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Effects of landscape context on the invasive species *Lantana camara* in Biligiri Rangaswamy Temple Tiger Reserve, India

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Abstract: Non-native invasive species establish in favourable habitats in alien regions. Such favourable habitats are largely determined by local climatic, soil and biogeographic factors. Modelling these factors can help managers to identify areas of possible risk of invasion. This paper uses logistic regression modelling to identify variables conducive to high invasion in a tropical mixed forest in a biodiversity hotspot region in India. Using presence-absence data of an invasive species *Lantana camara* and local habitat variables from increasing buffer distances around sampling locations along with broad scale climatic parameters, we identify the variables that support invasion and spread. Results indicated that the percentage of moist deciduous forest at a distance of 50 m around the plot was significantly related to the invasion of *L. camara.* The study demonstrates the facilitation by moist deciduous forests to the growth and spread of *L. camara* in this region, and highlights the importance of using data at multiple scales for modelling invasion.

Resumen: Las especies invasoras no nativas se establecen en hábitats favorables en regiones foráneas. Dichos hábitats favorables están determinados en gran medida por factores locales climáticos, edáficos y biogeográficos. La modelación de estos factores puede ayudar a los administradores a identificar áreas de posible riesgo de invasión. En este artículo se usa modelación por medio de regresión logística para identificar variables conducentes a una invasión alta en un bosque tropical mixto en una región que es un hotspot de biodiversidad en la India. Usando datos de presencia-ausencia de la especie invasora *Lantana camara* y variables locales de hábitat a través de distancias crecientes que definen áreas de influencia cada vez mayores alrededor de localidades de muestreo junto con parámetros climáticos de escala amplia, nosotros identificamos las variables que apoyan la invasión y la propagación. Los resultados indicaron que el porcentaje de bosque deciduo húmedo a una distancia de 50 m alrededor de la parcela estuvo relacionado significativamente con la invasión de *L. camara*. El estudio demuestra cómo el bosque húmedo deciduo facilita el crecimiento y la propagación de *L. camara* en esta región, y enfatiza la importancia del uso de datos multiescalares para modelar la invasión.

Resumo: Espécies invasoras não nativas estabelecem-se em habitats favoráveis em regiões exóticas. Tais habitats favoráveis são em grande parte determinados por fatores locais: climáticos, de solo e biogeográficos. A modelação desses fatores pode ajudar os gestores a

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identificar áreas de possível risco de invasão. Este trabalho utiliza modelos de regressão logística para identificar as variáveis conducentes à alta invasão numa floresta mista tropical numa região altamente sensível de biodiversidade na Índia. Usando dados de presença-ausência de uma espécie invasora, a *Lantana camara* e variáveis de habitats locais, desde o aumento de distâncias tampão em torno dos locais de amostragem, juntamente com parâmetros climáticos em escala ampla, identificamos as variáveis que suportam a invasão e a propagação. Os resultados indicaram que a percentagem de floresta decídua húmida a uma distância de 50 m em torno das parcelas estava significativamente relacionada com a invasão de *L. camara*. O estudo demonstra a facilidade, em florestas húmidas de folha caduca, para o crescimento e a propagação de *L. camara* nesta região, e destaca a importância do uso de dados em escalas múltiplas para a modelação da invasão.

Key words: Habitat buffer, invasive species, *Lantana camara*, logistic regression, scale, Western Ghats.

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Introduction

Invasive species are those non-native species that, having arrived in a given region through human activity, can establish and spread rapidly across large areas (Richardson *et al.* 2000; Simberloff *et al.* 2013). Many invasive plants are increasingly abundant in their non-native range, and pose major conservation problems at the global scale, as they cause harm to ecosystems as a whole as well as to species in particular (Simberloff 2006). Important drivers for adaptation and establishment of invasive species include favourable climatic factors, availability of resources such as light, water, and soil nutrients as well as ecological factors, pressure of incoming seed propagules (Lockwood *et al.* 2005; Thuiller *et al.* 2007) and the presence of habitat typologies that are suitable to their growth (Chytry *et al.* 2009; Richardson & Pysek 2006). For wild land managers, it is important that some management actions are put into place for controlling the spread of the invasive species. Preventing the establishment is the most efficient management strategy to control biological invasions, but when invasion has already taken place, early detection of new seeds becomes essential (Simberloff *et al.* 2013). Therefore, amongst many management activities, monitoring and mapping of the occurrence of invasive species is important for control action (Lindenmayer & Likens 2010). Similarly, for deployment of resources and planning ahead, predictive modelling of possible areas of invasion would greatly benefit management (Ficetola *et al.* 2010; Leung *et al.* 2012).

India hosts hundreds of different invasive species; recent inventories of Indian alien flora have identified more than one-third of these to have their origin in South America (Khuroo *et al.* 2012). Invasive alien plants have established in several types of habitats, and in different climatic regimes across India (Khuroo *et al.* 2012). Their persistent nature and adaptability has made it easy for them to grow and spread rapidly across diverse ecosystems in India (Khuroo *et al.* 2011). The Western Ghats biodiversity hotspot region is particularly vulnerable to these species due to its climatic similarity with the Central American landscape (Kohli *et al.* 2006; Rao & Sagar 2012), which makes it remarkably easy for species from the Central and South American continent to establish (Khuroo *et al.* 2012). Other studies on invasion in this region have reported vulnerability to disturbance such as forest fragmentation (Joshi, Mudappa & Shankar Raman 2015) and roads (Prasad 2009).

In recent times predictive modelling has advanced rapidly. Several tools and techniques have emerged which show robust model development using multiple input parameters, as well as prove effective predictors of the species to be modelled (Austin 2002; Gallien *et al.* 2012; Jiménez-Valverde *et al.* 2011; Thuiller *et al.* 2009). Using niche-based models by climate matching has shown promise for locating areas of introduction in invaded regions (Broennimann *et al.* 2007); while other modelling tools can be used for understanding the effects of niche conservatism which constrains the geographic expansion of invasive species (Wiens & Graham 2005). Predictive modelling using multivariate statistics, being inductive and empirical, can provide accurate predictions when tested against real habitat presence data (Fielding & Bell 1997). Logistic regression modelling is one among these techniques which can yield useful results, provided there is detailed presence-absence data for the variable being modelled and environmental variables at a suitable scale. While several advanced techniques using logistic regression have now evolved (Fleishman *et al.* 2001), simple logistic regression still proves to be very effective in predictions (Kumar *et al.* 2008; Manel *et al.* 2001).

The aim of this study was to evaluate the relationship between the presence of *Lantana camara* - a Central American native, and highly invasive shrub plant in India- and environmental and ecological parameters, so as to provide information useful for the management of this invasive species, in order to counter its further spread. We used logistic regression modelling to identify environmental variables conducive to the growth and spread of this particular species.

Lantana camara is a flowering shrub species of family Verbenaceae, native to Central and South America. It was introduced as an ornamental plant and is now reported to be invasive in several countries across the world, including India. It flowers and fruits throughout the year and the seeds are small, dispersed by birds (Walton 2006). The fruits are green when unripe and turn black on ripening, they are small and berry-like. In the past decade, studies have reported the occurrence (Murali & Setty 2001), and subsequently a ten-fold increase (Sundaram 2011), of invasive alien plant species, with special emphasis on the shrub *L. camara*. These studies provide important baseline information about invasion of *L. camara* in this landscape indicating increase not only in numbers of stems but also density (Sundaram 2011). Whereas Murali & Setty (2001) suggest that further studies are required for understanding how the invasive species impact regeneration in this landscape, Sundaram's (2011) study clearly indicates that *L. camara* invasion is more extensive than other invasive species, such as *Chromolaena odorata*, including within seed banks, which have potential to establish further. While these studies have identified the potential threat to the local ecosystems, no detailed study in this landscape has undertaken work on understanding the mechanisms which may be promoting the growth and spread of *L. camara* in the different mixed forest types of this area. For the management of the park and its biodiversity, it is imperative that the managers develop a fair understanding of the vulnerable areas, where this species is more likely to spread. Using the existing knowledge regarding the species occurrence (Muniappan & Viraktamath 1993; Sharma *et al.* 2005), it is possible to identify the factors promoting the suitability for this species, and the areas where the risk of invasion is greatest.

Materials and methods

The study was conducted as part of the Biodiversity Multi-Source Monitoring System: From Space To Species (BIO_SOS), a three-year research project (www.biosos.eu) of the European Union Seventh Framework Programme (EU 7FP). The BIO_SOS project aims to use remote sensing approaches for consistent monitoring of human-induced changes in the biodiversity of protected areas and their surroundings, such as the introduction of the invasive plant *L. camara* in the Biligiri Rangaswamy Temple Tiger Reserve. The BIO_SOS project focuses on sites in Europe, Brazil and India located within different climate zones.

Study area

The Biligiri Rangaswamy Temple Tiger Reserve (located between 11° 40′ - 12° 09′ N lat. and 77° 05′. - 77° 15′ E long.) (Kumara *et al.* 2012) is an area of high biodiversity lying in the Western Ghats hill ranges of the southern Indian peninsula. This 540 km^2 sanctuary is unique, with its heterogeneity of physiographic forms (elevation range - 620 - 1816 above m.s.l.) and climatic regime, as well as the endemic flora and fauna it supports. Rainfall varies spatially based on orographic effects and seasonality (annual average ranges from 940 mm - 1850 mm). The vegetation of the sanctuary has been classified into ten different types from dry scrub thickets to dense wet evergreen forests at high elevations (Ramesh 1989a).

Data collection

Field data were collected for 124 plots distributed uniformly in a 2 km by 2 km grid (Fig. 1) (Appendix Table 1). These plot locations were chosen so as to follow up on a previous exercise conducted for vegetation assessment (Murali & Setty 2001) at the exact same locations.

Plots were 5 × 80 m and all woody stems of all species > 1 cm diameter at breast height in were identified, counted and measured. (Sundaram 2011) Thus, presence or absence of *L. camara*

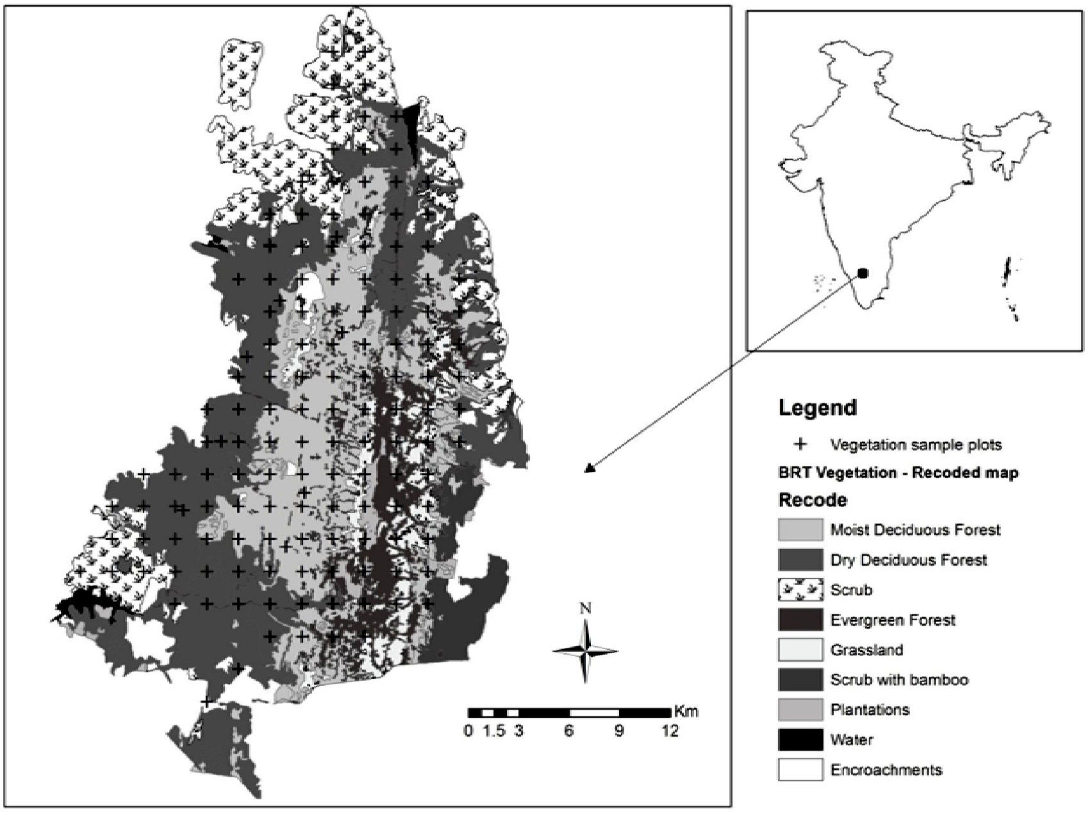

Fig. 1. Vegetation type map of BRT Tiger reserve with the sampling scheme.

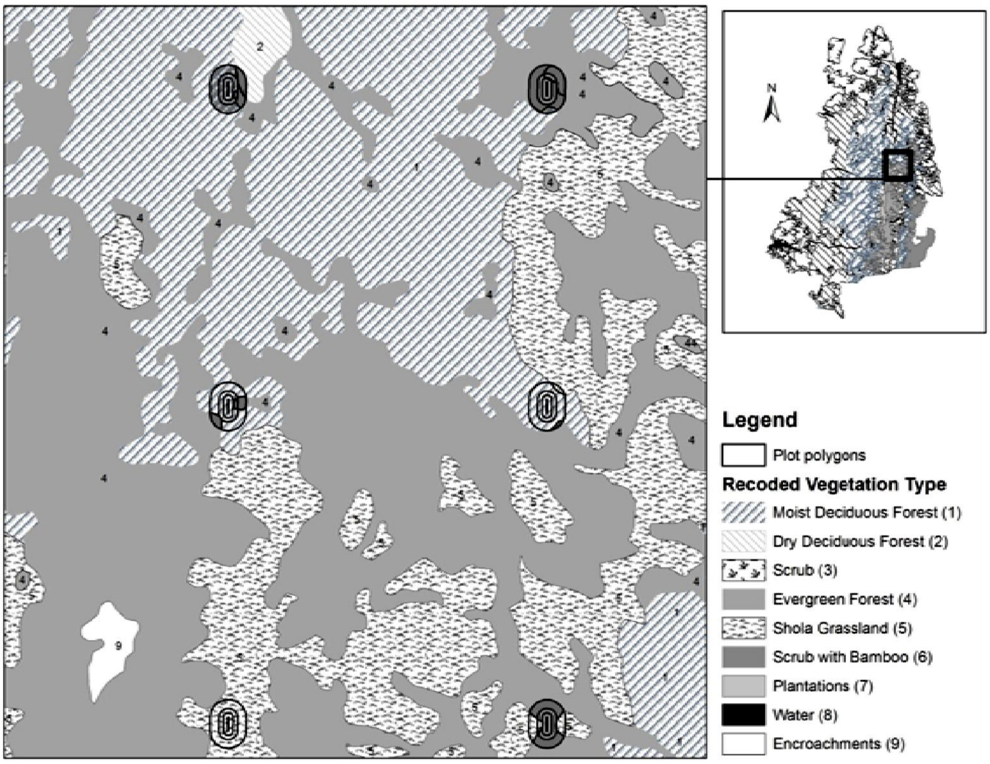

Fig. 2. Buffer polygons of 3 different distances around plots overlaid onto the vegetation type map. Partial sections of buffers indicate percentage of vegetation type within that buffer polygon.

was obtained for use as the dependent variable for modelling. Independent climatic variables used were obtained from the global BIOCLIM dataset version 1.4 at the 30 arc-second resolution (http://www.worldclim.org/bioclim) (Hijmans *et al.* 2005). Of the several climatic variables that are available in this dataset, we selected two variables that are likely to affect the growth of the study species (Rödder *et al.* 2009): the mean diurnal range (bio2) and annual precipitation (bio12). At the spatial scale of the study area, temperature is mostly determined by elevation. Therefore, we did not include temperature. Instead, a digital elevation model at 30 m resolution was used for obtaining elevation data at each plot location. Land use in the plots was obtained from a land cover map (scale 1:100,000 derived from SPOT data by visual interpretation (Ramesh & Menon 1997) which included, in the original form, 14 classes of land cover types.

Data preparation

The original land use map was reclassified into 9 cover types on the basis of similarity of habitats and phenological types within classes to limit redundancy (see Table 1).

Table 1. Table indicating original land cover types as per Ramesh 1989 reclassified into 9 cover types.

Original land cover types (14 -from Ramesh 1989b)	Merged types (9)
Scrub woodland to thickets (discontinuous)	Scrub
Scrub woodland to thickets (dense) Woodland to savanna woodland (short)	Dry Deciduous Forest
Scrub woodland to thickets with bamboo	Scrub with Bamboo
Woodland to savanna woodland (tall) tree savanna	Moist Deciduous Forest
Semi evergreen forests Evergreen forests Riparian forests	Evergreen Forests
Shrub savanna (grassland)	Shola Grassland
plantations	Plantations
Coffee plantations	(Coffee with *Grevillea robusta*, and *Eucalyptus* spp)
Water	Water
Encroachments	Encroachments

For each plot, percentage of area covered by each of these classes was calculated using a Geographical Information System (GIS). To evaluate relationship between the distribution of *L. camara* and land cover at different spatial scales, we generated three concentric GIS buffers around each of the plot polygons at 25, 50 and 100 m from the plot locations. These GIS buffers were created to generate concentric zones at specific distances away from the plot wherein the presence of *L. camara* would be evaluated in relationship with the amount of area occupied by certain cover types. The buffer polygons were then clipped to the vegetation type map and percentages were recorded for each of the cover types that were included within each of the buffer polygons (Fig. 2). Thus, for each plot location, we had data on cover type percentages within the plot as well as three concentric GIS buffers indicating progressive distances away from the plot location. A few land cover type variables were found to have zero values for all plots and were not considered for analyses. To improve the normality of data, percentage data were transformed using squareroot-arcsine. At the end of this data preparation, we had a total of 25 independent variables to be incorporated in the models (Appendix Table 2).

Statistical analyses

Species distribution analyses can be done using correlative modelling. Correlative models use distribution records of a species along with values of a set of predictor variables - such as resource gradients, or - to predict the likelihood of its occurrence, based on suitability of niche space. When these models use presence as well as absence records, they are considered a type of group discrimination techniques (Guisan *et al.* 2002; Robertson *et al.* 2003). We used generalized linear models with binomial error distribution to relate the Presence/Absence of *L. camara* to the independent variables. Each model included climatic variables, altitude data, and land cover variables. Models were built considering land use variables at the four spatial scales considered (i.e., within the plot and within 25, 50 and 100 m from the plot), as well as the model considering the variables at all the spatial scales together. We used an information-theoretic approach, based on Akaike's Information Criterion (AIC) (Burnham & Anderson 2002) to identify the scale at which landscape variables most strongly affect the distribution of *L. camara* (Ficetola *et al.* 2009). AIC trades-off explanatory power vs. number of predictors; parsimonious models explaining more variation have the lowest AIC values. We thus considered the model with lowest AIC values to be the "best AIC model" (Burnham & Anderson 2002). As sample size was limited compared to the number of independent variables, we used the AIC correction for small sample size (AICc), where AICc is calculated as :

$$AICc = AIC + \frac{2k(k+1)}{(n-k-1)}$$

where, n = sample size, and k = number of parameters in the model (Burnham & Anderson 2002; Kumar *et al.* 2006).

AICc gives a correction on the AIC value for finite sample sizes; thus AICc is AIC with an additional penalty if the sample size is small compared to the number of parameters (Burnham & Anderson 2002; Kumar *et al.* 2006). For each candidate model, we also calculated the AICc weight *w*, which represents the probability that a model is the best one within the set of candidate models, given the data (Burnham & Anderson 2002; Lukacs *et al.* 2007). We calculated the area under the curve (AUC) of the receiver operator characteristic plot as a measure of discrimination capacity of the best-AIC model; models with AUC = 0.5 do not discriminate better than random; AUC < 0.7 indicates limited discrimination, 0.7 ≥ AUC ≥ 0.8 indicates good discrimination and AUC > 0.9 indicates excellent discrimination (Liu *et al.* 2011; Manel *et al.* 2001). All analyses were performed using the R statistical software (R Development Core Team 2012).

Results

The natural land use types in the study site are dominated largely by two forest types - dry deciduous forest (approximately 38 %), and moist deciduous forest (approximately 23 %).

Table 2. Comparative table of the AICc for generalized linear models relating presence/absence of *L. camara* to environmental variables measured at different buffer distances from the sample plots. K: number of parameters in the model; *w*: AICc weight of the model.

Model	*K*	AICc	*w*
Dist 50	9	112.4	0.78
Dist 25	9	116.2	0.12
Dist 100	9	116.9	0.08
Dist 0	9	120.9	0.01
Global (all variables)	24	140.0	0.00

A comparison of AICc values indicated that the model at 50 m buffer distance was the best explanatory model for the *L. camara* distribution data. The AICc weight of the model at the 50 m scale was 0.78, indicating a good support for this scale. The model built at the 25 m scale had weight = 0.12, which indicates limited support, while the models built at the other scales had low weight, indicating essentially no support (Table 2). The model built using the 50 m buffer showed a good discriminatory power (AUC = 0.80). Thus the model at 50 m buffer distance explained the presence of *L. camara* best, indicating its possible relevance for the establishment of the species.

Among the 8 variables included in the 50 buffer distance model (Table 3), only 3 variables were significant: mean diurnal range of temperature, annual precipitation and % of moist deciduous forest within the 50 m buffer ($P = 0.05$). *L. camara* was associated with sites which had low temperature range, low annual precipitation and low percentage of deciduous forest.

Discussion

Invasion by *L. camara* is a long-established (Bhagwat *et al.* 2012; Kannan *et al.* 2013) and well-recognized problem in the Indian sub-continent (Kohli *et al.* 2006; Prasad 2010; Ramaswami & Sukumar 2011; Sundaram 2011). The steady invasion by *L. camara* across the Western Ghats has been documented in many case studies (Aravind *et al.* 2010; Murali & Setty 2001; Prasad 2009; Rao & Sagar 2012; Ramaswami & Sukumar 2011; Sundaram 2011). While mapping of the species using remote sensing has been attempted for some locations in India (Kandwal *et al.* 2009; Kimothi & Dasari 2010), predictive modelling has been restricted to Australia and China, to locations where this species is fairly common (Liu 2011; Robertson *et al.* 2004; Taylor *et al.* 2012). In India, predictive modelling of *L. camara* in view of climate change has also been attempted in protected areas (Priyanka & Joshi 2013). Such studies, working at larger spatial scales, show the importance of predictive modelling using a mechanistic approach (Priyanka & Joshi 2013). *L. camara* is reported to respond greatly to disturbance, and Sundaram (2011) indicated a steady but rapid increase over time in frequency as well as abundance of *L. camara*. Our analysis brings out some interesting results with respect to *L. camara* presence in different land cover types and at different scales. A comparison of the AIC values for the models at different distances indicated that the model at 50 m buffer distance

Table 3. Significance ($P \leq 0.05$) of variables included in the best-AICc model predicting the presence of *Lantana camara.*

Variables	B	χ^2_1	P
Altitude	-0.002	0.83	0.363
Mean diurnal range of temperature	-0.372	3.96	0.047
Annual precipitation	-0.005	4.34	0.037
% Moist Deciduous Forest within 50 m	-3.485	18.22	< 0.0001
% Dry Deciduous Forest within 50 m	-5.842	0.28	0.595
% Scrub forest within 50 m	-6.288	0.46	0.496
% Evergreen forest within 50 m	-5.814	0.12	0.731
% Grassland/Shola forest within 50 m	-6.281	0.79	0.374

had the lowest value, and hence provided the best explanation of the *L. camara* distribution.

Our results help to understand two important aspects of the invasion process of *L. camara*: (i) the habitat relevant for the diffusion of the invasive species and (ii) the buffer-scale that needs to be considered for that.

Fig. 3. *L. camara* in a patch of moist deciduous forest.

The above results indicate the importance of the moist deciduous forest type in the occurrence of *L. camara* along with two climatic variables: temperature and rainfall. Field observations confirmed these findings, having indicated that the presence of *L. camara* is high in the moist deciduous forest (Fig. 3), where the habitat is moister than the dry deciduous forests, and more open than the semi-evergreen or evergreen forest type.

Although it is also fairly common in the dry deciduous forest, as well as the scrub types of forest, the physical appearance of the shrub is greener for longer periods and larger in the moist deciduous type of forest than the shorter and thinner form in the dry deciduous forest type (Fig. 4), and remains so throughout most of the year in this study area. The shrub is also seen growing robustly along riparian tracts in dry forest patches, where moisture plays a major role.

Fig. 4. *L. camara* shrubs in the understorey of dry deciduous forest.

Our study, with a correlative regression approach, has helped to highlight the importance of specific variables in the spread and possible areas of occurrence of the invasive species *Lantana camara*. The use of buffers of different size around the plot areas helped to identify the scale at which landscape features take effect on the distribution of this species, and to build better models identifying the effect of environmental features. These results also point to the fact that more detailed studies need to be undertaken in different forest types to understand the role that they play in encouraging the establishment and spread of invasive species which occur in understorey habitats. Microclimatic differences in habitat also may affect the species' physiology and in turn its morphological or structural form. It may also prove worthwhile to explore other climatic variables, as well as other local variations such as edaphic factors or topographic complexity to test whether they have a role in changing the microhabitats so much as to promote the spread of invasive species. Thus, incorporating spatial heterogeneity in multiple ways would provide a much nuanced understanding of the non-native species distribution as exemplified by Kumar *et al*. (2006).

Correlative regression modelling (Jeschke & Strayer 2008; Wiens *et al*. 2009) has been used at two scales in this approach, incorporating fine scale information on habitat type with information at a broad scale on climatic factors, thus helping us to identify the variables in addition to climate that influence the distribution of invasive species (e.g. Stohlgren & Schnase 2006; Thuiller *et al*. 2006). The integration of fine-scale habitat information increases the performance of regression models, as has also been noted with other studies on invasive species (Ficetola *et al*. 2007). Thus, this study substantiates other research demonstrating that information collected at multiple spatial scales from the habitat to the regional, can help to meaningfully analyse and predict the distribution of invasive species. The results of this study also demonstrate the limitations of invasive species modelling based purely on climatic variables. These studies illustrate the need for incorporating biotic datasets at finer scales (Ficetola *et al*. 2007).

Our results reinforce the importance of an univocal habitat definition (*sensu* Bunce *et al*. 2008; Nagendra *et al*. 2013) in order to get stronger models of species distribution that can be widely applied. Deciduous forest cover at 50 m scale is very important, and disruption through these forests such as roads or plantations can prove to be the main driver of *Lantana* invasion at the boundary of this disturbance. Thus management may focus on these particular forest types and at such disturbance boundaries.

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References

Aravind, N. A., D. Rao, K. N. Ganeshaiah, R. Uma Shaanker & J. Poulsen. 2010. Impact of the invasive plant, *Lantana camara*, on bird assemblages at Malé Mahadeshwara Reserve Forest, South India. *Tropical Ecology* **51**: 325-338.

Austin, M. P. 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. *Ecological Modelling* **157**: 101-118.

Bhagwat, S. A., E. Breman, T. Thekaekara, T. F. Thornton & K. J. Willis. 2012. A battle lost? Report on two centuries of invasion and management of *Lantana camara* L. in Australia, India and South Africa. *PLoS ONE* **7**: e32407.

Broennimann, O., U. A. Treier, H. Muller-Scharer, W. Thuiller, A. T. Peterson & A. Guisan. 2007. Evidence of climatic niche shift during biological invasion. *Ecology Letters* **10**: 701-709.

Bunce, R. G. H., M. J. Metzger, R. H. G. Jongman, J. Brandt, G. Blust, R. Elena-Rossello, G. B. Groom, L. Halada, G. Hofer, D. C. Howard, P. Kovář, C. A. Mücher, E. Padoa-Schioppa, D. Paelinx, A. Palo, M. Perez-Soba, I. L. Ramos, P. Roche, H. Skånes & T. Wrbka. 2008. A standardized procedure for surveillance and monitoring European habitats and provision of spatial data. *Landscape Ecology* **23**: 11-25.

Burnham, K. P. & D. R. Anderson. 2002. *Model Selection and Multi-model Inference : A Practical Information-Theoretic Approach*. New York: Springer-Verlag.

Chytry, M., P. Pysek, J. Wild, J. Pino, L. C. Maskell & M. Vilà. 2009. European map of alien plant invasions based on the quantitative assessment across habitats. *Diversity and Distributions* **15**: 98-107.

Ficetola, G. F., L. Maiorano, A. Falcucci, N. Dendoncker, L. Boitani, E. Padoa-Schioppa, C. Miaud & W. Thuiller. 2010. Knowing the past to predict the future: land-use change and the distribution of invasive bullfrogs. *Global Change Biology* **16**: 528-537.

Ficetola, G. F., E. Padoa-Schioppa & F. De Bernardi. 2009. Influence of landscape elements in riparian buffers on the conservation of semiaquatic amphibians. *Conservation Biology* **23**: 114-123.

Ficetola, G. F., W. Thuiller & C. Miaud. 2007. Prediction and validation of the potential global distribution of a problematic alien invasive species - the American bullfrog. *Diversity & Distributions* **13**: 476-485.

Fielding, A. H. & J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* **24**: 38-49.

Fleishman, E., R. M. Nally, J. P. Fay & D. D. Murphy. 2001. Modeling and predicting species occurrence using broad-scale environmental variables: an example with butterflies of the Great Basin. *Conservation Biology* **15**: 1674-1685.

Gallien, L., R. Douzet, S. Pratte, N. E. Zimmermann & W. Thuiller. 2012. Invasive species distribution models - how violating the equilibrium assumption can create new insights. *Global Ecology and Biogeography* **21**: 1126-1136.

Guisan, A., T. C. J. Edwards & T. Hastie. 2002. Generalized linear and generalized additive models in studies of species distributions : setting the scene. *Ecological Modeling* **157**: 89-100.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones & A. Jarvis. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**: 1965-1978.

Jeschke, J. M. & D. L. Strayer. 2008. Usefulness of bioclimatic models for studying climate change and invasive species. *Annals of the New York Academy of Sciences* **1134**: 1-24.

Jiménez-Valverde, A., A. Peterson, J. Soberón, J. Overton, P. Aragón & J. Lobo. 2011. Use of niche models in invasive species risk assessments. *Biological Invasions* **13**: 2785-2797.

Joshi, A., D. Mudappa & T. R. Shankar Raman. 2015. Invasive alien species in relation to edges and forest structure in tropical rainforest fragments of the Western Ghats. *Tropical Ecology* **56**: 233-244.

Kandwal, R., C. Jeganathan, V. Tolpekin & S. Kushwaha. 2009. Discriminating the invasive species, 'Lantana' using vegetation indices. *Journal of the Indian Society of Remote Sensing* **37**: 275-290.

Kannan, R., C. Shackleton & R. Uma Shaanker. 2013. Reconstructing the history of introduction and spread of the invasive species, Lantana, at three spatial scales in India. *Biological Invasions* **15**: 1287-1302.

Khuroo, A., Z. Reshi, A. Malik, E. Weber, I. Rashid & G. Dar. 2012. Alien flora of India: taxonomic composition, invasion status and biogeographic affiliations. *Biological Invasions* **14**: 1-15.

Khuroo, A. A., Z. A. Reshi, I. Rashid & G. H. Dar. 2011. Towards an integrated research framework and policy agenda on biological invasions in the developing world: A case-study of India. *Environmental Research* **111**: 999-1006.

Kimothi, M. M. & A. Dasari. 2010. Methodology to map the spread of an invasive plant (*Lantana camara* L.) in forest ecosystems using Indian remote sensing satellite data. *International Journal of Remote Sensing* **31**: 3273-3289.

Kohli, R., D. Batish, H. P. Singh & K. Dogra. 2006. Status, invasiveness and environmental threats of three tropical American invasive weeds (*Parthenium hysterophorus* L., *Ageratum conyzoides* L. *Lantana camara* L.) in India. *Biological Invasions* **8**: 1501-1510.

Kumar, S., S. A. Spaulding, T. J. Stohlgren, K. A. Hermann, T. S. Schmidt & L. L. Bahls. 2008. Potential habitat distribution for the freshwater diatom Didymosphenia geminata in the continental US. *Frontiers in Ecology and the Environment* **7**: 415-420.

Kumar, S., T. J. Stohlgren & G. W. Chong. 2006. Spatial heterogeneity influences native and nonnative plant species richness. *Ecology* **87**: 3186-3199.

Kumara, H., S. Rathnakumar, R. Sasi & M. Singh. 2012. Conservation status of wild mammals in Biligiri Rangaswamy Temple Wildlife Sanctuary, the Western Ghats, India. *Current Science* **103**: 933-940.

Leung, B., N. Roura-Pascual, S. Bacher, J. Heikkila, L. Brotons, M. A. Burgman, K. Dehnen-Schmutz, F. Essl, P. E. Hulme, D. M. Richardson, D. Sol, M. Vila & M. Rejmanek. 2012. Teasing apart alien species risk assessments: a framework for best practices. *Ecology Letters* **15:** 1475-93.

Lindenmayer, D. & G. Likens. 2010. *Effective Ecological Monitoring*. Collingwood: CSIRO Publishing.

Liu, C., M. White & G. Newell. 2011. Measuring and comparing the accuracy of species distribution models with presence-absence data. *Ecography* **34**: 232-243.

Liu, X. 2011. Quantitative risk analysis and prediction of potential distribution areas of common lantana (*Lantana camara*) in China. *Computational Ecology and Software* **1**: 60-65.

Lockwood, J. L., P. Cassey & T. Blackburn. 2005. The role of propagule pressure in explaining species invasions. *Trends in Ecology & Evolution* **20**: 223-228.

Lukacs, P. M., W. L. Thompson, W. L. Kendall, W. R. Gould, P. F. J. Doherty, K. P. Burnham & D. R. Anderson. 2007. Concerns regarding a call for pluralism of information theory and hypothesis testing. *Journal of Applied Ecology* **44**: 456-460.

Manel, S., H. C. Williams & S. J. Ormerod. 2001. Evaluating presence-absence models in ecology: the need to account for prevalence. *Journal of Applied Ecology* **38**: 921-931.

Muniappan, R. & C. A. Viraktamath. 1993. Invasive alien weeds in Western Ghats. *Current Science* **64**: 555-558.

Murali, K. & S. Setty. 2001. Effect of weeds *Lantana* *camara* and *Chromolaena odorata* growth on species diversity, regeneration, and stem density of tree and shrub layer in BRT sanctuary. *Current Science* **80**: 675-678.

Nagendra, H., R. Lucas, J. P. Honrado, R. Jongman, C. Tarantino, M. Adamo & P. Mairota. 2013. Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators* **33**: 45-59.

Prasad, A. 2009. Tree community change in a tropical dry forest: the role of roads and exotic plant invasion. *Environmental Conservation* **36**: 201-207.

Prasad, A. 2010. Effects of an exotic plant invasion on native understory plants in a tropical dry forest. *Conservation Biology* **24**: 747-757.

Priyanka, N. & P. Joshi. 2013. Modeling spatial distribution of *Lantana camara* - A comparative study. *Canadian Journal of Basic and Applied Sciences* **1**: 100-117.

Ramaswami, G. & R. Sukumar. 2011. Woody plant seedling distribution under invasive *Lantana camara* thickets in a dry-forest plot in Mudumalai, southern India. *Journal of Tropical Ecology* **27**: 365-373.

Ramesh, B. R. 1989a. *Flora of Biligiri Rangan Hills*. Madras University.

Ramesh, B. R. 1989b. *Main Vegetation Types, in Evergreen Forests of the Biligirirangan Hills, South India : Ecology, Structure and Floristic Composition*. Ph.D. Thesis, Madras University.

Ramesh, B. R. & S. Menon. 1997. *Map of Biligiri Rangaswamy Temple Wildlife Sanctuary, Vegetation Types and Landuse Pondichery, India*. French Institute, India and ATREE, Bangalore, India.

Rao, R. R. & K. Sagar. 2012. Invasive alien weeds of the western ghats : taxonomy and distribution. pp. 139-161. *In*: J. R. Bhatt, J. S. Singh, S. P. Singh, R. S. Tripathi & R. K. Kohli (eds.) *In*: *Invasive Alien Plants: An Ecological Appraisal for the Indian Subcontinent, CABI Invasive Species Series*. Oxford, CAB International.

Richardson, D. M. & P. Pysek. 2006. Plant invasions: merging the concepts of species invasiveness and community invasibility. *Progress in Physical Geography* **30**: 409.

Richardson, D. M., P. Pysek, M. Rejmanek, M. G. Barbour, D. Panetta & C. J. West. 2000. Naturalization and invasion of alien plants: concepts and definitions. *Diversity and Distributions* **6**: 93-107.

Robertson, M. P., C. I. Peter, M. H. Villet & B. S. Ripley. 2003. Comparing models for predicting species' potential distributions: a case study using correlative and mechanistic predictive modelling techniques. *Ecological Modelling* **164**: 153-167.

Robertson, M. P., M. H. Villet & A. R. Palmer. 2004. A fuzzy classification technique for predicting species' distributions: applications using invasive alien plants and indigenous insects. *Diversity and Distributions* **10**: 461-474.

Rödder, D., S. Schmidtlein, M. Veith & S. Lötters. 2009. Alien invasive slider turtle in unpredicted habitat: a matter of niche shift or of predictors studied? *PLoS ONE* **4**: e7843.

Sharma, G. P., A. S. Raghubanshi & J. S. Singh. 2005. *Lantana* invasion: An overview. *Weed Biology and Management* **5**: 157-165.

Simberloff, D. 2006. Invasional meltdown : 6 years later: important phenomenon, unfortunate metaphor, or both? *Ecology Letters* **9**: 912-919.

Simberloff, D., J. L. Martin, P. Genovesi, V. Maris, D. A. Wardle, J. Aronson, F. Courchamp, B. Galil, E. Garcia-Berthou, M. Pascal, P. Pysek, R. Sousa, E. Tabacchi & M. Vila. 2013. Impacts of biological invasions: what's what and the way forward. *Trends in Ecology and Evolution* **28**: 58-66.

Stohlgren, T. J. & J. L. Schnase. 2006. Risk analysis for biological hazards: what we need to know about invasive species. *Risk Analysis* **26**: 163-173.

Sundaram, B. 2011. *Patterns and Processes of Lantana camara Persistence in Southern Tropical Dry Forests*. Thesis, Manipal Academy of Higher Education.

Sundaram, B. & A. Hiremath. 2011. *Lantana camara* invasion in a heterogeneous landscape: patterns of spread and correlation with changes in native vegetation. *Biological Invasions* **14**: 1127-1141.

Taylor, S., L. Kumar, N. Reid & D. J. Kriticos. 2012. Climate change and the potential distribution of an invasive shrub, *Lantana camara* L. *PLoS ONE* **7**: e35565.

Team, R. D. C. 2012. *R: A Language and Environment for Statistical Computing. Vienna, Austria*. R Foundation for Statistical Computing.

Thuiller, W., B. Lafourcade, R. Engler & M. B. Araújo. 2009. BIOMOD - a platform for ensemble forecasting of species distributions. *Ecography* **32**: 369-373.

Thuiller, W., D. M. Richardson & G. F. Midgley. 2007. Will climate change promote alien plant invasions? pp. 197-211. *In:* W. Nentwig (ed.) *Biological Invasions, Ecological Studies*. Berlin Heidelberg: Springer-Verlag.

Thuiller, W., D. M. Richardson, M. Rouget, S. Proches &

J. R. Wilson. 2006. Interactions between environment, species traits, and human uses describe patterns of plant invasions. *Ecology* **87**: 1755-1769.

Walton, C. 2006. *Global Invasive Species Database* : *Lantana camara.*: Invasive Species Specialist Group, IUCN Species Survival Commission.

Wiens, J. A., D. Stralberg, D. Jongsomjit, C. A. Howell & M. A. Snyder. 2009. Niches, models, and climate change: Assessing the assumptions and uncertainties. *Proceedings of the National Academy of Sciences* **106**: 19729-19736.

Wiens, J. J., & C. H. Graham. 2005. Niche conservatism: integrating evolution, ecology, and conservation biology. *Annual Review of Ecology, Evolution, and Systematics* **36**: 519-539.

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Appendix Table 1. Plot Numbers and GPS data for the locations of the plots in the study site.

Plot_no	Altitude	Latitude	Longitude
1	794	12.125	77.15833
2	1058	12.125	77.175
3	773	12.10833	77.15833
4	931	12.10833	77.175
5	774	12.09167	77.15833
6	855	12.09167	77.175
7	678	12.09167	77.19167
8	715	12.075	77.15833
9	913	12.075	77.175
10	761	12.075	77.19167
11	829	12.05833	77.14167
12	798	12.05833	77.15833
13	1252	12.05833	77.175
14	717	12.05833	77.19167
15	925	12.05833	77.20833
16	848	12.04167	77.125
17	974	12.04167	77.14167
18	822	12.04167	77.15833
19	1305	12.04167	77.175
20	730	12.04167	77.19167
21	920	12.04167	77.20833
22	915	12.025	77.125
23	1000	12.025	77.14167
24	937	12.025	77.15833
25	1246	12.025	77.175
26	913	12.025	77.19167
27	1134	12.025	77.20833
28	818	12.00833	77.10833
29	982	12.00833	77.125
30	1146	12.00833	77.14167
31	1170	12.00833	77.15833
32	1028	12.00833	77.175
33	966	12.00833	77.19167
34	1245	12.00833	77.20833
35	997	12.00833	77.225
36	925	11.99167	77.125
38	1186	11.99167	77.15833
39	1036	11.99167	77.175
40	880	11.99167	77.19167

Plot_no	Altitude	Latitude	Longitude
41	1262	11.99167	77.20833
42	894	11.99167	77.225
43	1047	11.975	77.125
44	1305	11.975	77.14167
45	1206	11.975	77.15833
46	1194	11.975	77.175
47	1138	11.975	77.19167
48	1486	11.975	77.20833
49	1053	11.975	77.225
50	737	11.95833	77.10833
51	1181	11.95833	77.125
52	1217	11.95833	77.14167
53	1188	11.95833	77.15833
54	1185	11.95833	77.175
55	1203	11.95833	77.19167
56	1563	11.95833	77.20833
57	1337	11.95833	77.225
59	702	11.94167	77.10833
60	1214	11.94167	77.125
61	1217	11.94167	77.14167
62	1104	11.94167	77.15833
63	1250	11.94167	77.175
64	1214	11.94167	77.19167
65	1591	11.94167	77.20833
66	1146	11.94167	77.225
67	728	11.925	77.09167
68	756	11.925	77.10833
69	1007	11.925	77.125
70	1065	11.925	77.14167
71	1102	11.925	77.15833
72	1408	11.925	77.175
73	1617	11.925	77.19167
74	1364	11.925	77.20833
76	726	11.90833	77.05833
77	733	11.90833	77.075
78	771	11.90833	77.09167
79	894	11.90833	77.10833
80	1087	11.90833	77.125
81	1079	11.90833	77.14167
82	1196	11.90833	77.15833
83	1444	11.90833	77.175

Contd...

Appendix Table 1. Continued.

Plot_no	Altitude	Latitude	Longitude
84	1479	11.90833	77.19167
85	1181	11.90833	77.20833
86	729	11.89167	77.04167
87	726	11.89167	77.05833
88	781	11.89167	77.075
89	802	11.89167	77.09167
90	870	11.89167	77.10833
91	1192	11.89167	77.125
92	1164	11.89167	77.14167
93	1333	11.89167	77.15833
95	1572	11.89167	77.19167
96	1287	11.89167	77.20833
97	751	11.875	77.04167
98	763	11.875	77.05833
99	800	11.875	77.075
100	1117	11.875	77.09167
101	1009	11.875	77.10833
102	1242	11.875	77.125
103	1206	11.875	77.14167
104	1193	11.875	77.15833
106	1575	11.875	77.19167
107	1429	11.875	77.20833
108	765	11.85833	77.05833
111	810	11.85833	77.075
112	1053	11.85833	77.09167
113	931	11.85833	77.10833
114	1009	11.85833	77.125
115	1149	11.85833	77.14167
116	1167	11.85833	77.15833
118	1257	11.85833	77.19167
119	1226	11.85833	77.20833
120	804	11.84167	77.075
121	1118	11.84167	77.09167
122	835	11.84165	77.10833
123	1009	11.84167	77.125
124	1133	11.84167	77.14167
127	1529	11.84167	77.19167
128	1053	11.84167	77.20833
129	910	11.825	77.125
130	1057	11.825	77.14167
131	1047	11.825	77.15833
132	1338	11.825	77.175
133	927	11.80833	77.10833
134	877	11.79167	77.09167

Appendix Table 2. List of variables used in the final model.

Altitude
Bio2
Bio12
AsinSqrt_1
AsinSqrt_2
AsinSqrt_3
AsinSqrt_4
AsinSqrt_5
Asinsqrt1_25
Asinsqrt2_25
Asinsqrt3_25
Asinsqrt4_25
Asinsqrt5_25
Asinsqrt1_50
Asinsqrt2_50
Asinsqrt3_50
Asinsqrt4_50
Asinsqrt5_50
Asinsqrt1_100
Asinsqrt2_100
Asinsqrt3_100
Asinsqrt4_100
Asinsqrt5_100
Asinsqrt7_100
Asinsqrt9_100