Remote Sensing And GIS For Mapping And Management Of Invasive Shrub *Chromolaena odorata* In Nepal

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SUMMARY

The applications of remote sensing have been restricted to those species dominating the canopy of ecosystems. Dominant invasive species determine the spectral signature received by the remote sensing scanner and thus allow detection using this spectral signature in a straightforward manner. Many invasive species however, do not dominate the canopy. They are rare or hidden below the ecosystem canopy. The aim of this study was to map the seed productivity of such hidden invasive species. We have selected Chromolaena odorata which is one of the world's worst invasive species invading the entire tropical region of the world. We applied ETM+ imagery, GIS and statistics to map and model its seed productivity. Light intensity and biomass of other forest under-storey vegetation significantly determined the productivity of the species. Data analysis showed that other variables such as grazing intensity and distance from forest edge and road to forest interior had an indirect effect on productivity of Chromolaena. Populations of Chromolaena were present, but failed to flower below a light intensity of 6.5 mJ m^{-2} day^{-1}. This suggests that light intensity segregates the species in reproductive and non-reproductive populations. These patterns in Chromolaena were mapped using remote sensing imagery and GIS. Localization of such populations could significantly reduce eradication/control costs. This may prove particularly valuable when implementing control measures under circumstances of limited capital and manpower.

KEY WORDS: *Chromolaena odorata, GIS, invasive species, light intensity, mapping, neural networks, remote sensing, seed productivity, species management*

INTRODUCTION

The spread of invasive species has stimulated interest in the prediction of their distribution. Many studies have been undertaken to map the distribution of invasive species (Anderson *et al*., 1993; McCormick, 1999). Typically, such maps display the presence and absence of an invader.

Why are we interested in distribution maps for invasive species? First of all, once an invader has been recognized as problematic, we are interested to localize its distribution and monitor its eventual further spread. Secondly, ecological knowledge is required to assess their density and impact. Distribution maps have been used since long to acquire such knowledge. For example species climate models have been used to assess the risk of further spread of invaders (Rouget *et al*., 2004). Thirdly, it has been argued that spatial information is needed to develop policies aimed at invasive species management (Wittenberg & Cock, 2001). Policy intervention derived from such maps may range from total eradication towards control or merely alleviation of its negative impacts. For instance, Goodall & Naude (1998) recommend that habitats be ranked according to criteria that encompass the habitat's status, protection and management. This is particularly so where financial resource and manpower do not suffice to cover the entire area infested. In such cases, information on the distribution of invasive species could be used to prioritize areas deserves interventions. One could for instance, focus on those areas where biodiversity or ecosystem services have been most badly affected. Alternatively, one might put priorities on areas where the invader poses a risk for further infestation. The common practice to predict presence and absence of an invader however, does not satisfy this purpose. Instead, it would be more useful to have spatial information on the density or the competitive ability of the invader or its reproductive success. Spatial segregation of seed productive and non-productive areas might allow one to concentrate control efforts to manage habitats so as to curtail the spread of invasive species.

Since the first satellite images reached the scientific community it has been recognized that remote sensing offers the possibility to map the distribution of invasive species at local scale (Anderson *et al*., 1993; Epp & Reed, 1986; McCormick, 1999; Ramsey *et al*., 2002; Underwood *et al*., 2003; Williamson, 1996; Zhang *et al*., 2002). However, applications have been restricted to those species dominating the canopy of ecosystems (Joshi *et al*., 2004). Dominant invasive species determine the spectral signature received by the remote sensing scanner and thus allow detection using this spectral signature in a straightforward manner. Many invasive species however, do not dominate the canopy. They are rare or hidden below the ecosystem canopy. Joshi *et al*., (2004) observed that 67 out of the one hundred of the world’s worst invasive species (ISSG, 2004) fall in this category. Such species would be more difficult to detect using their spectral signature, since they contribute only partly or not at all to the radiation received by a remote sensing device. Not surprisingly, none of these sixty seven species has been successfully mapped.

Joshi *et al*., (2004) proposed indirect mapping approaches to map their distribution. Indirect mapping approaches predict the distribution of species using knowledge on the ecological relation between a species and its environment. This approach is commonly used in determining niche dimensions of species geographical distribution (Baker *et al*., 2000; Sutherst, 2003). It has been recognized that the distribution of invaders is related to variability of the environment. Frenot *et al*. (2001) for instance related the distribution of invasive species to land cover and land use change. Similarly, Rouget *et al*. (2004) developed climatic envelop models to map potential ranges of 71 major plant invaders in South Africa, Lesotho and Swaziland. Species highly invasive in one environment may well be incapable of maintaining viable populations under different conditions. Hence, spatial information on environmental conditions affecting an invaders reproductive and competitive trait could be used to segregate its reproductive and non-reproductive populations.

Chromolaena odorata (L.) R. M. King & H. Robinson (*Eupatorium odoratum* L.) is one of the world’s worst invasive species (ISSG, 2004). The genus *Chromolaena* includes 129 species and all are found in the neotropics (King & Robinson 1970) and only *C. odorata* has spread to the Old World. Nowadays, it is distributed throughout the warm and humid tropical regions, latitudes about 30° North and South. A single mature plant of *Chromolaena* can produce up to 440,000 achenes (seeds) per year (see Erasmus, 1985, pp. 31). Seeds are very light (25,000 seeds/g) and are wind-borne.

The invadability of *Chromolaena odorata* is though depend on the combination of production of large amounts of easily dispersed achenes and its capability to outcompete native flora (Erasmus, 1985; Honu & Dang, 2000). These traits however, appear to be phenotypical, since the species shows a remarkable response to light (Witkowski & Wilson, 2001). It remains virtually absent from dense forest, but dominates and vigorously produces seed in forest clearings and ruderal environments outside forest. This information suggests that light intensity determines the competitive and reproductive traits of *Chromolaena odorata*. Hence, light intensity in the forest could possibly be used to map the distribution and reproduction of *Chromolaena*.

The aim of this study was to investigate the possibility to map the seed production of *Chromolaena odorata*. For this, a statistical model relating environmental factors and seed production was developed. Furthermore, how these predictive maps can be helpful for management of invasive species was discussed.

METHODS AND MATERIALS

Study Area

The study area (figure 1) is a forest corridor linking the Himalayan middle mountains to Royal Chitwan National Park in Nepal (27°31´ to 27°44´N and 84°24´ to 84°31´E).

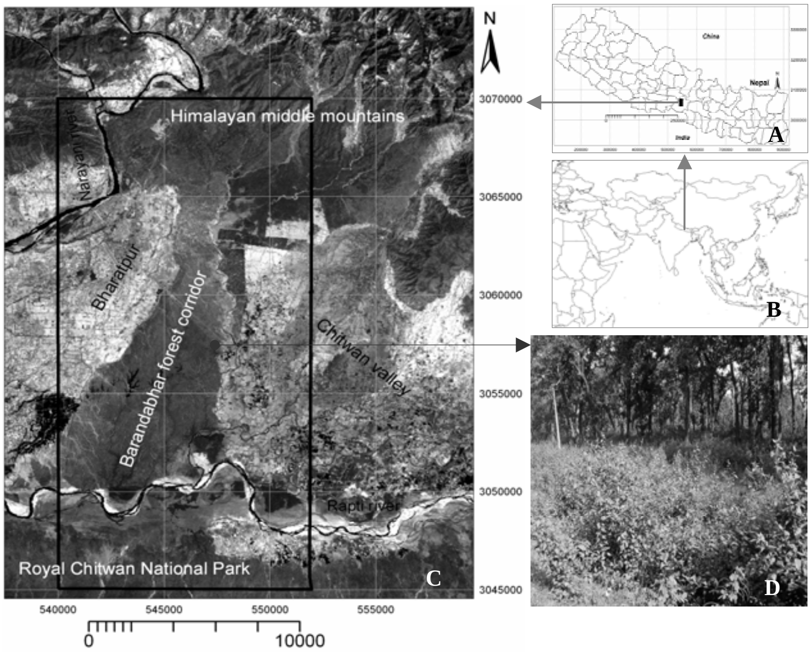

Figure 1: Location of the study area: A) Part of Asia, B) Nepal C) ETM+ image used for this study, the box indicates the study area and D) *Chromolaena odorata* growing under *Shorea* forest.

Data Collection and analysis

A total of 275 plots of 30 x 30m were visited in Sept-Oct. 2003 to measure forest canopy density and light intensity using hemispherical photography taken with a Nikon digital camera with a fisheye lens attached. Total light intensity was calculated from the digital hemispherical photographs using Gap light analyzer software version 2 (Frazer *et al*., 1999; Frazer, 2001). A smaller sub sample of 153 plots from the above sample was used to estimate the cover and average height of *Chromolaena*. Next, five plants were randomly selected per plot on which were measured: number of flowering stems per plant (*st*), number of flowering branches per stem (*br*), number of inflorescence per flowering branch (*in*), number of capitulum per inflorescence (*ca*) and number of cypsela (achenes or seeds) per capitulum (*cy*). From these we calculated a seed production index (SPI): *Seed Production Index (SPI)=* $st * br * in * ca * cy$.

The cover (c) and height (h) of other herb (H) and shrub (S) layer in the forest under-storey were estimated and from these a biomass index was calculated.

$$Biomass\ index = Hc * Hh + Sc * Sh.$$

Furthermore, grazing intensity was scored based on sign of grazing, height and cover of palatable species and dung density.

Topographic maps (scale 1:25000) of 1996 of the study area were digitized to obtain maps of land use/land cover. The settlements, roads and distances from these infrastructures were calculated using ILWIS 3.2. Waterlogged depressions with open grassland which did not represent the forest environment were classified using maximum likelihood image classification method. Image classification and analyses were done with ENVI 4.0, IDL 6.1 and Erdas 8.7.

Mapping Light Intensity

Field measurements on light intensity were combined with an ETM+ image to produce a map of light intensity in the forest under-storey. A three-layer feedforward backpropagation artificial neural network (ANN) consisting of an input, a hidden and an output layer was used for image classification. The Landsat ETM+ image of October 24, 2001 was registered with subpixel accuracy (±17m). The first seven bands were used as input to the network. Light intensity calculated from the hemispherical photographs was used to train the ANN. The total data set of 275 samples was randomly divided into two groups. One subset of 138 samples was used for training and the other 137 samples for testing. The backpropagation algorithm used is designed to minimize the root mean square error (RMSE) between the actual output of a multi-layered feed forward perception and the desired output (Skidmore *et al*., 1997). The best results were obtained with a learning rate of 0.9, a momentum of 0.7 and two hidden nodes. Finally 20 iterations of 7000 epochs were performed (the RMSE stabilized after approximately 7000 epochs) and we selected the best classification based on least RSME. Forest canopy density in percentage was also calculated using the same data set and procedure.

RESULTS

Reproductive Ecology of *Chromolaena*

Exploratory data analysis revealed that light intensity had a much stronger relationship with the cover of *Chromolaena* than any other environmental variable (table 1). The relation with light intensity was therefore analyzed before considering the contribution of other factors.

Environmental variable	***r***
Light intensity	0.71*
Forest canopy density	-0.69*
Grazing intensity	0.32*
Distance from road/trail	-0.34*
Distance from forest edge	-0.25*
Biomass of other forest under-storey species	-0.50*

Table 1: Correlation (r) between six environmental variables and the cover of *Chromolaena odorata*. Significance levels: * = 0.001.

Figure 2 shows the relationship between light intensity and seed reproduction index (SPI) of *Chromolaena*. The figure reveals that *Chromolaena* does not produce seed below light intensity of 6.5 mJ m^{-2} day^{-1}.

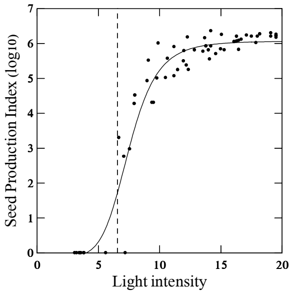

Figure 2: ^{10}Log of seed production index of *Chromolaena odorata* in relation to the light intensity. The dotted line indicates the light intensity threshold between reproductive and non reproductive populations of *Chromolaena*.

The relation between seed production index and light intensity was best explained by an MMF (Multiple Multiplicative Factor) model:

$$^{10}\text{Log}(Y+1)=\frac{-6528.2+6.11*X^{5.257}}{31049.76+X^{5.257}} \qquad \text{……..……..…. (1)}$$

Where, Y is the seed production index and X is light intensity received at the forest floor. The equation explained 93% of the variation in ^{10}Log Y+1.

Other Factors Affecting Seed Productivity of *Chromolaena*

The results presented above indicated that *Chromolaena* produces seed at light intensities above 6.5 mJ $m^{-2}day^{-1}$. This does not imply however, that *Chromolaena* was always present above or absent below this threshold. Out of 153 cases, *Chromolaena* was absent in 22 where light conditions were suitable for seed production. Also, the species was present in 17 cases where light conditions were unsuitable for seed production.

The reproductive biometry of *Chromolaena* was significantly correlated to a number of environmental variables (table 1). These variables were strongly interrelated. Some may have had a direct influence on *Chromolaena*, while others may have affected its productivity indirectly through other variables. Therefore, we conducted a path analysis (Sokal & Rohlf, 1995) to determine the degree to which single environmental factors made an independent contribution to the prediction of *Chromolaena* seed productivity. Path analysis (figure 3) revealed that distance from forest edge and from road had a direct influence on seed production of *Chromolaena* as well as indirect through grazing which influenced the biomass of forest under-storey vegetation. Similarly, forest canopy density influenced it through light intensity.

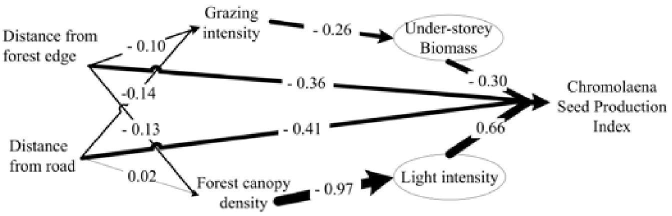

Figure 3: Path diagram showing the effect of independent variables on seed production of *Chromolaena odorata*. Number between arrows indicate significant effects with path coefficients, width of the line is proportional to the size of path coefficients.

Mapping Light Intensity and Other Environment Data Layers

Figure 4A and B shows the distance data layers used for spatial predictions of seed productivity. The resulting light intensity map predicted by the artificial neural network (figure 4C) explained about 81 % of the variance in observed light intensity.

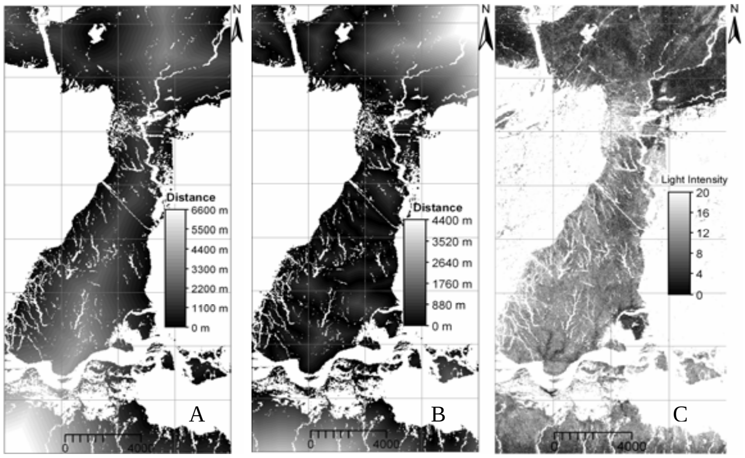

Figure 4: A) Map displaying distance from forest edge, B) distance from road and C) the light intensity (mJ m^{-2} day^{-1}) map predicted by the artificial neural network.

Figure 5 presents the performance of the artificial neural networks in scatterplots of observed versus predicted canopy cover. It revealed that the prediction of light intensity by the artificial neural network was unbiased. The t-statistic of the slope (b) and intercept (a) reveal that these did not differ significantly from 1 and 0 respectively ($a = -0.002$, $se_a = 0.005$, $t_a = -0.361$, $b = 1.003$, $se_b = 0.035$, $t_b = 0.086$, $r^2 = 0.81$).

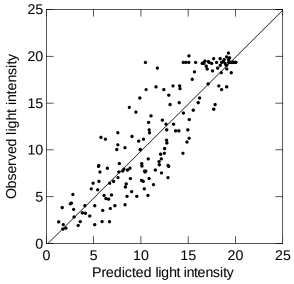

Figure 5: Scatterplot of light intensity reaching the forest floor observed in the field, against the predicted light intensity derived from a classification of a Landsat ETM+ image.

Spatial Prediction of Seed Productivity of *Chromolaena odorata*

Although biomass of the forest under-storey vegetation and grazing intensity were two variables influencing the seed productivity of *Chromolaena*, we could not include this in our spatial prediction of *Chromolaena* seed productivity. The reason was that it proved to be difficult to predict the spatial variability of this factor from remotely sensed variables, only light intensity, forest canopy density, distances from road forest and forest edge could be utilized for spatial prediction of *Chromolaena odorata*. Hence, we used regression and selected the best fitting model:

$$^{10}\text{Log } Y+1= 0.79 + 0.35* X_1 - 0.0014* X_2 - 0.00009* X_3 \ldots\ldots\ldots (2)$$

Where, Y is seed reproduction index, X_1 is light intensity, X_2 is the distance from road to the forest interior and X_3 is the distance from edge to the forest interior.

This model explained 75% of the variation in $^{10}\log (Y+1)$. We inverted this model to map seed production index (^{10}Log of number of seeds) of *Chromolaena odorata* in the Chitwan region of Nepal (figure 6). *Chromolaena* currently present along the forest edge and road, however, it has a high potential to substantially increase its range. It could potentially invade large areas of the forest interior which are climatically suitable for seed production.

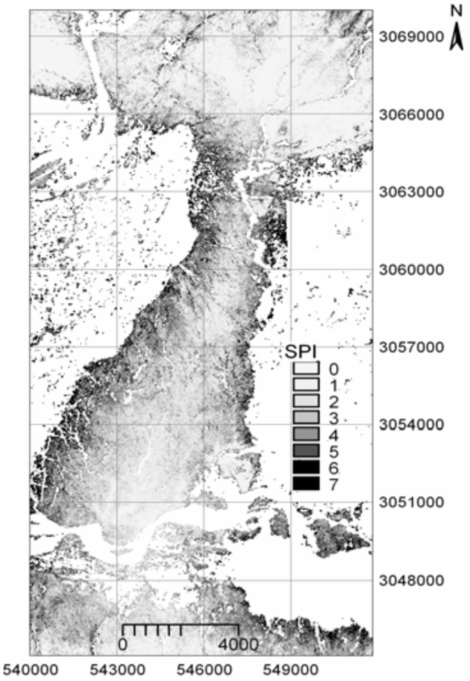

***Figure 6**:* Map displaying the seed production index (SPI) of *Chromolaena odorata.*

DISCUSSION

In this research we demonstrated the possibility to map the seed production of a forest under-storey invasive species. Light intensity was the predominant factor in the models used to predict seed production. This study shows that seed productivity of *Chromolaena* increases exponentially with light intensity.

As we mentioned earlier, our results indicated that *Chromolaena* was not always present above or absent below light threshold we established. Results have shown that when cover of *Chromolaena* is not limited by light intensity other limitations could be closed under-storey vegetation. The under-storey biomass is significantly and negatively correlated with cover and ultimately with invasion success of *Chromolaena*. High under-storey vegetation decreases amount of light intensity reaching to the soil. *Chromolaena* achenes are positively photoblastic, hence few or no seedlings emerge under dense vegetation canopy (Erasmus, 1985). Furthermore under-storey vegetation increases inter-specific competition where successful incursion of *Chromolaena* seedlings is almost impossible. This suggests that even if the forest canopy were open, successful establishment of *Chromolaena* population would be doubtful. *Chromolaena* may be a strong invader in disturbed forest areas. However, *Chromolaena* populations in more stressful (low light) environments appear sterile. In Chitwan, Nepal, plants that have matured beyond the seedling stage with some potential to flower are only present in an area that receives transmitted light at least above 6.5 (mj /m^2 /day).

The productive populations of *Chromolaena* have been found to differ significantly along the distance gradient from the road towards the interior of the forest. Only source populations have been restricted to the disturbed areas. However, vegetative populations had probably once become established via dispersal from road edges, grazed and disturbed sites, where a continuous flow of surplus seeds is produced and transported to the new environment. We noted that, notwithstanding suitable light conditions, *Chromolaena* was absent in natural gaps in the forest in the well protected Chitwan National Park. Here other native grass species reached a height of 2m, thus limiting the possibility of *Chromolaena* to establish and rise to dominance. Outside these well protected areas however, the forest under-storey was intensively grazed. In these areas the density and height of the grass and herb layer was generally much lower. We thus concluded that under suitable light conditions grazing might break the suppression of *Chromolaena* by native plant species.

Reproductive success in many species is determined by physical factors such as light, moisture nutrient availability or distance related seed dispersal mechanisms. Spatial distribution of these factors are increasingly available or can be mapped using GIS and remote sensing (Austin *et al*., 1996; Baker *et al*., 2000; Corsi *et al*., 2000; Dennis & Brusven, 1993; Guisan & Zimmermann, 2000; Kerr & Ostrovsky, 2003; Robinson & Valentine, 1979; Stone *et al*., 1997). Our study showed how these physical factors linked to GIS and remote sensing techniques in mapping the distribution and productivity of an invasive species. The invasion success in suitable habitat and limitations in stressful environment as presented here could be highly useful as studies on response of invasive plant species to its environment appear extremely limited (Hobbs & Huenneke, 1992; Stohlgren *et al*., 1999).

The seed production approach taken in this study could be well applied to other invasive species. Incorporation of remote sensing and GIS techniques with species biometry would yield instantaneous, useful, cost effective, multi-scale and temporal information on productive population of an invasive species. Segregation of the *Chromolaena* population into productive and non productive habitat could significantly reduce control cost by allowing one to concentrate control efforts to manage habitats so as to curtail the spread of 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 spatial segregation of source and sink populations of the *Chromolaena odorata*, which will support efficient habitat ranking to restore invaded areas and protect non-invaded ecosystems.

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