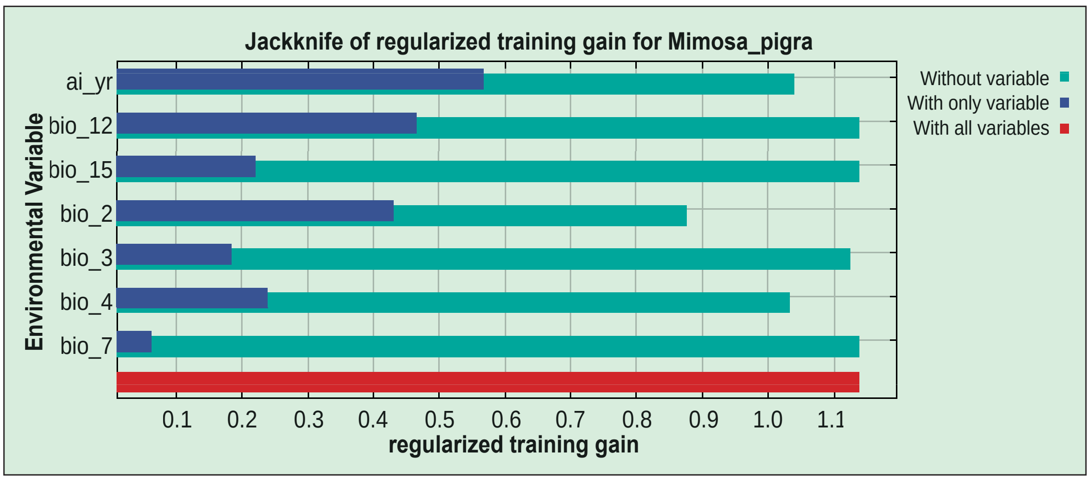

Fig. 1. Results of Jackknife test of variable importance in the regularized training gain for *Mimosa pigra* model

training presence threshold level are shown in Fig. 2. The predicted range of *M. pigra* lies mainly in the central and Eastern parts of Sri Lanka whereas the predicted range of *A. glabra* is limited only to the South-western coastal areas. The prediction of *L. camara* lies mainly in South-eastern part of the country. The predicted range of *P. juliflora* lies only in the two relatively dry areas located in the North-western and South-eastern Sri Lanka, however, a greater predicted area could be observed in South-eastern coastal areas. The predicted range of *P. histerophorus* lies mainly in the Jaffna peninsula. The Central and Southern parts of Sri Lanka are predicted as not suitable for this species distribution.

Localities where the study species has not been recorded may not be directly causing significant differences to the model prediction if the study area is large enough to capture the environmental variability of the study species. Natural barriers, soil type, predators and competition by closely related species limit the distribution of species and therefore, omission of one or several of these factors can over-estimate the predictions (Xavier and Van Zonneveld, 2010). Alternatively, the threshold value which is set for suitable area prediction is an arbitrary value (Liu *et al.*, 2005), hence the prediction of potential area could change with the selected threshold value.

Basically, there are three climatic zones in Sri Lanka, *viz.*, wet zone, dry zone and intermediate zone and yet again topographically the country is divided into three regions, up country, mid country and low country. Forty six unique ago-ecological zones can be identified in Sri Lanka based on features such as topography, soil type, land use, rainfall etc. (Punyawardena, 2008). Fig. 3 shows Maxent prediction for *M. pigra* overlaid on agro-ecological map of Sri Lanka. Thirty four agro-ecological zones out of 46 are vulnerable to *M. pigra* invasion. Spreading in a wide range of agro ecological zones indicates that this species has adaptations to survive in a wide range of climatic conditions. Southern coastal belt, South-eastern intermediate and wet zones are most vulnerable for *L. camara* invasion in this climatic regime. The potential distribution of this species also overlaps with many number of agro ecological zones. Since *M. pigra* and *L. camara* are widespread, they could be very aggressive invaders and need considerable effort for controlling measures. Potential distribution of *A. glabra*, *P. julifora* and *P. histerophorus* overlap with few agro ecological zones indicating that these species have rather narrow range of climatic preferences in this climate regime.

Maps produced in this study can be a useful tool for protected area managers to take information based

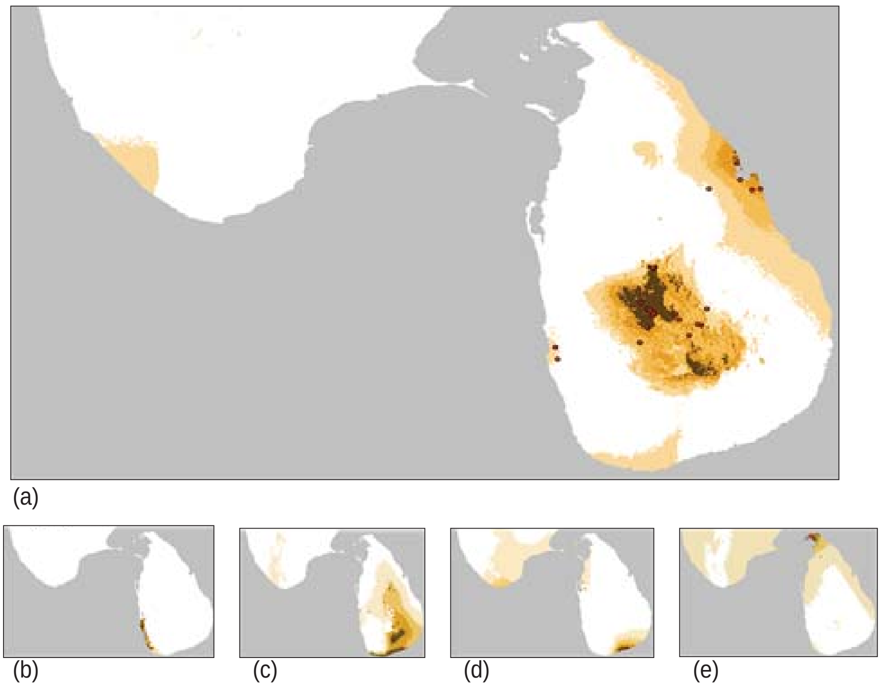

Fig. 2. Predicted areas of *Mimosa pigra* (a), *Annona glabra* (b), *Lantana camara* (c), *Prosopis juliflora* (d) and *Parthenium histerophorus* in Sri Lanka at minimum training presence (cumulative threshold).
Red dots indicate occurrence records of the species in Sri Lanka

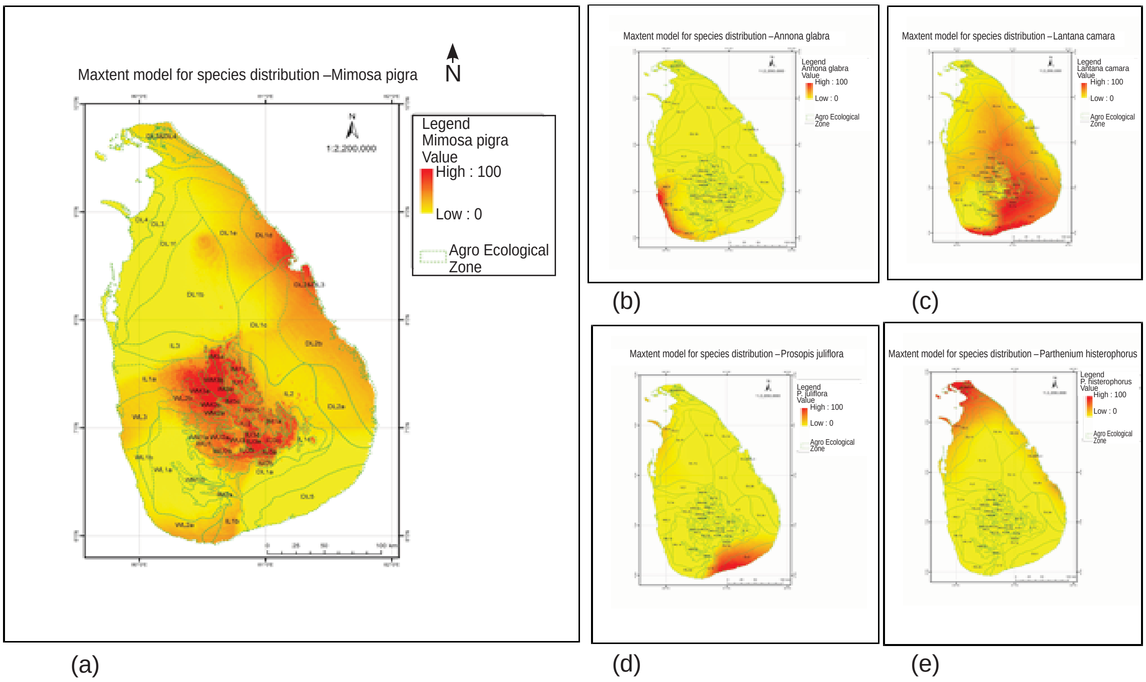

Fig. 3. Maxent prediction overlaid on agro-ecological map of Sri Lanka for *Mimosa pigra* (a), *Annona glabra* (b), *Lantana camara* (c), *Prosopis juliflora* (d) and *Parthenium histerophorus* (e) in Sri Lanka

decisions. Also they can be used in public awareness campaigns so as to enlist the help of local communities in the management of existing infestations and the prevention of further invasion.

References

Araujo MB, RG Pearson, W Thuillers and M. Erhard (2005) Validation of species–climate impact models under climate change. *Global Change Biol.* **11:** 1504-1513.

Baldwin RA (2009) Use of maximum entropy modeling in wildlife research. *Entropy* **11:** 854-866.

Fielding AH and JF Bell (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environ. Conser.* **24:** 38-49.

Gormley AM, DM Forsyth, P Griffioen, M Lindeman, DSL Ramsey, MP Scroggie and L Woodford (2011) Using presence-only and presence-absence data to estimate the current and potential distributions of established invasive species. *J. Appl.Ecol.* **48:** 25-34.

Graham CH and RJ Hijmans (2006) A comparison of methods for mapping species ranges and species richness. *Glob. Ecol. Biogeogr.* **15**: 578-587.

Liu CR, PM Berry, TP Dawson and RG Pearson (2005) Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* **28:** 385-393.

Phillips SJ, RP Anderson and RE Schapire (2006) Maximum entropy modelling of species geographic distributions. *Ecol. model* **190**: 231-259.

Phillips SJ, M Dudik, J Elith, CH Graham, A Lehmann, J Leathwick and S Ferrier (2009) Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecol. Appl.* **19**: 181–197.

Punyawardena BVR (2008) *Rainfall of Sri Lanka and agro-ecological zones*, Department of Agriculture, Sri Lanka.

Ramírez-Villegas J and A Bueno-Cabrera (2009) *Working with climate data and niche modeling: Creation of bioclimatic variables*. International Center for Tropical Agriculture (CIAT), Cali, Colombia.

Taylor SL, L Kumar , N Reid and DJ Kriticos (2012) Climate Change and the Potential Distribution of an Invasive Shrub, *Lantana camara* L.. *PLoS ONE* **7**: e35565. doi:10.1371/journal.pone.0035565.

Ward DF (2007) Modelling the potential geographic distribution of invasive ant species in New Zealand. *Biol. Invasions* **9**: 723-735.

Xavier S and M Van Zonneveld (2010) *Training Manual on Spatial Analysis of Plant Diversity and Distribution*. Bioversity International, Rome, Italy.