Sciencia Acta Xaveriana
An International Science Journal
ISSN. 0976-1152

Vol. 9 No. 1
pp. 35-44
March 2018

EFFECTIVENESS OF PROTECTED AREAS IN MAINTAINING THE FOREST COVER: A MODELING APPROACH USING GEOMOD

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Received : January 2018 *Accepted : February* 2018

Abstract. Conservation priorities have increased in protected areas to reduce biodiversity loss. Analysis of spatial and temporal forest cover dynamics are confronting in the protected areas due to limited research and difficulty in acquiring ground data from the past. The present study was aimed to assess the forest cover dynamics and to predict the future forest cover in 2020 at the Mudumalai Tiger Reserve, Southern Western Ghats. LANDSAT and Indian Remote Sensing satellite (IRS) images of 1973 and 2010 were used to classify the forest cover density. Overall forest cover classification accuracy of 2010 was 86.5% and kappa coefficient was 0.82. The open forest occupied a maximum of 192.13 km^2 and very dense forest covered the minimum of 31.95 km^2 in 2010. We identified three major proximate variables such as fire, distance to settlements and roads that influence the spatial pattern of forest cover loss. As the study area was primarily dominated by open forest, it was reclassified as forest and the other density types as non-forest. GEOMOD model was applied to simulate the future forest cover of 2020 using the suitability map. We also estimated the change in forest cover between 1973 and 2010. It was found that, the major change in forest cover was due to human-induced forest fire between 1989 and 2010.

Keywords: Protected areas, Forest cover, GEOMOD, Fire, Variables.

1. Introduction

Tropical forests are one of the richest terrestrial ecosystems that support a variety of life forms. Forest cover dynamics are the quantity of changes in the forest cover to other land cover types due to natural or human-induced disturbances (Rakesh et al., 2014). Forests are disappearing at a high rate due to several factors acting in various combinations at different geographical locations (Geist and Lambin, 2002). Recently, information on forest cover change has become a main emphasis for managing forest ecosystem and monitoring environmental dynamics. Over 15.5% of the world's land surface was nationally designated as protected areas (Soutullo, 2010) and two-thirds of the protected areas were located in developing countries (Zimmerer, 2006). Establishment of global protected area had substantially increased the forest cover from 12.2% in 2008 (UNEP-WCMC, 2008) to 13% in 2010 (FAO, 2010) in which major change has occurred in tropical forests (Brambilla et al., 2010).

In India, protection on forest cover was strengthened by the implementation of forest state policy in 1952, which excludes the local people's participation in the forest land and its management (Guha, 1983). Later, the enforcement of the Forest Conservation Act in 1980 and National Forest Policy in 1988 enabled the regulation of forest land and recognised the people's participation (Arora, 1994) to maintain the forest ecosystem. Forest Survey of India (FSI) estimated that the forest cover of India has increased marginally from 64.08 million ha in 1987 to 69.79 million ha in 2013 (FSI, 2013).

Prior to policy intervention, a forest decline was analysed by identifying and understanding the influence of proximate driving forces in forest cover at a given location. Forest cover models are powerful tools to analyse the spatial and temporal simulation and impact of drivers over forest cover. Among the various statistical models, Geographical modeling (GEOMOD) represents a powerful tool to predict land-use change (Francesco et al., 2011). It is a non-linear multiple-regression model, determines the pattern and location of pixels changing over time based on the weightage of each driver (Dushku and Brown, 2003). The advantage of GEOMOD over the other models includes minimum inputs to determine the rate of land use conversion from forest to non-forest for ending time, location of land cover change and extrapolates the change to the future.

Undertaking an assessment of management effectiveness allows the government to understand, and improve their management regimes. Previous assessments used temporal satellite images to study the effectiveness of forest cover change in the protected areas before and after its declaration (Oliveira et al., 2007; Giriraj et al., 2008, Adhikari and Jane, 2012). In this study, we aimed to assess the effectiveness of forest cover management in the Mudumalai Tiger Reserve (MTR) between 1973 and 2010 and to predict the future scenario using GEOMOD.

2. Materials and methods

2.1. **Study area.** Mudumalai Tiger Reserve (Mudu-Old; Malai- hill - ancient mountain) lies between 11° 32' - 11° 43'N latitudes and 76° 22' - 76° 45' E longitudes and covers an area of 321 km^2. It is the largest habitat contiguity with three other protected areas, namely Nagarhole and Bandipur Tiger reserve in Karnataka and Wynaad Wildlife Sanctuary in Kerala. The terrain is highly undulating towards the eastern portion with an average elevation ranging from 440 m to 1260 m. There is a distinct rainfall gradient from east to west varying from 600 mm to 1200 mm (Suresh et al., 2010). Major vegetation types are tropical dry thorn forest, tropical dry deciduous forest, tropical moist deciduous forest and tropical semi-evergreen (Champion and Seth, 1968) and dominated by the dry deciduous vegetation type with a secondary succession. MTR is an important site for socio-cultural activities as several tribal settlements and pilgrim sites are located inside the reserve. Several threats like forest res, encroachment, invasion of exotic species, logging and hunting exist within the study area.

2.2. **Data acquisition.** Multi-temporal, cloud free Landsat Multi Spectral Scanner (MSS) image of 10 February 1973, and Indian remote sensing satellite (IRS) P6 Linear imaging and self-scanning sensor (LISS) III image of 6 February 2010, were downloaded from U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) (http://glovis.usgs.gov) and BHUVAN (http://bhuvan.nrsc.gov.in) websites. The dates of these two images were chosen to be as closely as possible to maintain the assessment during the same season. Pixel dimensions of all images were resampled to facilitate better comparison.

2.3. **Image-processing and classification.** IRS LISS III image of 2010 was geo-referenced using 30 ground control points collected from the study site apart from using Survey of India (SOI) topographic maps with ERDAS Imagine 11.0 software. The root-mean-square (RMS) error was 0.43 pixels. The image of 1973 was then geo-referenced using image to image registration. Based on the knowledge obtained through extensive field surveys, the forest cover density maps of 1973 and 2010 were prepared using normalised difference vegetation index (NDVI). Major density types were delineated according to the standards of Forest Survey of India (http://www.fsi.nic.in/details.php?pgID=sb_8) viz., very dense forest, moderately dense forest, open forest and scrub forest.

2.4. **Selection of drivers.** Many countries do concern to estimate and quantify the importance of drivers of deforestation (Kissinger et al., 2012). Understanding the trend and extent of forest cover change enables to improve the variability of drivers at multiple scales (Ostram, 2006; Ewers, 2008). The present modeling of forest cover change considered three major proximate drivers in MTR: Frequency of fire, distance from roads and settlements. Kodandapani (2008) reported that induced seasonal fire or human-set fire was one of the major drivers for degradation of forest in MTR. Human activities were the primary agents considered as a direct driver responsible for forest cover change (Turner et al., 2007). Giriraj et al., (2008); Rashmi and Lele, (2010) demonstrated that primary roads, secondary roads, and settlements were the major drivers of forest cover change in Western Ghats.

2.5. **Preparation of drivers.** Fire maps from 1989 to 1999 were collected from Tamil Nadu forest department and the fire burnt areas from 2000 to 2010 were digitised from satellite images to prepare the fire frequency map (Fig. 1). Road networks and locations of human settlements were digitized from the SOI topographic map using ArcGIS 10 software.

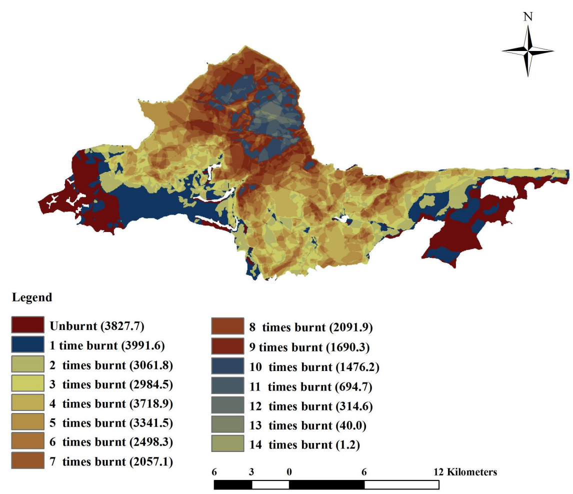

FIGURE 1. Fire frequency map of 1989 to 2010 of Mudumalai Tiger Reserve. The values in the parenthesis indicate the extent of fire burnt (ha) in each fire frequency class.

2.6. **Preparation of suitability map.** Multi-criteria evaluation (MCE) is a decision support tool, used to combine selected drivers and generate suitability map. Fuzzy membership function was applied to detect the pixels that are suitable and non-suitable for forest cover change based upon the shape and type of the parameters of the input drivers. For example, symmetric membership function and sigmoid were used to road, as the distance from forest increases, the degradation decreases and vice versa (Fig. 2a). Later, the factors were rescaled between 1 and 255. To obtain the variable distances of roads and settlements (Fig. 2a, b), the DISTANCE module of IDRISI Selva was used. The fire frequency between 1989 and 2010 (Fig. 2c) was also used to derive the suitability map. The control points were assigned for the drivers based on the distance prone for degradation. Each criterion and factor received a weight, which represented its relative importance in the derivation of suitability map. Though many input layers could be used to create a single suitability map, it is well known that all the drivers are not equally significant (Jayakumar et al., 2002). Based on this concept, weightage was given to each layer. The advantage of MCE is that it has a choice of assigning weightage by the user to macro-level drivers based on the priority, which cause higher chances of disturbances. The suitability map (Fig. 2d) resulting from fuzzy standardization of the topographic variables was created through the iterative process of testing drivers and measuring goodness of fit represents those areas that exhibit the greatest likelihood of forest cover change for the future.

2.7. **Modelling for forest cover change.** GEOMOD is a grid-based predictive module in IDRISI SELVA software used to detect forest cover change between two time periods. It simulates a one way change, either from non-forested to forest, or vice-versa. MTR is primarily dominated by open forest cover density and thus for the present model, we reclassified the open forest cover as "forest" and the other forest cover density classes as "non-forest". The annual rate of forest change (number of pixels) at starting time (1973) was estimated and simulated to ending time (2010) of the predicted image. The future forest cover in 2020 was predicted using the actual forest cover of 2010 as a starting time. Finally, these maps were used to calculate the area of each forest cover change at time periods from 1973 to 2010 and from 2010 to 2020.

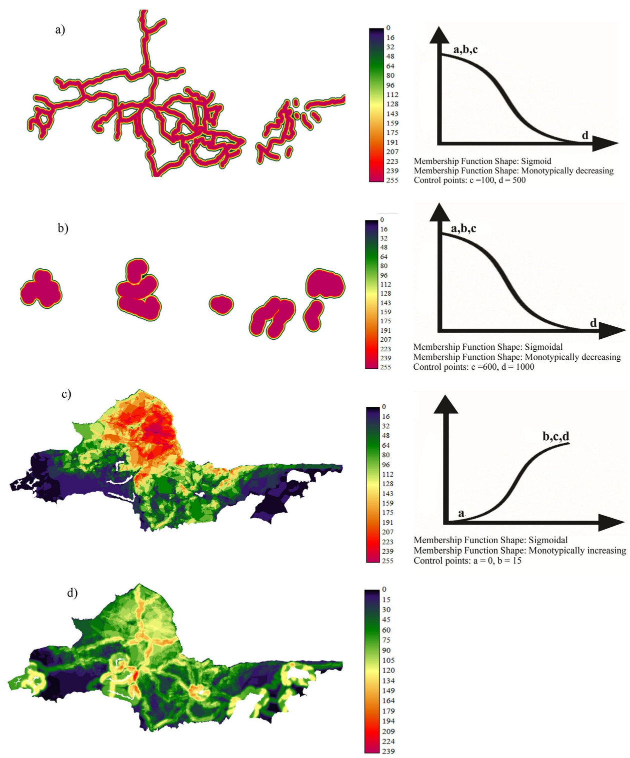

FIGURE 2. Drivers influencing forest cover change a) Road; b) Settelments; c) Fire frequency of 1989-2010; d) Suitability Map

2.8. **Validation.** Assessing the accuracy of forest cover data permits to determine whether the data generated reaches a minimum acceptable level of accuracy (Lillesand et al., 2007). Classification accuracy was evaluated by calculating Kappa index of agreement (Congalton, 1991). The simulations that produced the highest kappa were done applying the constrained neighbourhood search mode and the contiguity rule using 3×3 filter. The accuracy of actual forest cover map (2010) was assessed using confusion matrix with ground truth data (200 ground control points). Further, the actual forest cover map was validated against the predicted map of 2010 to test how well the drivers succeeded in predicting the spatial pattern of forest cover change and later predicted for the year 2020. The test of ‘goodness of fit’ measures a degree of the simulated map agrees with a reality map by employing Kappa for location (measure of spatial accuracy with a reality map) and Kappa for quantity (measure of overall proportion correctly classied versus the expected proportion correctly classied) (Pontius, 2000).

3. Results

3.1. Forest cover density. Of the total area (321 km^2), about 59.8% covered by open forest and very dense forest occupied 9.9% in 2010 (Table 1 and Fig. 3a, b). In 1973, the open forest covered 61.4% followed by moderately dense and very dense forest with forest cover of 14.8% and 8% respectively (Table 1). Accuracy estimated from the confusion matrix for the actual map of 2010 showed an overall accuracy of 86.5% with Kappa coefficient of 0.82 (Table 2).

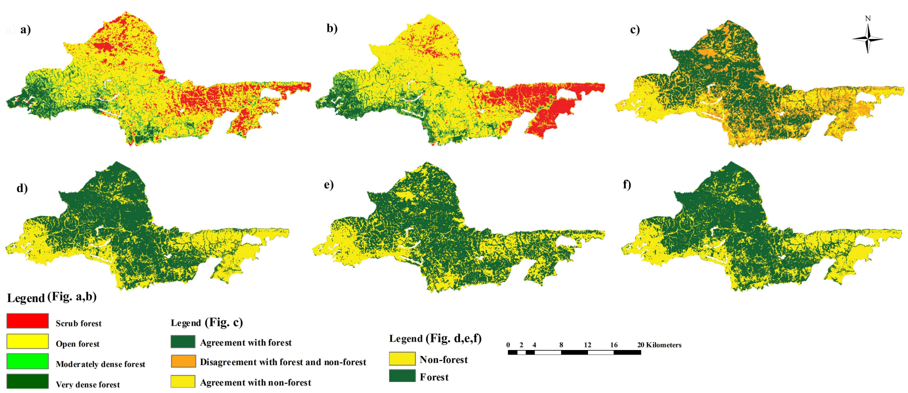

Figure 3. Forest density types of MTR a) 1973; b) 2010; c) Cross-classification map of 2010; d) Actual forest cover map of 2010; e) Predicted forest cover map of 2010; f) Predicted forest cover map of 2020

Table 1. Forest cover between 1973 and 2010 in MTR

Density type	**Area in km^2**		**Net change from 1973-2010**
	1973	**2010**	
Scrub forest	51.08	55.04	3.96
Open forest	197.10	192.13	-4.97
Moderately dense forest	47.50	42.01	-5.49
Very dense forest	25.72	31.95	6.23

Overall classification accuracy = 86.5%; Kappa coefficient = 0.82

TABLE 2. Forest cover between 1973 and 2010 in MTR

Density type	**Scrub forest**	**Open forest**	**Moderately dense forest**	**Very dense forest**	**Total**	**Users accuracy (%)**
Scrub forest	42	8	0	0	50	84.0
Open forest	4	43	3	0	50	86.0
Moderately dense forest	1	4	43	2	50	86.0
Very dense forest	0	0	5	45	50	90.0
Total	47	55	51	44	200	
Producers' accuracy (%)	89.36	78.18	84.31	95.74		

3.2. **Change in forest cover density.** Change detection analysis was performed between 1973 and 2010. Decrease in area was observed in the moderately dense forest (13%) and open forest (2.5%) categories in 2010 (Table 1) with the proportionate increase in the very dense and scrub forests. Change matrix analysis between 1973 and 2010 revealed that about 2968 ha of open forest, 175 ha of moderately dense forest and 32 ha of very dense forest were changed to scrub forest in 2010 (Table 3).

TABLE 3. Change matrix for the density types between 1973 and 2010 in MTR

1973 / 2010	**Scrub (ha)**	**Open forest (ha)**	**Moderately dense forest (ha)**	**Very dense forest (ha)**
Scrub forest	3050	2581	109	60
Open forest	2968	13928	1714	630
Moderately dense forest	175	1833	1646	988
Very dense forest	32	328	704	1354

3.3. **Model validation and future trends of forest cover.** The cross-classification map was produced using the actual and simulated forest cover of 2010. It resulted in four categories namely, agreement with forest types, agreement with non-forest types, disagreement with forest types and disagreement with non-forest types (Fig. 3c). The first two categories depicted the correct classification with the simulated map and latter two represented the errors in the simulated map. Model validation performed between the actual (reference) and the simulated forest cover for the year 2010 (Fig. 3d, e) showed 80.4% of Kappa for quantity and 77.4% of Kappa for location accuracy. The forest cover was decreased by 4.1 km^2 between 1973 and 2010 (Table 4). Table 4 and Fig. 3f show decreased trend forest cover of 1.44 km^2 in 2020 when compared to 2010.

TABLE 4. Present and future scenario of forest cover in MTR

Year	Forest km^2	
	Actual forest cover	**Predicted forest cover**
1973	197.10	—
2010	192.13	188.60
2020	190.69	—

4. DISCUSSION

Knowledge on the spatial information of future forest cover is very important, which can be used for decision making. Globally, protected areas are still considering for an alternative conservation measure to protect the biodiversity of the forest (Jenkins and Joppa, 2009; Tattoni et al., 2010). However, it is important to evaluate how the current protection measures help in lowering deforestation and effective in maintaining the existing forest cover.

Forest cover change detection in MTR revealed that all the density classes changed between 1973 and 2010, which emphasised that the forests undergo constant changes in these assessment periods (Table 3). GEOMOD helped to assess the probabilistic nature of model and to predict the progressive loss or gain of forest cover. The results of GEOMOD showed a better agreement between the predicted and the actual forest cover in terms of quantity and location (Francesco et al., 2011). It simulated the forest cover with 80% accuracy in 2010, which was categorized as "substantial" (Landis and Koch, 1977). A similar study of creating a zone of vulnerability and quantification of forest cover using GEOMOD was also reported in southern Chile (Echeverria et al., 2008) and in Western Ghats (Menon et al., 2000; Pontius and Pacheco, 2005; Giriraj et al., 2008; Rashmi and Lele, 2010) and reported decline in forest cover due to rapid deforestation.

Indigenous communities generally set fires to alter vegetation characteristics for many thousands of years in the Western Ghats (Gadgil and Chandran, 1988). Kodandapani et al., (2008) also reported that the forest cover of MTR was severely affected by human-induced forest fire. In the present study, we also estimated that the forest fire was the predominant factor responsible for forest cover dynamics. In spite of stringent regulations and protection, the forest fire occurs in MTR every year. Within a short span of 22 years, a maximum of 14 fire frequencies was recorded in which 1476 hectares of forests were burnt continuously for 10 times (Fig. 1). The unburnt area in the MTR for the above periods was estimated to only 11% (Fig. 1). Thus, forest fire in this region seems to be one of the major drivers responsible for the change in forest cover, which requires implementation of better management practices.

5. CONCLUSION

GEOMOD exhibits the advantage of using remote sensing and GIS data along with validation approach to identify the spatial and temporal pattern of forest cover dynamics. Our analysis suggests that change in forest cover may be due to forest fire. Even though MTR has a formal protection of forest and wildlife by the implementation of strict protection act, collective inter-state fire preventing measures should be taken up to avoid the loss of forest cover due to fire. For future policy intervention, however, inclusion of multiple variables will enhance a deeper understanding of impact of drivers on forest cover loss.

6. Acknowledgements

Authors are thankful to Department of Science and Technology-Innovation in Science Pursuit for Inspired Research (INSPIRE) fellowship program for the funding support. Authors are grateful to Tamil Nadu Forest Department and field assistants for necessary field support.

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