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Land use/cover change detection and analysis for Dzalanyama forest reserve, Lilongwe, Malawi

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Abstract

Natural ecological systems continue to be under severe threat from human influence in Malawi and Dzalanyama forest reserve in particular. To assist the relevant stakeholders understand the full extent of the problem and push for a reversal of the trend, a scenario analysis of the near-past, present and near-future deforestation levels was presented using fuzzy classification, the basic overlay and Markov chain analysis techniques. In trying to draw awareness by quantifying the gravity of the situation, the analysis has established that not only are the deforestation magnitudes worrisome but also that the trends will continue in the foreseeable future. The analysis also hinted on the complex factors driving the land cover changes. While acknowledging the roles played by population growth and poverty on deforestation, the influence of the changing economic opportunities triggered by social, political and infrastructural changes impacting on the rural population surrounding the forest reserve cannot be overemphasized. Upon deriving the direction and magnitude of change it is therefore only prudent that measures to address the problem should invoke and build on an all inclusive approach towards provision of a sustainable solution.

Keywords: fuzzy classification, Markov chain, deforestaion, land cover change;

1. Introduction

Understanding the dynamics of land use/cover changes has been fundamental in rural land management especially for sustainable agriculture and forestry management in sub-Saharan Africa [1]. This stems from the fact that the majority of the population living in rural areas of central and southern Africa depend on subsistence agriculture and other natural resources for their day-to-day needs [2, 3]. Endowed with vast natural resources essential for its socioeconomic development, the region's sustainable development efforts continue to be obscured by the escalating deforestation and soil degradation rates due to population growth and poverty among many other factors [1]. Not spared of this predicament is Dzalanyama Forest Reserve which is one of the most threatened natural ecological systems in Malawi due to tobacco curing, brick burning, firewood and charcoal selling that has intensified in the rural communities surrounding it [4]. It is understood, generally that the degradation resulting from these human pressures is exceeding the regenerative capacity of the forest reserve. While it is imperative to employ tools that support the understanding of the causes and consequences of land use dynamics, the

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objective of this paper is to present a scenario analysis that will quantify and highlight the near-past, current and near-future deforestation trends of Dzalanyama forest reserve. We do this to draw awareness on the gravity of the situation and hence push for concerted efforts to reverse the current trends. The following section presents a description of the study area, and the approach used. We then discuss the results and provide a conclusion.

2. Methods

2.1. Study area

Dzalanyama forest reserve is located to the south west of Lilongwe district (see Figure 1). It is some 60km from the capital's city centre and lies between latitudes 14.18° and 14.61° S and longitudes 33.35° and 33.92° E. Sitting on a range of hills bearing the same name, Dzalanyama forest reserve covers approximately 935 km^2 of land. And while the local name Dzalanyama means "full of wild animals" the story is different lately due to poaching. Game life in the reserve has deteriorated such that as of present only monkeys, rabbits, and deer exists though it still boasts of a vast variety of natural forest cover with a little exotic breeds introduced on its commercial plantations [4]. Physiographically, the reserve overlooks the Lilongwe plains and it rises between 1100 to 1713m above sea level. It was declared a forest reserve in 1922 with some parts of it being shared by the districts of Mchinji and Dedza [4].

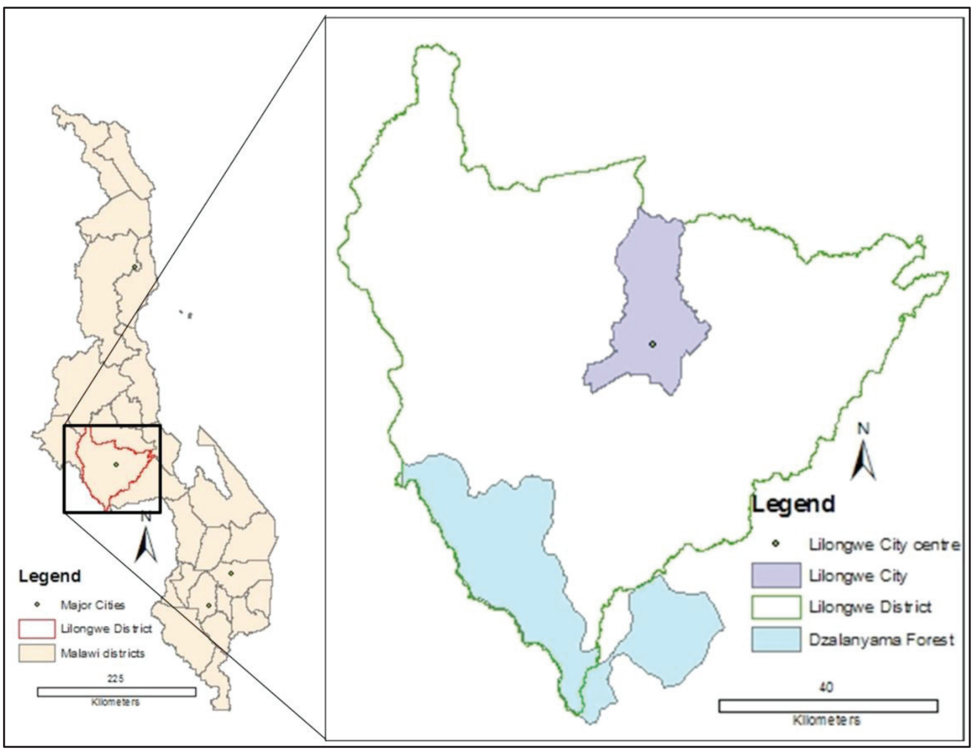


Fig.1. Study area, Dzalanyama Forest Reserve, Lilongwe, Malawi

2.2. Methodology

2.2.1. Data sources

We used remote sensing data from Landsat for the years 1990 and 2000. The Thematic Mapper (TM) imagery was observed on July 11, 1990 while the Enhanced Thematic Mapper Plus (ETM+) was observed on July 21, 2000. The Landsat images consist of all bands 1 to 7 and have a ground resolution of 30m. For 2008, an ALOS (Advanced Land Observing Satellite) multi-spectral Advanced Visible Near Infrared 2 (AVNIR2) sensor image observed on July 5, 2008 was used. Launched in 2006 [5], AVNIR2 is relatively new. It has a sensor swath width of 70km at nadir and consists only of the visible and near infrared bands 1 to 4 with a ground spatial resolution of 10m. These images were selected for the study as they provided suitable cloud-free spatial coverage and relatively high spatial and spectral resolutions.

Due to sensor inherent data acquisition inaccuracies and also data handling, preparation and processing errors, ground reference data in image analysis is very important [6]. Therefore aerial photographs for accuracy assessment purposes were acquired for selected areas in the forest reserve from Malawi Government's Department of Survey. Because of poor record keeping, August 1986 aerial photographs were the closest we could find as reference data for 1990 and due to lack of resources the department does not have aerial photographs for the later years after 1995. So for the 2000 image we used aerial photographs observed in June and July of 1995 and Google Earth's GeoEye 2010 aerial photograph was used as reference data for 2008.

2.2.2. Fuzzy Classification

Anderson and colleagues [7] noted that frameworks for organizing and categorizing information extractable from a remotely sensed image should be determined from classes that are not only important to the study but also discernible from the present data. Visual interpretability of the images was enhanced using contrast stretch and false color composites (Bands: 4, 3 and 2 for Red, Green and Blue respectively) together with aerial photographs for selected areas. Unsupervised classification [8] was used to initially categorize all the pixels in the images into a manageable number of 50 classes. Spectrally similar classes were then merged and labeled accordingly to prepare training areas to be used to define spectral signatures for four final classes (water, forest, wet/grassland and bare land). We settled for the class wet/grassland for conventional purposes as the current land use literature for the area has grassland and not wetland as a category [4] despite the areas being wet soils generally following streams with a mixture of grass.

Because of lack of definite boundaries of categories owing to the imprecise nature of the area resulting in each pixel having the potential to belong to several classes, the Fuzzy classification approach was adopted in this study. The approach uses a membership function, where a pixel's value is determined by whether it is closer to one class than the other [9, 10]. Working on Jensen's [10] premise that it is possible to obtain information on the various constituent classes found in a mixed pixel; the training sites for each class did not exactly have pixels that were strictly the same as is demanded in traditional classification methods. Fuzzy classification generated two map outputs that were then used in a Fuzzy convolution function. The first output was a multilayer fuzzy classification map of the multiple possible output class assignments while the second was a distance file map [8]. Performed on a 7×7 window of pixels, the fuzzy convolution operation then created a single classification layer by calculating the total weighted inverse distance of all the classes in the window assigning the centre pixel to the largest total inverse distance summed over the entire set of the fuzzy classification layers [8]. This procedure allows for the creation of a context-based classification with reduced speckle. While classes with a very small distance value remain unchanged, those with higher distance values may change to a neighbouring value given that there is enough number of neighbouring pixels with class values and small corresponding distance values.

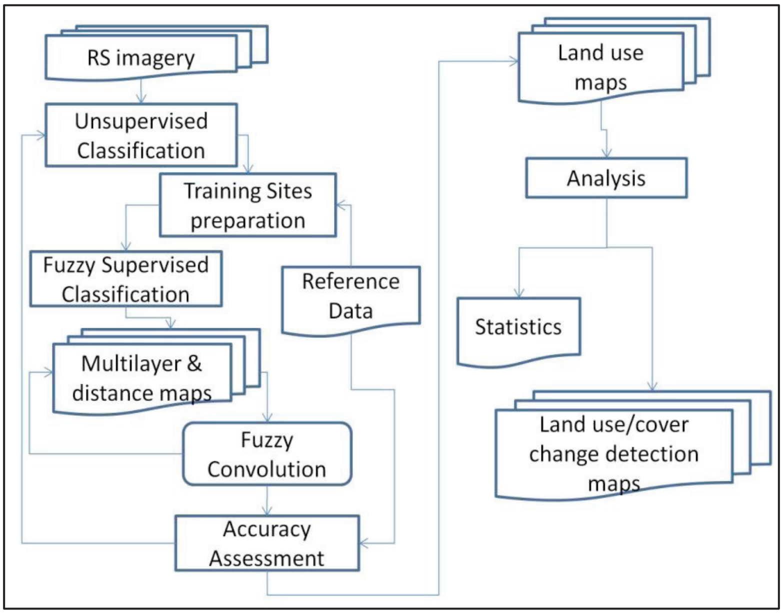


Fig. 2. Classification and analysis procedure summary

Spatial correctness in image classification analyses is very important such that accuracy of the thematic maps produced is often compared in remote sensing studies [6]. Accuracy assessment therefore, compares the predicted (i.e. classification) results to geographically referenced data that are assumed to be true [11, 12]. This is achieved through a subjective assessment of the observed difference in accuracy undertaken in a statistically rigorous fashion [13]. A set of 100 reference pixels, selected randomly to reduce possibility of bias [14], was used in this study obtained from sources as discussed earlier under data sources. Among the several measures of accuracy assessment two were of importance in this particular study. The first was the percentage of correctly classified samples also known as overall accuracy and the kappa coefficient. The Kappa coefficient expresses the proportionate reduction in error generated by the classification procedure by accounting for all the elements of the confusion matrix excluding all agreements that occur by chance thereby providing a more rigorous statistical assessment of the classification [14]. Figure 2 below summarizes the classification and analysis procedure.

2.2.3. Change detection and Markov chain analysis

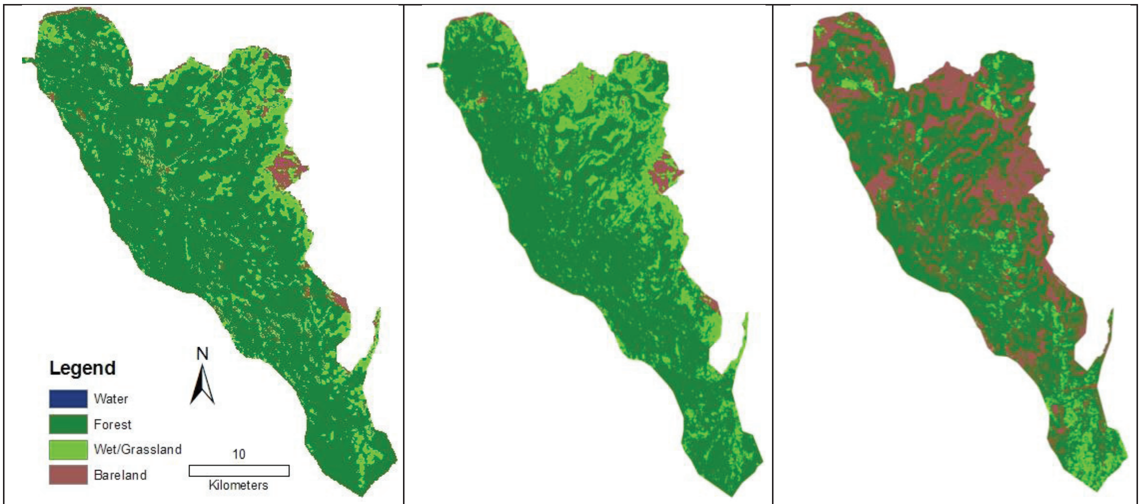
To achieve the overall objective of painting the present scenario and its progression in the near-past, present and near-future cases we employed change detection and Markov chain analysis techniques. This was mainly to quantify the changes rather than to spatially locate where the changes are occurring. The change detection used the simple overlay procedure between the 1990 – 2000 and 2000 – 2008 time periods.

Markov chain analysis is a stochastic process for which for a particular system of interest there is a set of discrete states. In the case of land use/cover change the states correspond to the class categories for which a particular parcel of land can belong to at a particular instance. The parcel of land can only be in one state at a given time moving successively from one state to the other with a probability which depends only on the current state and not the previous states [15]. The probability of moving from one state to the other is called a transition probability which can be represented in a transition probability matrix whose elements are non-negative and the row elements sum up to 1 [16]. For this case of an area subdivided into a number of cells each of which can be occupied by a given type of land use (forest, wet/grassland or bare land) at a given time, the transition probabilities were computed on the basis of classification data between time periods which show the probability that a cell will change from one land use type to another within the same particular period in the future [16]

3. Results and Discussion

The dominant land covers, following the classification, in 1990 and 2000 are forest and wet/grassland however in 2008 the situation has changed with bare land overtaking wet/grassland areas as the second most dominant land cover type (see Figure 3 a, b and c). This is the case as much of the grass patches that characterized the wet/grassland land cover type in the years 2000 and 1990 have disappeared.

Overall classification accuracy was determined to be 81, 78 and 79% for the land use classification maps of 1990, 2000 and 2008 respectively. The Kappa coefficient was 0.63 for 1990, 0.58 for 2000 and 0.72 for 2008. The proportion of classification error for 1990 and 2000 was much higher due to in part the disparities in observation time of the imagery and reference data which had 4 and 5-year gaps respectively.



(a) 1990 (b) 2000 (c) 2008

Fig.3. Land cover classification

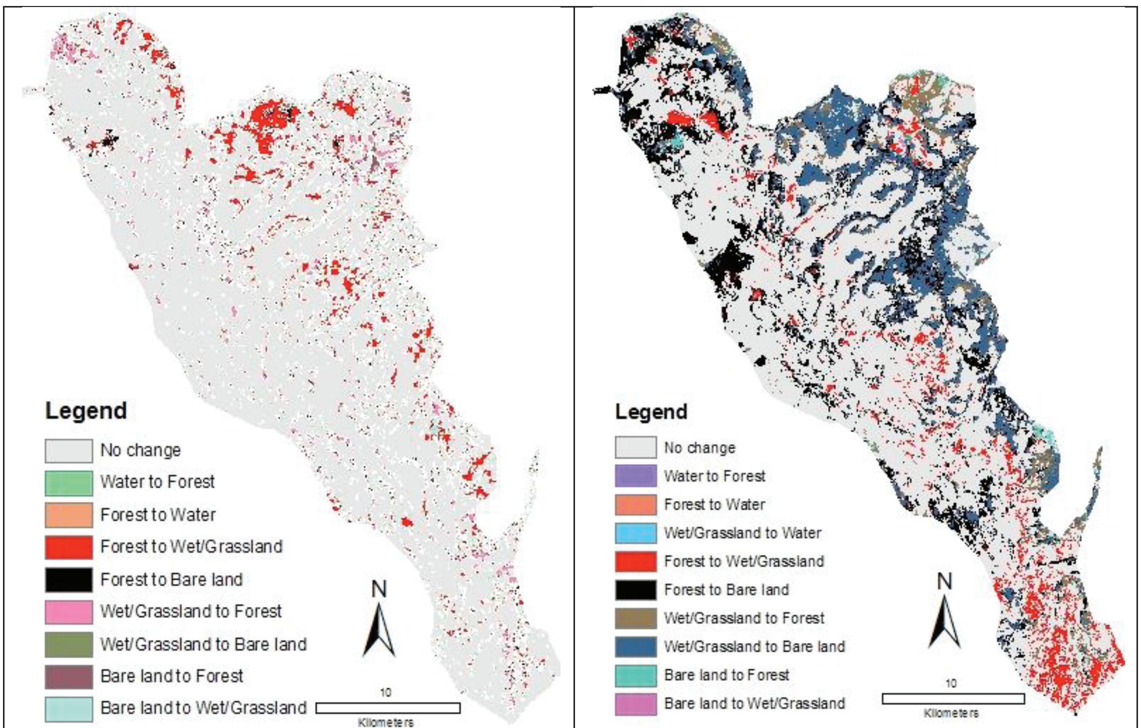
Table 1. Land cover change between time intervals in hectares

1990 and 2000	*Water*	*Forest*	*Wet / Grassland*	*Bare land*	**Total**
Water	0	3.45	0	0	3.45
Forest	0.06	0	7078.03	329.81	7407.9
Wet / Grassland	0	3204.44	0	264.57	3469.01
Bare land	0	957.39	747.49	0	1704.88
2000 and 2008					
Water	0	0.06	0	0	0.06
Forest	19.85	0	3560.9	9758.24	13338.99
Wet / Grassland	1.07	3913.29	0	8544.08	12458.44
Bare land	0	344.36	28.36	0	372.72

Despite environmental management measures being taken by the surrounding communities, the results show a staggering 20,747 hectares (see Table 1) of forest loss between 1990 and 2008, 64% of which occurred between 2000 and 2008. In that latter period 73% of the forest loss was lost to bare land as opposed to just 4% in the period 1990 to 2000 where 7078 hectares (96% of total forest lost) of the forest was lost to wet/grassland. Again between 2000 and 2008 significant proportions of the wet/grassland was lost to bare land. Table 1 summarizes the land cover conversion dynamics in hectares and Figure 4 shows the changes spatially.

In Table 1 above, each row value represents the number of hectares lost from that land cover type to any one of the column land cover types. These land cover changes suggest a dynamic population behavior in which case the reported increased poverty levels and urban sprawl start to explain the situation for the 1990 to 2000 and 2000 to 2008 periods respectively. The economic opportunities of urban sprawl triggered collective responses such that in the typical subsistence communities a wide selection of nutritive requirements for household survival were taken directly from the forested environments than in the limited-scope subsistence agricultural activities. This underlies a situation of deforestation that is worsening in the area.

To ascertain the situation in the near-future we employed a Markov chain model. Here the paper assumed land use change from time 1990 to 2000 and then 2000 to 2008 is a Markov chain with stationary transition probability. Each of the four land use categories was assumed to be a possible state at any given time of the chain. A Markov chain equation ($p_{ij} \times \mathbf{v}_j = \mathbf{v}_{j+1}$) was used. p_{ij} is the transition probability of state i changing to state j and $\mathbf{v}_j$ represent a vector of land use state j at time t_1 and $\mathbf{v}_{j+1}$ is the projection of land use properties at time t_2. In this study, land use change was projected for the years 2010 and 2020 by computing first and second order Markov chains. Using water, forest, wet/grassland and bare land categories as states in the Markov chain model, a transition matrix was computed and land



(a) 1990 to 2000 (b) 2000 to 2008

Fig. 4. Land cover change detection

use change statistics for 2010 and 2020 were predicted. Bare land and water are almost constant while forest continuously reduces. Compared to observed satellite imagery for 2008, the 2010 prediction does perform poorly as it under predicts forest loss by 10%. The study has predicted 77% of the study area to have been forested in 2010 and to be reduced to 75% in 2020 representing a meager 1376 hectares of forest loss. Compared to the observed forest losses between 1990 to 2000 and 2000 to 2008, the Markov chains under predict the land cover changes given that the status quo triggering the changes is assumed to be maintained. Figure 5 shows the Markov chain predictions and a projection to 2020 graphically.

The Markov chains analysis's predictions in this study do suffice in indicating that the situation of deforestation in the forest reserve will not abate in the near future as they are understood in the context of the memory-lessness nature of the model. That is, while in the observed cases the factors causing the land cover changes evolved, for instance the intensification of commercial charcoal burning leading to massive deforestation between the years 2002 to 2005 [4], the Markov chains analysis assumed a maintained status quo in as far as the drivers of change were concerned. This is not withstanding the fact that we grossly assumed that the observed land cover changes are Markov processes and stationary Markov processes for that matter a condition we did not prove though (see [16, 17, 18 and 19] on why testing these assumptions is difficult) and therefore we could not guarantee. We understand too that in our attempt to substantiate the degrading conditions of the forest reserve in the near future, we did not include constraints on possible transitions or other constraints like availability of land and other resources [16]. This is because the focus was on the possible quantities of change regardless of whether they can actually occur or not.

The foregoing analysis highlights two related issues facing the forest reserve: first being that indeed the forest reserve is under heavy ecological threat of extinction and secondly, there is indeed dynamism in the factors driving this degradation. Regardless of the under predictions of the Markov chains, the observed forest cover loss between 1990 to 2000 and 2000 to 2008 suggests there is more to the factors affecting deforestation of the reserve as the forest cover lost almost doubled in the latter period (see Table 1). While not denying the role of population growth and poverty, the trend established in this study cannot be pinned down to these two factors only especially in this area where shifting cultivation is not practiced nor is there presence of any known large scale transmigration to settlement schemes and/or plantations. Despite Markov chains' failure to depict underlying factors influencing the land cover changes, a cross examination of the results against the reports that between 2002 to 2005 deforestation intensified [4] suggests changing economic opportunities to be one of the main driving forces as it coincides with socio-political change in 2004 that saw a change of government policy to relocate all central government

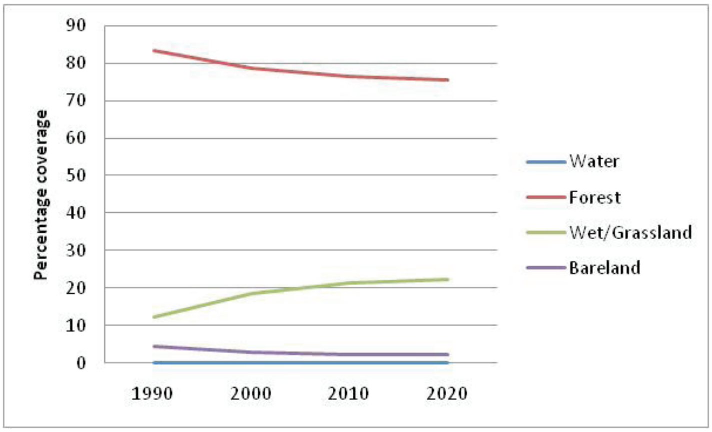


Fig.5. 2020 projected land cover trends for Dzalanyama

personnel to the capital city with the aim of cutting central government expenses. This created demand for infrastructural materials especially bricks and wood for extra housing for the city dwellers and firewood for those pushed into the city peripherals. It is difficult indeed to expect stationarity in transition probabilities when such complex dynamic factors are dragged into the picture [20], however, the not-too-long 30-year period in this study made the requisite Markov chains assumptions practically achievable as supported by [21]. Overall, the relative ease with which we inferred understanding of the dynamic driving factors from the multi-temporal land cover data surpassed the limitations the Markov chain analysis posed for the purposes of this analysis. Indeed for a forest reserve to be losing its forest cover at such rates is very worrisome. As such the direction and magnitudes of the deforestation trends established in this study demand a rigorous approach that should incorporate the behavioral dynamics of the population living in the surrounding community including the social, political and infrastructural changes to achieve positive results. Being a largely subsistence farming based community [4], a model that will invoke and build on the activities at the individual farm household levels would be the most appropriate to reverse the trends and provide sustainable solutions.

4. Conclusion

The ecological landscape of Dzalanyama forest reserve is under massive degradation and the trends show no signs of abating if the situation is left unattended. Such rates defeat the whole essence of calling the study area a forest reserve. Much as population growth and poverty play important roles, the complex forces of changing economic opportunities have the most significant impacts on deforestation of the forest reserve. It is therefore important that any measures taken to curb this deforestation should build and base on the dynamic social, political and infrastructural changes of the population of the rural community surrounding the reserve.

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