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Mapping and predicting deforestation patterns in the lowlands of Sumatra

MATTHEW LINKIE*, ROBERT J. SMITH and NIGEL LEADER-WILLIAMS
*Durrell Institute of Conservation and Ecology, University of Kent at Canterbury, Canterbury, Kent CT2 7NS, UK; *Author for correspondence (e-mail ml33@kent.ac.uk; fax: +44-1227-827289)*

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Abstract. Protected area managers have limited resources and so need fine-scale information to decide where to focus their budgets for law enforcement and community outreach. This study used satellite imagery to map and analyse forest loss in an area that overlaps with Kerinci Seblat National Park, Sumatra, to identify areas most susceptible to illegal logging. Between 1985 and 1992, forest located at lower elevation and close to roads was most vulnerable to clearance. These factors were also significant between 1992 and 1999, along with distance to newly created logging roads. The presence of these roads probably explained why the deforestation rate increased from 1.1% per year to 3.0% per year over the two study periods. The accuracy of the 1985–1992 model was measured in the field and successfully predicted subsequent deforestation patterns, suggesting that this methodology could be used to identify where future patrolling effort and community outreach programmes should be focussed. In addition, this approach could be used more widely in conservation planning to prioritise the protection of vulnerable sites.

Introduction

Tropical forests contain some of the most species-rich and highly threatened habitats in the world (Myers et al. 2000). Threats to these habitats generally come from deforestation and habitat degradation, which reduces biodiversity both directly and indirectly through habitat fragmentation (Laurance and Bierregaard 1997). Reducing rates of deforestation will involve action at a range of political levels (Jepson et al. 2001; Whitten 2001), but an important element is patrolling the existing protected areas (PAs), to prevent illegal logging and encroachment (Bruner et al. 2001; Sánchez-Azofeifa et al. 2003). Island biogeography theory has encouraged the creation of large PAs (Diamond 1975), but the cost of patrolling such areas is generally high and most PAs in developing countries are under-financed (James et al. 2001). Therefore, there is a need to focus resources on small areas where patrolling would be most effective (Leader-Williams and Albon 1988).

This means there is a priority to identify where deforestation is most likely to occur in the future and this can be achieved by using satellite imagery to measure and predict deforestation patterns. These remote sensing data have been used to identify where forest loss has taken place (Green and Sussman 1990; Mendoza and Dirzo 1999; Sánchez-Azofeifa et al. 1999), to identify the key factors involved (Dirzo and Garcia 1992; Vina and Cavelier 1999) and to predict regional-scale changes (Laurance et al. 2001). However, there is also a need to develop a new approach that can provide the fine-scale data needed by PA managers, because the factors that influence deforestation are often site and scale specific (Geist and Lambin 2002). For example, the correlates of deforestation have been shown to differ between continents (Bawa and Dayanandan 1997) and, even when the same causal factors are identified, they are unlikely to be equally important.

This makes it necessary to study deforestation on a site-by-site basis, which has now been made feasible by the development of inexpensive geographical information system (GIS) software. By using a GIS and remote sensing data it is possible to map deforestation, determine the causal factors and use the resultant models to produce habitat threat maps (Mertens and Lambin 1997). These maps can provide one input for PA managers to identify those areas most at risk, to predict patterns of future forest loss, and to illustrate these issues to local communities, and governmental and non-governmental organisations. Therefore, there is a great need to produce maps that can be easily interpreted, and one way to achieve this is to use logistic regression modelling, which allows a single, multivariate model to be produced that expresses predicted risk as a simple probability value (Sokal and Rohlf 1995). This study exemplifies such an approach for Tapan Valley, an area of lowland forest that overlaps with Kerinci Seblat National Park (KSNP), Sumatra.

Deforestation rates on the Indonesian island of Sumatra are some of the highest in the world (Laurance 1999; Holmes 2001). Despite its importance, this forest is being cleared by illegal loggers and by commercial and subsistence agriculturalists, leading to recent estimates that all of the island's lowland forest will be cleared within several years (Jepson et al. 2001). Here we map patterns of forest loss in Tapan Valley using a time-series analysis from 1985 to 1999, and test whether elevation, slope and proximity to roads and rivers affects the distribution of forest loss. The factors found to be significant in causing forest loss are then used to produce predictive habitat threat maps for Tapan Valley, and the accuracy of these predictions is tested using field data on forest clearance.

Study area

The Tapan Valley study area (2°13′ S/101°12′ E) covers 200 km^2 and contains five villages located on either side of the Tapan–Sungai Penuh asphalt road that runs through KSNP (Figure 1). Tapan Valley contains 29 mammal species, and is an important area for tigers (Linkie et al. 2003). Many threats face the forest along the KSNP border in Tapan Valley, because there has been selective logging in the region since the late 1980s, coal exploration since 1995 and ongoing unsustainable farming (WWF 1999).

KSNP has an area of 13,300 km^2 and a permanent staff of 105 forest police. Additional law enforcement is provided by the 11 members of the Kerinci Seblat Tiger Protection and Conservation Units, giving a combined field staff density of one member per 114 km^2. Between 1996 and 2002, KSNP was the focus of an

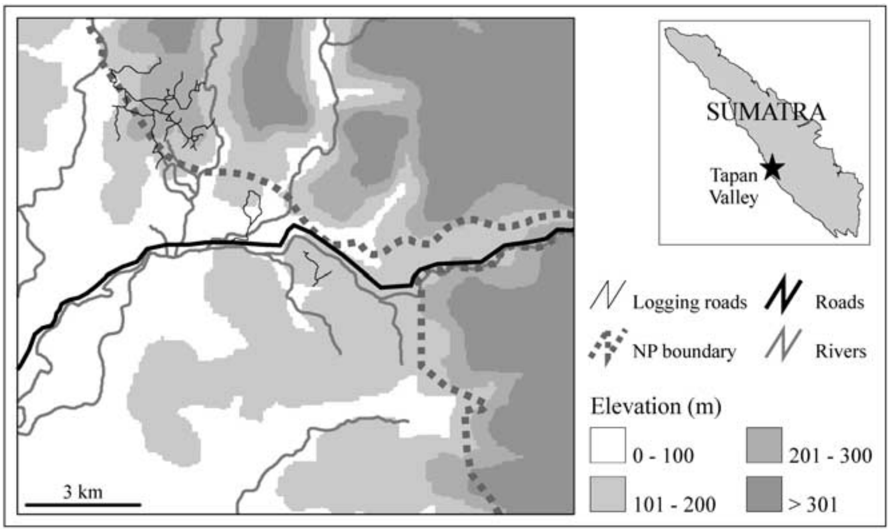

Figure 1. The position of Tapan Valley in Sumatra (inset) and the rivers, roads, elevation and the PA boundary of the study area.

Integrated Conservation and Development Project (ICDP) that aimed to secure the biodiversity of KSNP and stop further habitat fragmentation.

Methods

GIS and remote sensing methodology

A time-series analysis was conducted, using the Idrisi v.3.2 GIS software, to determine deforestation rates using three different land-cover maps from 1985, 1992 and 1999. The 1985 land-cover map was produced from a supervised classification of a Landsat MSS satellite image using training sites to identify forest, water, rice fields and subsistence farming fields. The same methodology was applied to produce the 1992 and 1999 land-cover maps with Landsat TM images, which were then re-sampled to have the 80 m resolution of the MSS-derived map. These maps were used to calculate the area of each land-cover type at each time period and to measure the deforestation rate from 1985 to 1992 and from 1992 to 1999.

Other GIS maps were obtained from several different sources. The locations of government-built roads, as well as logging roads, were recorded using a global positioning system (GPS) unit and rivers were digitised from an unsupervised classification of the satellite images. These spatial data were then used to produce maps showing distance from government-built roads, distance from water and distance from logging and mining roads. A digital elevation model (DEM) was generated from 25 m contour lines and this was used to produce a slope map.

Statistical methodology

The GIS data were imported into the ArcView v.3.2 GIS software. The 'Animal Movement' extension (Hooge and Eichenlaub 2000) was used to select 50 points in areas that had been deforested between 1985 and 1992, and 50 points in areas that remained forested over the same period. These points were chosen randomly, apart from the specification that they should be separated by at least 1000 m to reduce the effects of spatial autocorrelation (Koenig 1999). However, the deforested areas were relatively limited in extent and so a separation distance of 400 m was used instead. The spatial characteristics of each of these points were then found by extracting data from the distance to roads and rivers maps, as well as the DEM and slope map.

These data were imported into SPSS and logarithmically transformed. A binary logistic regression model was then used to find which of the factors significantly determined the probability of an area being cleared of forest. The performance of the model was evaluated by calculating the area under the curve (AUC) of the receiver operating characteristics plot (Pearce and Ferrier 2000). These values range from 0.5 to 1.0: above 0.7 they indicate an accurate model fit and above 0.9 they indicate a highly accurate model (Swets 1988). The presence of spatial autocorrelation in the model was tested by calculating the Moran statistic of the regression residuals using the CrimeStat software (Levine 2000).

This resultant model was then used to combine the relevant GIS maps to produce a habitat threat map, which was ground-truthed by randomly choosing 50 sites that remained forested in 1992. These were visited in the field in 1999 by using a GPS unit and the presence or absence of forest at each site was recorded. A Mann–Whitney *U* test was then used to find whether those sites that had been cleared by 1999 had a higher predicted risk of clearance from the 1985 to 1992 model.

The same methods were used to produce a habitat threat map based on the deforestation patterns that took place between 1992 and 1999, although in this case the separation distance was set as at least 1000 m for both the deforested and forested areas. In addition, the second analysis included data on distance from logging roads, as all of these roads were constructed during this second period (Holden 1997).

Results

A total of 13.4 km^2 of forest was cleared between 1985 and 1992 (Figure 2), equivalent to a mean deforestation rate of 1.1% per year. During this period, the probability of an area being cleared of forest was significantly and negatively related to $\log_{10}$ elevation (Wald = 13.03, df = 1, $P < 0.001$) and $\log_{10}$ distance to roads (Wald = 7.40, df = 1, $P = 0.006$) (Figure 3). The logistic regression model explained 73.0% of the original observations, had an AUC value of 0.819 and was not affected by spatial autocorrelation.

Randomly selected sites that were cleared of forest between 1992 and 1999 had a mean predicted risk of deforestation of 0.630 based on the 1985–1992 habitat threat

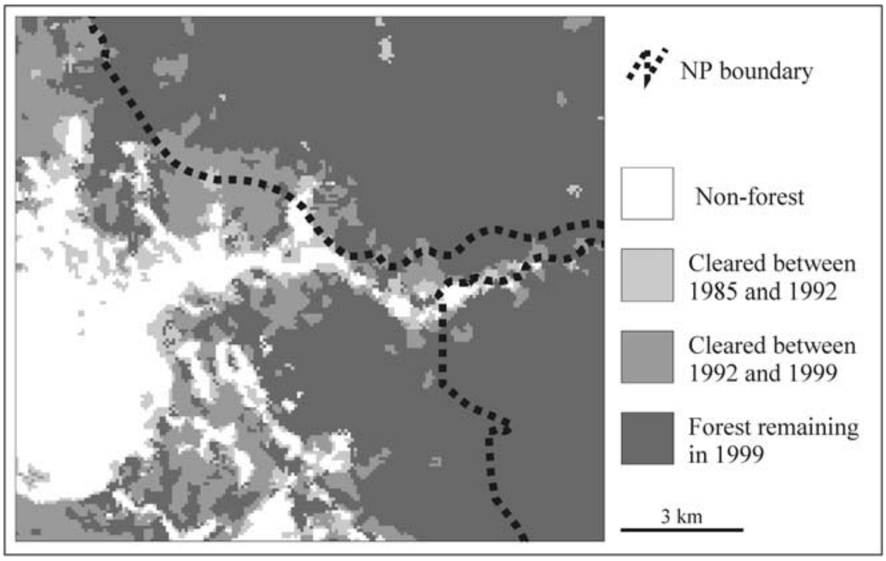

Figure 2. Forest loss in Tapan Valley between 1985 and 1999.

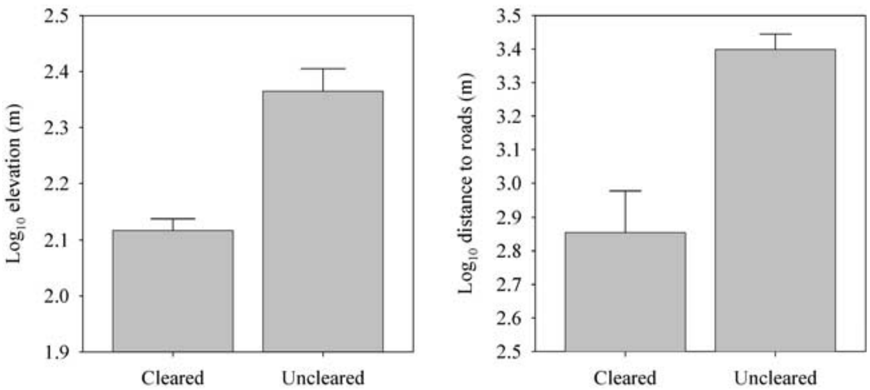

Figure 3. Mean $\log_{10}$ elevation and mean $\log_{10}$ distance to roads of cleared and uncleared forest sampling points between 1985 and 1992.

model. In contrast, the randomly selected sites that were not cleared of forest between 1992 and 1999 had a mean predicted risk of deforestation of 0.283, which was significantly lower than that of the cleared sites ($n = 100$, $Z = -6.201$, $P < 0.001$; Figure 4).

A total of 32.6 km^2 of forest was lost between 1992 and 1999 (Figure 2), equivalent to a mean deforestation rate of 3.0% per year. During this period the probability of an area being cleared of forest was significantly and negatively

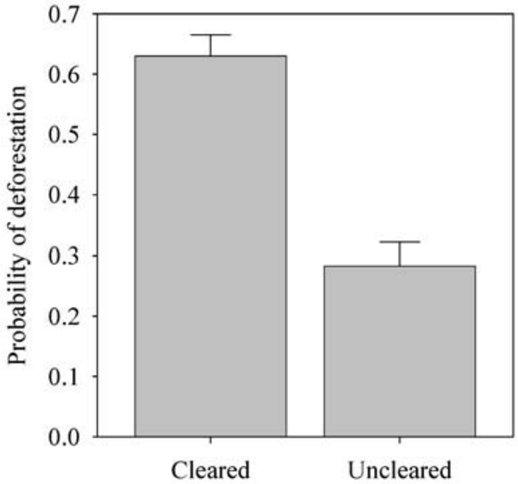

Figure 4. Mean predicted probability of deforestation from the 1985 to 1992 model for sites visited in 1999.

determined by $\log_{10}$ elevation (Wald = 11.39, df = 1, $P < 0.001$), $\log_{10}$ distance to logging roads (Wald = 7.24, df = 1, $P = 0.007$) and $\log_{10}$ distance to roads (Wald = 6.58, df = 1, $P = 0.010$) (Figure 5). The logistic regression model, which was used to produce the final habitat threat map (Figure 6), explained 81.0% of the recorded observation, had an AUC value of 0.907 and was not affected by spatial autocorrelation.

Discussion

The rates and causes of tropical forest loss have been measured previously, but this new approach illustrates that these data can also be used to predict future patterns of habitat loss and to guide fine-scale management strategies. This time-series analysis found that the spatial pattern of forest loss was dependent on several physical and anthropogenic factors and that the logistic regression models could be used to accurately predict future deforestation trends. The results also showed that the significance of these factors changed over time, as the most accessible forest patches were cleared. Several previous studies have used GIS and remote sensing to measure and predict rates of forest loss (Mertens and Lambin 1997; Laurance et al. 2001; Kinnaird et al. 2003), but this study has shown the value of producing site-specific models based on logistic regression that can be used in PA management and fine-scale conservation planning.

The deforestation rate in Tapan Valley during the first study period (between 1985 and 1992) was 1.1% per year and 3.0% per year in the second period (between 1992 and 1999). The former deforestation rate is consistent with other deforestation

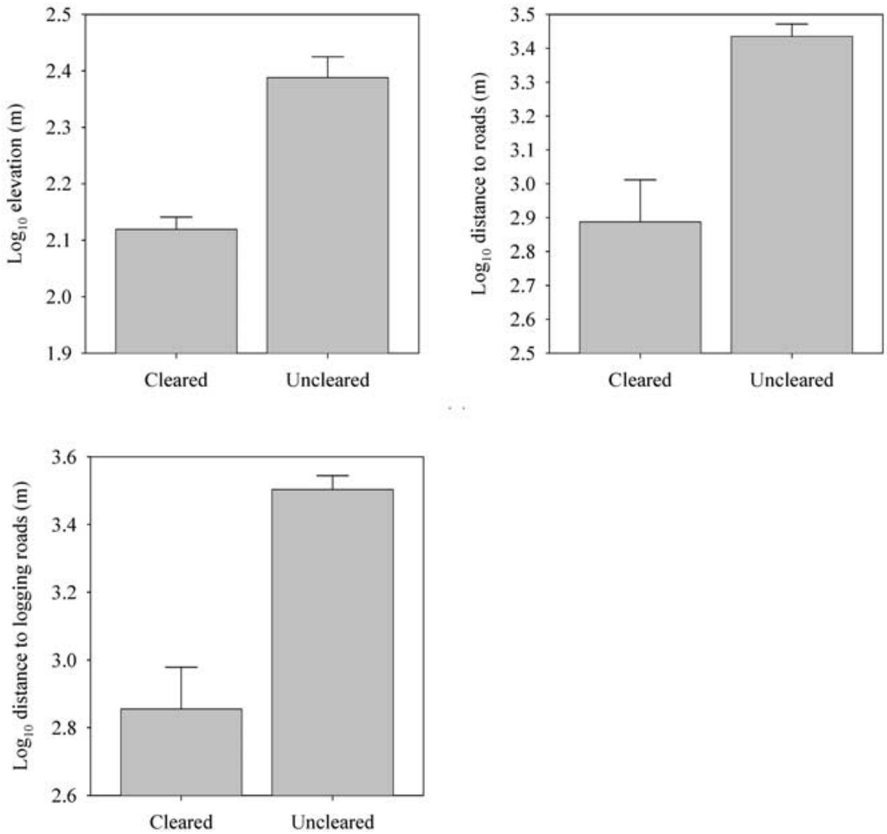

Figure 5. Mean $\log_{10}$ elevation, mean $\log_{10}$ distance to logging roads, and mean $\log_{10}$ distance to roads of cleared and uncleared forest sampling points between 1992 and 1999.

studies from Columbia (1.5% per year) and Mexico (1.4% per year) (Vina and Cavelier 1999; Trejo and Dirzo 2000). The latter deforestation rate is much higher, but comparable with other studies from Sumatra, where rates ranged from 3.2 to 5.9% per year (Achard et al. 2002). However, these rates from Tapan Valley would probably have been lower if data from neighbouring, more remote, areas had been included in the calculations.

The spatial distribution models for deforestation in Tapan Valley included several factors that were all related to accessibility. The first of these factors was elevation, which was important during both periods because these high-lying areas tended to include more rugged terrain (Dirzo and Garcia 1992) and are further from existing deforestation fronts. This may also partly explain why lowland forests are the most threatened forest type across Indonesia (Holmes 2001). As expected from previous studies (Sader and Joyce 1988; Mertens and Lambin 1997; Laurance et al. 2002), the position of roads was important in determining deforestation patterns during

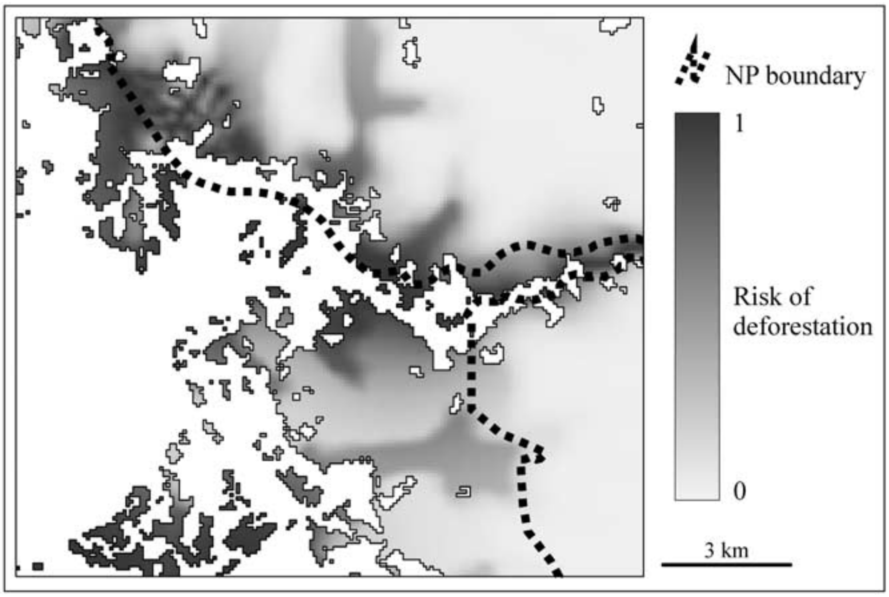

Figure 6. Habitat threat for forested areas in Tapan Valley for 1999.

both study periods. However, these problems were exacerbated in the second period with the development of logging roads, which were then used by local villagers to clear forest for farmland. Similar links have been described elsewhere (Kummer and Turner 1994) and help to explain why the deforestation rates increased over time in Tapan Valley.

The methodology and results described above provide important insights into the factors causing deforestation around KSNP. However, the production of habitat threat maps allows these models to be converted into a format with important applications for management. In particular, the threat models could be used to identify where preventing access by illegal loggers would most reduce predicted deforestation (Peres and Terborgh 1995). This is particularly important for large PAs, which often have limited financial resources and need to focus their efforts for greatest effect (Leader-Williams and Albon 1988). These models could also be used to identify areas that are most threatened and where conservation projects that involve local communities should be focussed to reduce deforestation. In some cases, identifying such strategies may be possible without this type of analysis, but the threat maps could still be used to illustrate to the government bodies and funding agencies the predicted patterns of loss based on *laissez-faire* policies. In addition, these methods could be used more widely when planning the development of representative PA systems (Margules and Pressey 2000), as incorporating threat data into reserve selection algorithms would allow planners to identify vulnerable sites that required urgent protection (Pressey and Taffs 2001).

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