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# Assessing and Predicting Decadal Forest Cover Changes and Forest Fragmentation in Kinnerasani Wildlife Sanctuary, Telangana, India

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## Abstract

This study aims to analyse the spatial pattern of deforestation and fragmentation in forests of Kinnerasani wildlife sanctuary and surroundings, Telangana, India. This study has found the annual deforestation rates between 2005 and 2015 as 1.38% and 1.50% inside and surroundings of the study area respectively. The fragmentation analysis reveals the high reduction in large core areas over the period of 2005–2015. Temporal forest cover change analysis was linked with predictive modelling to generate future forest cover scenario. The multi-layer perceptron neural network modelling was used for forecasting the deforestation for 2025. This study evaluates the nature of changes in deforestation and its affecting explanatory drivers such as slope (in degrees), elevation (in m), and the shortest distance to roads (in m), the shortest distance to nearest settlements (in m) and the distance from water bodies (in m). Spatial modelling has forecasted the annual change rate of forest as 0.19% in Kinnerasani wildlife sanctuary which indicates decreasing trend of forest loss in near future. The results of the study are useful as spatial input for conservation of forests in Kinnerasani wildlife sanctuary, Telangana, India.

**Keywords** Forest · Conservation · Predictive modelling · Protected area · India

## Introduction

Up-to-date information on the spatial distribution of forest is intended for sustainable forest management (Franklin 2001). Deforestation and fragmentation are among the key components of global change and has direct implications on ecosystem functioning and biodiversity (Tapia-Armijos et al. 2015). Continuous monitoring of regions undergoing high level of deforestation requires analysis at finer spatial resolutions (Ingram et al. 2005). Fragmentation is one of the important reasons for the loss of corridors and consequently affects species distribution (McCollin 1993; Spellerberg 1995). Riitters et al. (2000) studied global-scale patterns of forest fragmentation. The models of space simulation will introduce a new way of understanding the

dynamic processes in geographical space. Mas et al. (2004) have reviewed the approaches used for modelling land cover changes. Quantification of the forest cover change is an important step toward establishing links between the policy decisions and conservation effectiveness. Spatial land cover change modelling could be an immensely useful activity to understand the future of the forests (Kumar et al. 2014). The land change modeler (LCM) is the widely used spatial model for prediction developed by IDRISI (Reddy et al. 2017). A crucial constituent of the efficient conservation strategy is an accounting of ecosystem vulnerability (Nackoney and Williams 2012). Several case studies in India have been conducted using low and medium resolution remote sensing data (Reddy et al. 2013, 2016).

The degradation of dry tropical forests proceeds more rapidly than that of moist tropical forests, despite their importance for human populations as a source of products (Tucker et al. 2005). Tropical dry forests are among the most threatened and overlooked forest formations in the world (Bianchi and Haig 2013) and conversion to pasture and agriculture are major threats, reflecting a long history of human occupation attracted by relatively flat landscapes,

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timber extraction and favourable climatic conditions for agriculture. The national data aggregates all forest types into one category; therefore, they obscure the fact that deforestation in regions dominated by tropical dry forests has advanced faster than for regions dominated by other forest types (Tucker et al. 2005). The studies in India found large scale deforestation in the regions where dry deciduous and moist deciduous forests are dominant (Reddy et al. 2013, 2016).

Protected areas are recognised as core units for biological conservation. As the human population increases, pressures on habitats are intensifying for protected area management (Curran et al. 2004). The significance of protected areas in the conservation of biodiversity is now enshrined in Aichi Target 11 (CBD 2010). Few studies have addressed the land cover change before and after the establishment of protected areas that can help to evaluate the impact of the management regimes over time (Sader et al. 2001). There is a debate over the effectiveness of protected areas in reducing deforestation, especially when local people have rights to use the forest (Nelson and Chomitz 2011). A global level study for 198 protected areas showed that nearly 70% of the surrounding buffers have shown a decline in forest area, while 25% have experienced reduction within their administrative boundaries (Defries et al. 2005). Kinnerasani Wildlife Sanctuary is one among the near-deserted sanctuaries which are no longer home to any other wild beasts, especially large mammals, which were once found in abundance (https://innlivenetwork.wordpress.com). As per Telangana Forest Department's 'State of Forest Report 2014, maximum encroachment in protected areas was in the Kinnerasani Wildlife Sanctuary (http://forests.telangana.gov.in/Docs/SFR/2014). In view of the current concern for biodiversity conservation, there is a necessity to map and monitor forests to develop spatial explicit modelled data for monitoring the patterns of deforestation and fragmentation in protected areas.

## Study Area

Kinnerasani natural landscape is located in Bhadradri Kothagudem district, Telangana state of India. It is declared as wildlife sanctuary in 1999. It is lies on the Deccan plateau between 17°41′29″ to 17°59′56″N latitudes and 80°27′10″E to 80°47′19″ longitudes. The total study area has been estimated as 1118 km$^2$ area (including 316 km$^2$ area under 2 km buffer). The wildlife sanctuary represents 802 km$^2$ (71.74%) of study area. It contains terrain of both plains and hills. This region represents very warm and dry condition during the summer (March–May) and continues to be warm in other months of the year, but

for December and January, the temperature drops during nights. The maximum and minimum temperatures have been recorded as 45 and 16 °C, respectively (Reddy et al. 2015a, b). The forests can be broadly grouped into two main forest types, i.e. tropical moist deciduous and tropical dry deciduous (Reddy et al. 2015a, b).

## Materials and Methods

### Mapping of Forest Cover

The orthorectified Landsat 8 OLI images were downloaded from USGS Earth Explorer site (http://earthexplorer.usgs.gov/). Forest cover map of 2015 was generated using Landsat 8 OLI images. IRS P6 LISS III data was procured from National Remote Sensing Centre, Hyderabad. The forest cover map of 2005 was prepared using IRS P6 LISS III data. Hybrid classification techniques in combination of NDVI and visual interpretation were used to map forest cover. Spatial buffer of 2 km was generated to analyse changes in surroundings of wildlife sanctuary. The present study has referred to the natural forest definition (Reddy et al. 2016). This work considers forest loss as depletion of forest canopy cover to less than 10%. The long-term forest cover database of India prepared from Indian Remote Sensing (IRS) 1B Linear Imaging Self-Scanning System (LISS-1) for 1995 was utilised in the study (Reddy et al. 2016). Spatial forest changes for the period of 2005–2015–2025 were analyzed. A random sampling technique was used to validate the accuracy of forest cover map for 2015. In total, 100 random sample pixels were selected and visually compared with the Google Earth images. An error matrix was used to calculate the overall accuracy of the classification (Lillisand and Kiefer 1994). The annual rate of forest cover change is calculated by comparing the area under forest cover in the same region at two different times using compound interest formula (Puyravaud 2003).

### Forest Fragmentation Modelling

Vogt et al. (2007) developed an improved method for classifying forest fragmentation. The Landscape Fragmentation Tool (LFT v2.0) is available for ArcGIS 10.2 spatial analyst extension has been used (ArcGIS 2015). In this study, the forest cover map is classified into four main categories–patch, edge, perforated and core–based on a specified edge width. An edge width of 100 meters was assumed. The core pixels are outside the "edge effect" and thus are not degraded by fragmentation. Core pixels are sub-classified into 3 categories based on the area of a given core patch–small core (< 101 ha), medium core (101–202 ha), and large core (> 202 ha). Fragmentation

maps were generated for 2005, 2015 and 2025 from forest cover 2005, 2015 and simulated forest cover of 2025 respectively. The classified fragmentation maps were further utilized for fragmentation change analysis.

## Predictive Modelling for Forest Cover Change

The methodology of Land Cover Change Modeler (LCM) is highlighted in the flowchart in Fig. 1. LCM was adopted to analyze the forest cover changes during the period 2005–2015 to predict the forest cover of 2025. Change analysis and modelling were undertaken in IDRISI LCM

module in stepwise manner (1) change analysis, (2) transition potential modelling and (3) change prediction. LCM works on evaluating the trend of change and it's affecting explanatory variables. In LCM, there are a set of tools for the rapid assessment of change, allowing one to generate one-click evaluations of gains and losses, net change, persistence and specific transitions both in map and graphical form (http://clarklabs.org/terrset/land-change-modeler/). A multi-layer perceptron (MLP) is a one of the method of artificial neural network analysis capable of modeling complex relationships between variables. A multi-layer perceptron was trained in order to estimate the



**Fig. 1** Flow chart of predictive modelling
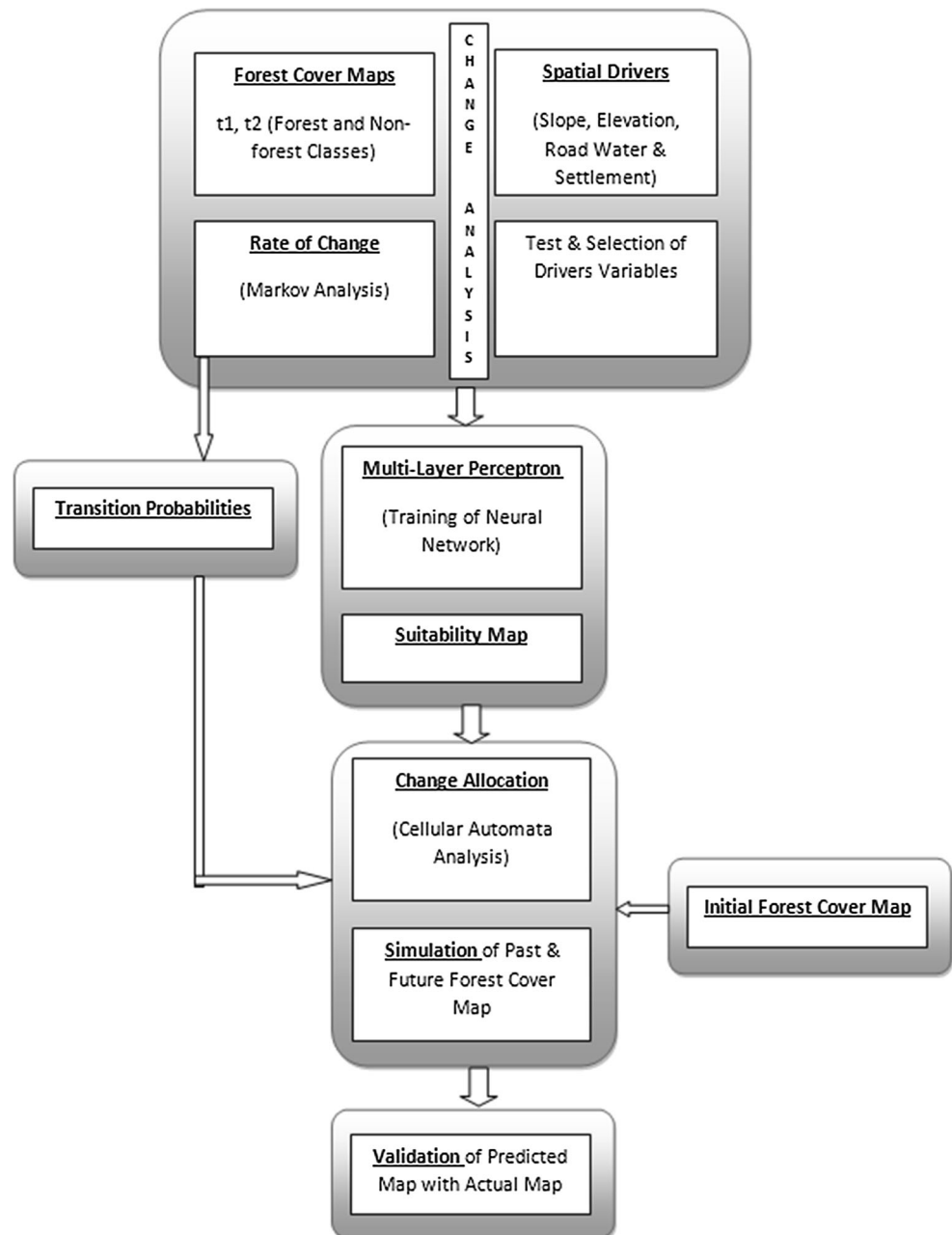
inclination to deforestation as a function of the explanatory variables and was used to develop deforestation risk assessment maps (Mas et al. 2004; Reddy et al. 2017).

This study mainly assess the nature of changes in deforestation and its affecting explanatory drivers such as elevation (in m), slope (in degrees), and the shortest distance to roads (in m), the shortest distance to nearest settlements (in m) and the distance from water bodies (in m). The elevation data from the NASA SRTM were used (Jarvis et al. 2008). The transition probability for 2005–2015 was calculated using the Markov chains. The 2005–2015 transition probabilities were used for 2015–2025. The model was set to run from 1995 (the initial year of simulation) to 2005, which is the year of the actual forest cover map to get 2015. The simulated forest cover map (2015) was compared to the actual forest cover map (2015), in order to validate the accuracy of the model.

LCM provides an optional quick test of the potential explanatory power of each driving force represented by Cramer's V, it acts as a guide to determine whether the driving force is worth being considered or not (Eastman 2006). The driver variable test procedure is based on a contingency table analysis. The quantitative measure of association used is Cramer's V wherein Cramer's V is a statistic that transforms Chi-square (for a contingency table larger than two rows by two columns) to a range of 0–1 unit value. These unit values indicate complete agreement between the two nominal variables. The variables that have a Cramer's V of about 0.15 or higher are useful (Eastman 2006). Thus, the selected factors were found to be relevant and worth consideration. After the selection of the predictor variables, both transitions were modelled in one transition sub-model, as they had the same driving forces, with the aim of producing the transition maps. However, it is a good indication that a variable can be rejected if the Cramer's V is low. The $p$ value expresses the probability that the Cramer's V is not significantly different from 0. A high value of p is a definite sign that it can be excluded.

## Results and Discussion

### Analysis of Forest Cover

The classified forest cover maps of 2005 and 2015 indicate that forest cover, accounting to an area of 781.2 $km^2$ (69.87%) and 678.6 $km^2$ (60.69%) of total study area respectively. Figure 2 shows the forest cover maps of study area. The total predicted forest cover is 668.2 $km^2$ (59.77%) for 2025. The actual loss of forest cover was estimated as an area of 102.6 $km^2$ from 2005 to 2015. Based on prediction, the forest cover loss was estimated as

10.3 $km^2$ from 2015 to 2025. Forest area inside sanctuary is estimated as 591.1 $km^2$, 514.9 $km^2$ and 505 $km^2$ in 2005, 2015 and 2025 (predicted) respectively. This study helps to analyze the deforestation rate of forests inside and surroundings of Kinnerasani wildlife sanctuary. Deforestation rate for inside sanctuary represents the annual change of 1.38% in 2005–2015. Calculation of annual rate of deforestation for surroundings (under 2 km buffer of sanctuary) indicates change of 1.50%. The predicted deforestation rate for 2015–2025, is 0.19% within the boundaries and 0.03% in surroundings which indicates low deforestation rate in future. Producer's accuracy for forest cover map of 2015 is estimated as 91% and user's accuracy is 90%. The overall accuracy of the classification is 90.5%. Kappa statistic is 0.86.

### Forest Fragmentation

The classified forest map of 2005 and 2015 were used for fragmentation analysis along with the simulated forest cover map of 2025. In 2005, 90.53% of the forest area in sanctuary was classified as large core forest, 6.72% as edge forest, 2.33% as patch forest, 0.26% as small core and 0.15% as perforated forest (Table 1). In 2015, 70.63% of the sanctuary forest area was classified as large core forest, 12.26% as edge forest, 12.19% as patch forest, 2.65% as perforated forest, 1.21% as small core and 1.06% as medium core. The remarkable increase of perforated forest, patch forest and edge forest from 2005 to 2015 indicates degree of anthropogenic effects on configuration of forest. The predicted fragmentation map also indicates all the fragmentation classes going to experience changes by 2025. The large core area was lost with an estimated area of 171.50 $km^2$ and predicted to dropped further 10.31 $km^2$ (2.83%) of area by 2025. Distribution of fragmentation classes for 2005, 2015 and 2025 is given in Fig. 3.

### Model Validation

The kappa statistic was used to compare the predicted and actual forest cover maps for 2015 (Table 2). The explanatory power of the variables was verified based on the Cramer's V statistic, which ranges from 0 (no relation between variables) to 1 (perfect relation between variables). According to the Cramer coefficients, the distance to slope was strongest associated with deforestation in study area (V = 0.27) followed by distance to water-bodies (V = 0.26), distance to road (V = 0.12), distance to settlement (V = 0.11) and distance to elevation (V = 0.10). The Cramer's values is described in Table 3.
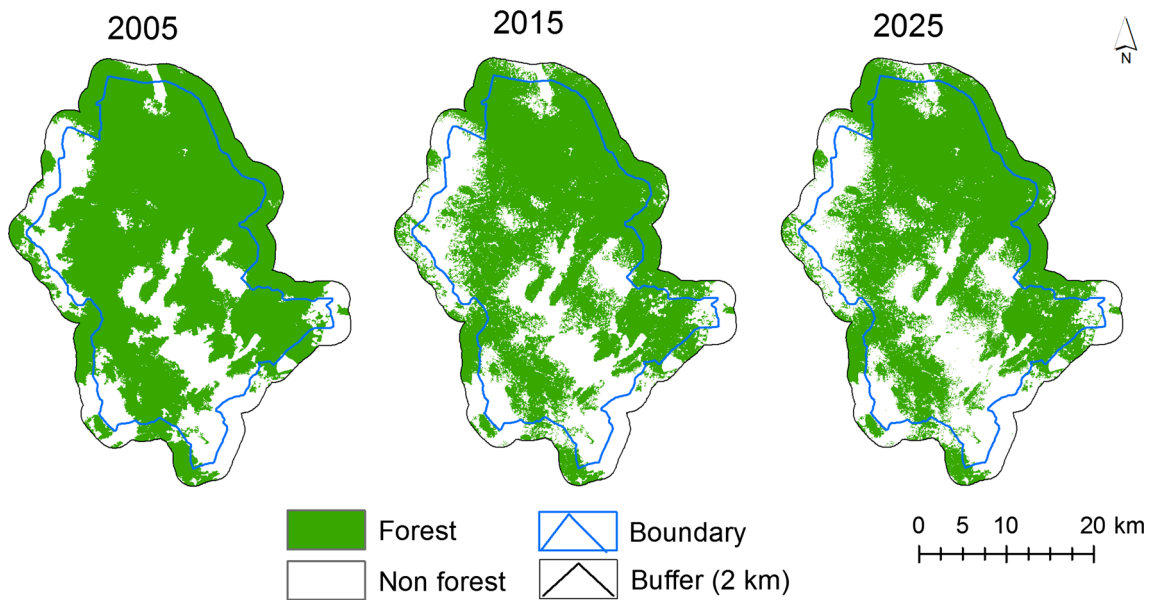
Fig. 2 Classified and predicted forest cover maps of Kinnerasani wildlife sanctuary

Table 1 Distribution of forest fragmentation classes (% of area)

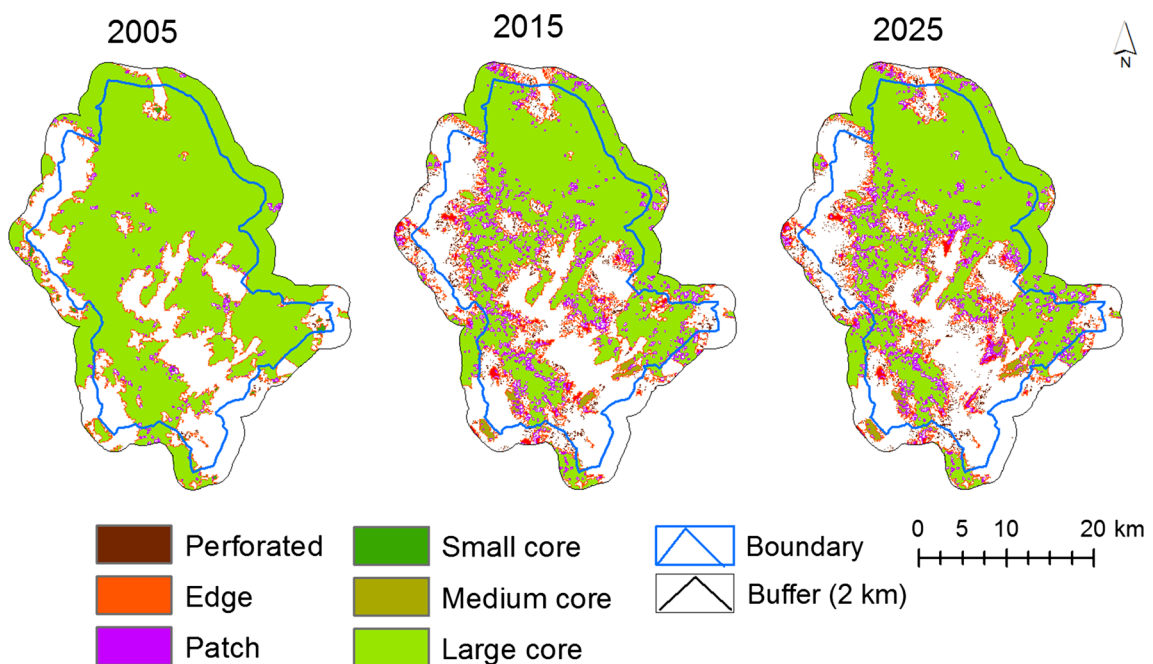| Study area | Within the sanctuary | | | Outside the sanctuary (2 km buffer) | | |
|---|---|---|---|---|---|---|
| Fragmentation class | 2005 | 2015 | 2025 | 2005 | 2015 | 2025 |
| Perforated | 0.15 | 2.65 | 2.95 | 0.25 | 3.03 | 3.35 |
| Edge | 6.72 | 12.26 | 11.45 | 9.76 | 13.55 | 12.78 |
| Patch | 2.33 | 12.19 | 13.31 | 2.70 | 11.24 | 11.05 |
| Small core | 0.26 | 1.21 | 1.27 | 0.71 | 1.76 | 1.47 |
| Medium core | 0.00 | 1.06 | 1.05 | 0.14 | 1.01 | 1.12 |
| Large core | 90.53 | 70.63 | 69.96 | 86.45 | 69.42 | 70.24 |
| | 100 | 100 | 100 | 100 | 100 | 100 |



Fig. 3 Forest fragmentation maps of Kinnerasani wildlife sanctuary

**Table 2** Kappa statistic for the predicted forest cover map for 2015 with the actual forest cover map for 2015

| Kappa | Standard error | 0.95 confidence interval | |
| --- | --- | --- | --- |
| | | Lower limit | Upper limit |
| 0.8675 | 0.0025 | 0.8626 | 0.8724 |

**Table 3** Cramer coefficient for forest cover change from 2005 to 2015

| Elevation | Slope | Distance to road | Distance to settlement | Distance to water bodies |
| --- | --- | --- | --- | --- |
| 0.1092 | 0.2712 | 0.1252 | 0.1168 | 0.2618 |

$$Kappa = \frac{(Observed\ accuracy - expected\ accuracy)}{(1 - expected\ accuracy)}$$

Forest cover change analysis in Pranahita wildlife sanctuary, Telangana from 1993 to 2004 showed annual deforestation rate as 0.28% (Giriraj et al. 2008). No significant forest cover changes have been found in 28 protected areas of Rajasthan from 2005 to 2010 (Harikrishna et al. 2013). Results have indicated effectiveness of conservation of forests in Bandipur, Nagarhole, Mudumalai, Mukurti, Wayanad and Silent Valley (Satish et al. 2014). The study by Dutta et al. (2016) has not reported loss of forests after 2001 in three wildlife sanctuaries—Shendurney, Peppara, Neyyar and one Tiger reserve—Kalakad Mundanthurai. Four protected areas in North East India, namely Manas, Sonai-Rupai, Nameri and Marat Longri are still experiencing deforestation (Reddy et al. 2017). The study in protected areas of Kerala shows management effectiveness in controlling deforestation (Athira et al. 2017).

## Conclusions

This research presents the results for forest cover change by using remote sensing data, Multi-layer Perceptron (MLP) neural network model and landscape fragmentation tool in Kinnerasani wildlife sanctuary and surroundings, India. The study focuses on the changes occurred in past along with simulated predictive forest cover as well as the degree of fragmented forest. This study results could be used for restoration and conservation plans which have direct benefits for biodiversity and ecosystem services. The fine scale understanding of forest ecosystem will provide the factors behind the forest degradation and community-species level conservation effectiveness.

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