UPSCALING SPECIES INVASION PATTERNS FROM LOCAL TO REGIONAL FOR FOREST ECOSYSTEM MANAGEMENT

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Commission VI, WG VI/7

KEY WORDS: Upscale, Invasion, *Chromolaena odorata*, Forest ecosystem, Management

ABSTRACT:

Almost all remote sensing studies model invasion of species dominating ecosystems canopies, typically in predicting their presence or absence. However, a vast majority of invasive species do not dominate ecosystems canopies. Remote sensing experts have traditionally overlooked such cryptic invaders spatial distribution and productivity pattern within map units for a variety of reasons including spectral response limitations and inadequate quantitative data. Almost none attempted to model and upscale such populations distributed across forest understorey environment. These inclusions reduce the capability of remote sensing and GIS techniques or importance of maps. This is crucial in invasive species management. In this study, we synthesized data from different remote sensing and GIS sources to (1) model the actual and potential area and forest types in Nepal vulnerable to invasion of the *Chromolaena odorata*, one of the world's worst cryptic invasive species and (2) segregate the reproductive and non-reproductive populations at national scale using local scale information. Results reveals that invasive species models developed at local scale could successfully be up scaled at national scale. The map of current potential distribution of *C. odorata* shows that out of 75 forest communities of Nepal, 9 are currently infested by the *C. odorata*. They are: *Acacia – Dalbergia*, Alder, Hill *Shorea*, Pine, Pine - broad leaved forest, Riverine broad leaved, *Schima – Castanopsis*, Terai *Shorea* and Upper tropical riverine forest. Such information is crucial for land managers to focus their precious funds and efforts to control the spread of this species and so that the control methods are practical.

1. INTRODUCTION

The spread of introduced plant species around the world has been recognized and considered to be a key area of biological investigation (Hooker 1864; Elton 1958). Despite growing awareness and the extensive amount of research carried out on introduced plant species worldwide (Groves & Burdon 1986; Mooney 1986; Usher 1986; Drake *et al.* 1989; Lodge 1993; Williamson 1996), little attention has been given in mapping their distribution.

Mapping actual and potential distribution of invaders is considered crucial for their management (Reichard & Hamilton 1997; Rejmánek 2000). Maps predicting the severity of the impact and damage could thus be used to localize areas requiring interventions most urgently. To this end, the development of advanced remote sensing and GIS technologies offers remarkable possibilities to map the actual and potential distribution of invasive plant and animal species (McCormick 1999; Haltuch *et al.* 2000; Stow *et al.* 2000). Remote sensing applications however, appear to be restricted to detection of invasive species dominating the upper layer of the invaded community. Joshi *et al*. (2004) observed that 67% of the world's 100 worst invasive species (ISSG 2004) do not dominate the ecosystem canopy. Most of these cryptic invaders are small and go unnoticed or are hidden from remote sensing devices for instance when growing in the understorey of forest (Pysek & Prach 1995; Gerlach 1996; Chittibabu & Parthasarathy 2000). The data captured by remote sensing devices will be most directly related to the properties of that canopy. Applying remote sensing to mapping cryptic invasive species which do not appear as canopy dominant species is not straightforward since the captured spectral information will not be directly attributable to these species. Species spectra models can thus not be inverted to predict their distribution.

Although the spectral response of cryptic invaders is not directly sensed by remote sensing device, knowledge of their ecology could significantly enhance our remote sensing understanding. The need for stronger links between ecology and remote sensing technology is evident for all taxa, but it is especially critical for invasive species groups since they pose a serious risk to the invaded ecosystems. Hence, a combination of remote sensing techniques, GIS and ecological knowledge could potentially be used in mapping non-canopy dominant invasive species as well as predicting the probability of actual and potential sites and areas where environmental conditions are susceptible to infestation. Such cases might occur in degraded forests invaded by exotic species which are adapted to increased light intensities associated with the opening of the forest canopy. Consequently, mapping forest canopy openings could be a potential factor to predict the distribution of forest understorey heliophytic invaders. Joshi *et al.* (2005) demonstrated that 89% of variance of observed canopy density was explained by the predictions using artificial neural network. High accuracy in forest canopy classification may hold particular promise since growth of forest understorey heliophitc invasive species depends on light intensity reaching to the forest floor which is regulated by the canopy itself.

Recently, Joshi *et al*. (2006) indicated that *Chromolaena odorata* (L.) R. M. King & Robinson thrives in areas with high light intensities, which correspond to reduced canopy density.

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Light intensity under closed canopy in natural forest remains below the threshold for seed production. They further demonstrated that the seed production per plant differed between highly and poorly reproductive populations by more than five orders of magnitude and *C. odorata* did not produce seed below a light intensity of 6.5 mJ m-2 day-1 that corresponds to forest canopy density above 60%. Up to one million seeds per plant were produced in areas with open forest canopy, while no seeds were produced in forest with a canopy density over 60%. Their analysis reported so far was undertaken at local level. For the national level planning and management purpose this information is not sufficient.

At micro-scale, light intensity (forest canopy density) strongly limits *C. odorata*'s productive and non-productive population and plays a key role in determining its invasion success in Nepalese forest ecosystems. At national scale, the presence of *C. odorata* could be strongly related to environmental variables namely altitude (temperature) and precipitation. Following common practice in invasive species distribution modeling (Pysek *et al.* 1998; Higgins *et al.* 1999; Baker *et al.* 2000) we searched for the climatic envelope within which *C. odorata* is present. The climatic envelope models assume that extreme climatic conditions restrict the distribution of species. Recently, climate databases have been developed with a resolution of 1 km^2. This WORLDCLIM dataset offers the opportunity to model species climate relationship at finer resolution (Hijmans et al. 2005). This would be attractive, particularly in countries with complicated topography for instance Nepal where climatic conditions change over short distances.

The aim of this study is to upscale and spatially segregate productive and non-productive populations of invasive species *C. odorata* at national scale using local scale information. We followed Joshi *et al.,* (2006) and combined this local scale information with bioclimatic envelop at national scale. We upscaled the reproductive pattern of *C. odorata* to the national scale by integrating remotely sensed data, GIS, and statistics. We investigated the correlation between high resolution climate surfaces for Nepal and developed and compared climate based distribution models for *C. odorata* in Nepal. This information could help land managers in understanding where to focus their precious funds and efforts on to control the spread of this species, and so that the control methods are practical.

2. MATERIAL AND METHODS

2.1. Elevation, Forest Types and Cover Maps

An elevation model of the study area was created from 26 scenes of SRTM (Shuttle Radar Topography Mission) images downloaded from Global Land Cover Facility site (GLCF 2004). The 26 scenes were mosaiced and an elevation model of Nepal was derived using ArcGIS 9.0 (ESRI 2004).

Similarly, 16 scenes of ETM+ images between September–December of the year 2000 (table 1) were downloaded from Global Land Cover Facility site. The mosaic image was classified into 4 forest canopy density classes according to Joshi *et al.,* (2005).

Dobremez *et al*., (1975), Dobremez (1976), Dobremez and Shakya (1977), Dobremez and Shrestha (1980), Dobremez (1984) and Dobremez *et al*., (1984) produced maps of the actual and potential distribution of forests communities in Nepal. A digital version of these maps updated by IUCN (Nepal), ICIMOD and HMG, Nepal (unpublished) is used and referred to in this article as the Dobremez forest community map.

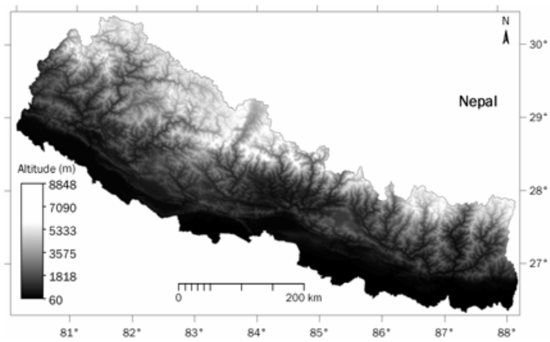

Figure 1. Mosaic of 26 scenes of Shuttle Radar Topography Mission images showing elevation map of Nepal

SN	Path/row	Acquisition date	Producer
1	139/041	12/26/2000	EarthSat
2	139/042	11/6/1999	USGS / GLCF
3	140/041	10/30/2000	EarthSat
4	140/042	10/28/1999	EarthSat
5	141/040	11/22/2000	EarthSat
6	141/042	10/24/2001	EarthSat
7	142/040	12/13/1999	EarthSat
8	142/041	12/13/1999	EarthSat
9	143/039	10/3/2000	EarthSat
10	143/040	12/25/2001	EarthSat
11	143/041	10/17/1999	EarthSat
12	144/039	10/13/2001	EarthSat
13	144/040	11/091999	USGS
14	144/041	11/11/2000	EarthSat
15	145/039	10/15/1999	EarthSat
16	145/040	10/15/1999	USGS

Table 1. Landsat ETM+ Images used in this study, including path and row number, acquisition date and source.

SN	Data type	Date	Source*
1	SRTM images (Elevation)	2000	USGS / GLCF
2	Monthly Precipitation	50 years average	(Hijmans et al. 2005)
3	Monthly Temperatures	50 years average	(Hijmans et al. 2005)
4	Monthly Evapotranspiration	50 years average	New LocCLIM (FAO)
5	ETM+ images mosaic of Nepal	Sept-Dec 2000	USGS/GLCF
6	Forest communities	2000	Dobermez/IUCN /HMG
6	Topographic maps	1996	DoS
7	Chromolaena odorata	Field observation	2002-2005
8	Herbarium records	1954-2005	KATH, BM

Table 2. Description of the data used in this study

*DoS = Department of Survey, Nepal; KATH = National Herbarium, Kathmandu, Nepal; BM = British Museum, London, England; USGF/GLCF = the Earth Science Data Interface (ESDI) at the Global Land Cover Facility website (http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp)

2.2. Climate Data

We compiled a dataset with ~1 km^2 resolution of fifty years average of monthly precipitation, potential evapotranspiration, minimum, mean and maximum daily temperature. Temperature and precipitation surfaces with 1 km^2 resolution were downloaded from the WORLDCLIM database (www.worldclim.org/), described by (Hijmans et al. 2005). The New LOCCLIM software from FAO site (www.fao.org/sd/2002/en1203a_en.htm) was used to generate local climate data of mean monthly potential evapotranspiration and length of growing season for 4550 geographical locations systematically distributed across the country. These point data were converted into point maps. Co-Kriging point interpolation method was applied in a GIS environment using elevation as a co-variable. All raster maps were then resampled to a 1 km^2 grid. The details of the data type, date of acquisition and the source is presented in table 2.

2.3. Principal Component Analysis

We calculated 10 principal components (PC) using all environmental variables (monthly mean temperatures (mean, maximum and minimum), monthly mean evapotranspiration, mean monthly precipitation) to reduce data dimensionality. Principal components analysis (PCA) is a multivariate technique that produces a set of components (variables) called principal components which are weighted linear combinations of the original variables (Chatfield & Collins 1980; James & McCulloch 1990). We selected all these variables as inputs in an expert PCA model to predict the distribution of *C. odorata* in Nepal. The model was a logistic regression model using the first ten components of the PCA as inputs.

2.4. Field Data

We compiled a dataset of 773 sites located throughout Nepal for which we recorded the presence and absence of *C. odorata*. Part of these site descriptions were obtained during botanical surveys undertaken by the first author prior to 2001. Also included were the sites of herbarium records from the National Herbarium in Kathmandu (KATH) and the British Museum (BM). A further sample of 594 site observations was captured during various surveys in 2002, 2003 and 2004. Geographical locations were recorded using Garmen GPS. This sample was used to develop and validate the distribution models for *C. odorata*. A sub-sample of 387 records (50%) was used to develop the models described above. The remaining 50% (386 observations) of the sample was used to validate the models.

3. RESULTS

3.1. Correlation between Climatic Factors

Figure 2 shows a matrix revealing the pairwise correlation between the fifty-year averages of monthly potential evapotranspiration, precipitation and the monthly mean of minimum, maximum and average daily temperatures. Also included are altitude, length of the growing season and latitude/longitude in Nepal. The matrix shows all monthly temperature values were extremely highly correlated. Correlation between temperature and precipitation and potential evapotranspiration was lower. The length of the growing season showed low to intermediate correlation to the above-mentioned climatic variables. Elevation, latitude and longitude generally showed lower correlations to climate variables. This figure shows that multi-collinearity would be a real problem when entering these climate variables as independent variables in a statistical analysis.

The figure also reveals the correlation of the first ten principal components derived from the climate data. PC 8 and PC 10 were highly correlated to thermoclimate. The other components were showing medium correlations to precipitation in various months. The figure reveals that the principal components were not or poorly correlated among each other.

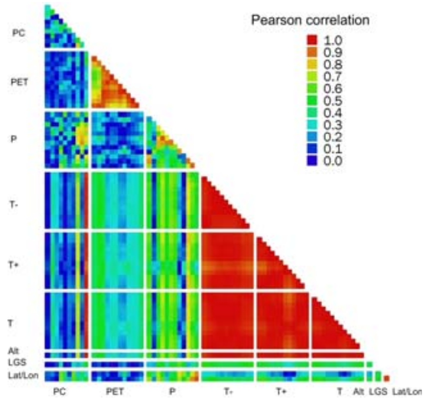

Figure 2. Matrix revealing the Pearson correlation between pairs of climate variables. Abbreviations: PC = Principal components (1-10); PET = mean monthly potential evapotranspiration; P = mean monthly precipitation; T^- = mean monthly minimum Temperature; T^+ = mean monthly maximum temperature; T = average monthly temperature; Alt = Altitude; LGS = Length of growing season; LatLon = Latitude and longitude.

Figure 3 shows the distribution of *C. odorata* in Nepal. The figure suggests a relation with longitude and elevation, which is confirmed in figure 4.

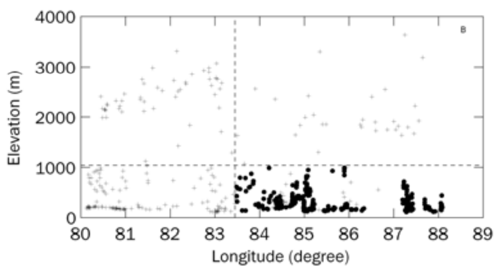

Figure 3 . Distribution of *C. odorata* in Nepal according to 773 records throughout the country showing relation of the observed distribution (+ Absence, • Presence) with longitude and elevation.

Six components were selected (table 3) when running a logistic regression model with the first ten principal components as dependent variables ($-2*(LL_6-LL0) = 357.98$, df = 6, $p<0.000$).

Variable	Coefficient	SE	t	P
Intercept	-13.52	7.630	-1.77	0.071
PCA 1	0.023	0.003	6.69	0.000
PCA 5	0.045	0.010	4.48	0.000
PCA 6	-0.113	0.032	-3.45	0.000
PCA 7	-0.117	0.019	-5.90	0.000
PCA 8	-0.264	0.058	-4.53	0.000
PCA 10	0.054	0.025	2.15	0.031

Table 3. Results of logistic regression between *C. odorata* presence absence and principal components

The distribution resulting from this model is displayed in Figure 4. The figure reveals a close match between observed and predicted distribution.

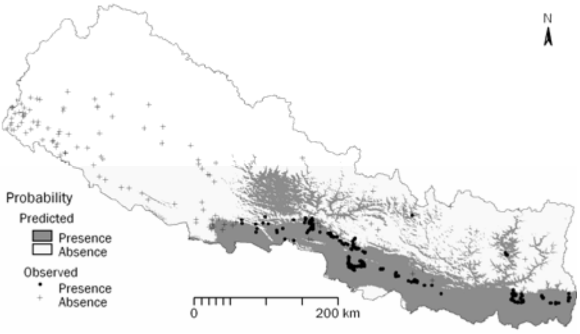

Figure 4. Observed (test sample) and principal components based predicted distribution of *C. odorata* (+ Absence, • Presence) in Nepal at pixel resolution of 100 m.

Assessment of the accuracy of the predictions made by the model revealed that the model had overall accuracy of 94% with Kappa 0.86 and standard error 0.0289.

Figure 5 presents the spatial distribution of forest canopy density in 4 classes in Nepal.

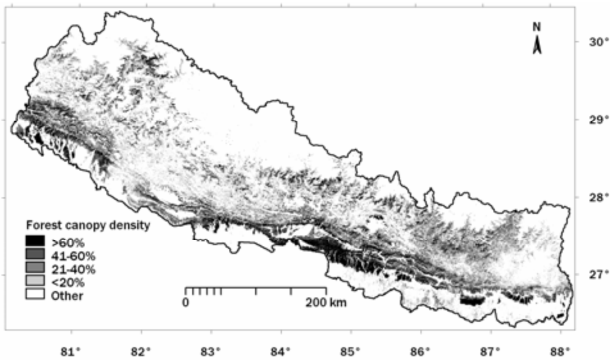

Figure 5. Forests canopy density map of Nepal

Derived from figure 4 and 5 we produced a map (figure 6) showing Forests canopy density map of Nepal within the suitability range of *C. odorata*.

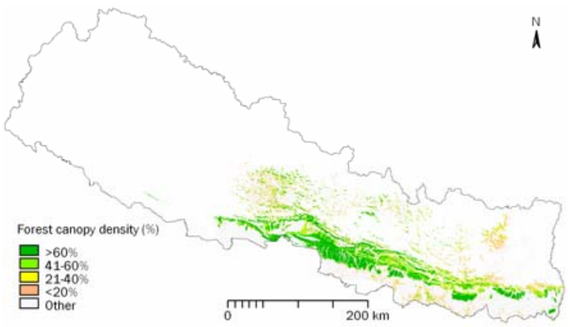

Figure 6. Forests canopy density map of Nepal within the suitability range of *C. odorata*

Error matrix (table 4) revealed that the <20% and 21-40% canopy density class were classified with producer's accuracy of over 77% and 67% respectively with much of the error attributed to confusion with the other and 40-60% canopy density class. The high canopy density class (>60%) had the larger producer's accuracy of 98%.

Forest canopy density	Other	<20 %	21-40%	41-60%	>60 %	Total	Ommission error	Producer's accuracy
Other	26	4	2	0	0	32	18.75	81.25
<20%	2	14	2	0	0	18	22.22	77.78
21-40%	1	2	21	7	0	31	32.26	67.74
41-60%	0	1	1	23	6	31	25.81	74.19
>60%	0	0	0	1	51	52	1.92	98.08
Total	29	21	26	31	57	164		
Commission error	10.3	33.3	19.2	25.8	10.5		135	
User's accuracy	89.6	66.6	80.7	74.2	89.4	Overall Accuracy		82.3 %

Table 4. Error matrix for observed versus predicted canopy density class by an artificial neural network.

Information derived from local scale (see Joshi *et al.*, 2006) figure 6 shows the potential distribution and probability of presence of seed producing populations of *Chromolaena odorata* in Nepal in forest environment.

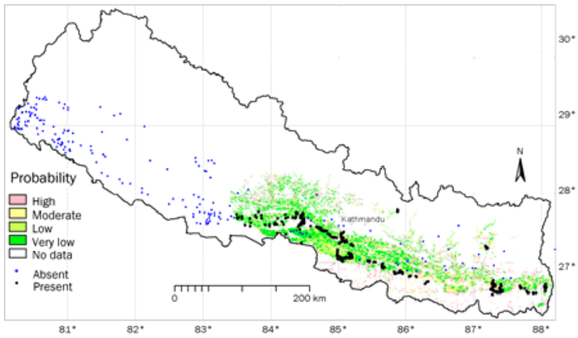

Figure 7. Potential distribution of *Chromolaena odorata* in Nepal and probability of presence of seed producing populations in forest environment. Points represent all of observed presence (•) and absence (·) of the species

We finally combined figure 7 with the Dobremez forest community map. The combined map of forest communities and current potential distribution of *Chromolaena odorata* in Nepal shows that out of 75 forest communities only 9 are currently under *C. odorata* invasion. They are: *Acacia – Dalbergia*, Alder, Hill *Shorea*, Pine, Pine - broad leaved, Riverine broad leaved, *Schima – Castanopsis*, Terai *Shorea* and Upper tropical riverine forest (figure 8).

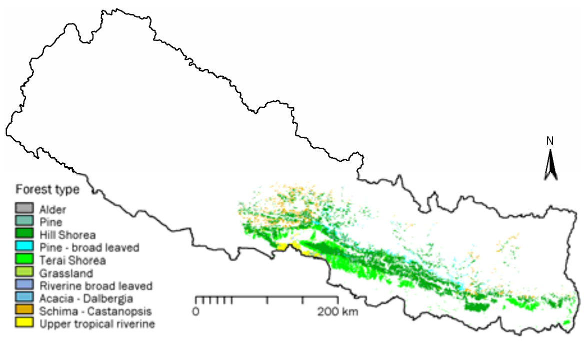

Figure 8. Forest communities of Nepal under *Chromolaena odorata* infestation

4. DISCUSSION

Our results demonstrated that identifying spatial extent of potential *C. odorata* invasion over large areas can be successfully accomplished and upscaled using local empirical knowledge and climatic variables. In this study, we also demonstrated that very high resolution interpolated climate surfaces derived from the SRTM and weather stations allowed us to predict the distribution of *C. odorata* with 86% accuracy. Furthermore, higher resolution interpolated climate surfaces have potential to map climate boundaries with higher precision in terrain with complicated topography such as Nepal.

Species, for instance *C. odorata* having worldwide distribution may not allows us to draw a climatic envelop. Based on the expert knowledge on the ecology of *C. odorata* we could not draw a fine line of climatic envelop. Certainly, image resolution, and predictor variables are two components that must be carefully chosen when constructing any distributional model. The problem in mapping of the presence and absence of a species at national or regional scale could be solved by using finer resolution interpolated climate surfaces or remote sensing images which usually provides better predictive ability in models (Guisan & Thuiller 2005). Thus, an increase in spatial resolution of climate data is one of the primary factors necessary to increase model prediction accuracy, particularly for areas with microtopographic variation (Guisan & Zimmermann 2000). The climate data layers used for modeling are available at various resolutions, but even the highest resolution, multi-collinearity among the predictive variables could easily mislead our judgment.

High bioclimatic variation and altitudinal gradient in the Nepalese mountains would suggest that ecological effects on organisms should be strong. This means the potential for effective modeling should be high. However, spatial scale certainly plays a significant role since climate could change within a distance of few hundred meters. The high-altitude distribution limits of a species can be constrained by the low winter temperatures or the amount of frost below which level a plant species could stops its photosynthetic activity or simply could not survive. *C. odorata* could not survive above frost line. Our model assumes that lower lethal temperature could be the strongest influential climatic variable, which limits *C. odorata*'s vertical distribution i.e. northern boundary. This is reasonable because many literatures mentioned that *C. odorata* couldn't survive at this temperature (Kriticos et al. 2005). Our empirical observation also showed that *C. odorata* was not observed beyond 1100 m altitude. Our analysis showed that altitude and temperature variables were highly correlated among each other. Hence, using any one of these variable could equally predict the presence and absence of *C. odorata*, which would reinforce our conclusions regarding the reduction of effect of multi-collinearity among climatic variables.

Temperatures or altitude limits did not predicted the horizontal distribution of *C. odorata* because altitude does not change horizontally in Nepal. However, length of growing season for *C. odorata* significantly differs. *C. odorata* needs length of main growing season of at least 7 months time to complete its life cycle. The summer monsoon (summer rainy season), a strong flow of moist air from the southwest, follows the pre-monsoon season. The arrival of the summer monsoon can vary by as much as a month, in Nepal, it generally arrives in early June starting from Eastern Nepal and lasts through September, when it begins to recede. The plains and lower Himalayas receive more than 70% percent of their annual precipitation during the summer monsoon. The amount of summer monsoon rain generally declines from southeast to northwest as the maritime wedge of air gradually becomes thinner and dryer. Although west Nepal receives sufficient pre and post monsoon rain, the main growing season for most of the areas are below 150 days, which is not long enough where *C. odorata* could complete its life cycle. A long dry season between winter and summer monsoon season could potentially prevent *C. odorata* invasion in west Nepal.

C. odorata is a problem worldwide. It invades natural ecosystems and poses a serious threat to the maintenance and enhancement of biodiversity values of native vegetation. Land managers currently control the spread of invasive non-native plant species after they have already become established instead of trying to prevent the establishment of the species, but its management requires preventative approaches, both at the local and national level. The early detection of new species invasions and the development of rapid response plans are vital for successful eradication programmes. Upscaling is highly crucial for invasive species management, since limitation of resources forces invasive species managers to carefully plan and prioritize interventions in areas more severely affected by invaders or localize areas requiring interventions most urgently. And they could focus their precious funds and efforts to control the spread of this species and so that the control methods are cost effective and practical. The approach we presented can be well applied for mapping of other species if there biometry and environmental requirement is known.

The findings of our study illustrate how remote sensing and GIS technologies can provide ecologists and land managers with an innovative perspective with which to study the factors influencing the patterns of invader population dynamics at local to national landscape scales. Incorporation of remote sensing techniques with species biometry yields instantaneous, useful, cost effective, multi-scale and temporal information on distribution pattern of an invasive species. In this respect, the immediate benefit of this research has been to contribute to the knowledge base of land managers by providing improved information on the rate of spatial and temporal distribution populations of *Chromolaena odorata*, which will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems.

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