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Estimating the Extent of Degradation in the Bounfum Forest Reserve, Ghana, Using Historical Remotely Sensed Data and Landscape Fragmentation Indices

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Abstract
Land use and land cover changes, especially deforestation and forest degradation and its driving factors, are key factors hindering sustainable forest management. Currently, there is limited knowledge concerning the detection of the extent and interpretation of the spatial and temporal pattern of forest cover dynamics in the Bounfum Forest Reserve, which when available will inform sustainable policies. Using the Landsat TM image of 1986, Landsat ETM+ image of 2002 and Landsat 8 OLI image of 2014, the study identified and quantified the forest cover dynamics in the Bounfum Forest Reserve from 1986 to 2014. The ERDAS maximum likelihood classification algorithm was used to classify the pixels into five major land cover classes namely, bare/built areas, farmlands, closed forest, open forest and shrub/grassland. The Kappa coefficients of 0.83 (1986), 0.72 (2002) and 0.75 (2014) respectively were obtained for the classified images. The findings showed that the closed forests decreased by 3.5% (563.90 ha) per annum whilst the open forests and farm lands increased by 19.5% (385.60 ha) and 2.9% (65.00 ha) per annum within the 28-year period. This implies that the Bounfum forest reserve has been highly degraded over the past 28 years, evident through the trends of its patch densities and the number of patches. Collaborative forest management is required in the management of the forest reserve to conserve the socio-ecological and economic benefits derived from the resource on sustainable basis.
Keywords: Land use and land cover change, Bounfum forest reserve, deforestation, forest degradation, remote sensing, sustainable forest management

1. Introduction

Land use and land cover (LULC) changes have been recognized as important drivers of the global environment change (Turner *et al*., 1996). They either directly or indirectly modify the natural habitats and impact on the ecology of the area. Land use and land cover is, therefore, dynamic and provides a comprehensive understanding of the interaction and inter-relationship of anthropogenic activities with the environment (Prakasam *et al*., 2010). The pattern of land use/cover of an area provides important information about the natural and socio-economic factors, human livelihood and development (Yadav *et al*., 2012). Dimyati *et al*. (1994) clearly distinguished between land cover and land use although the two terminologies are often used interchangeably. The land cover reflects the biophysical state of the earth's immediate surface, including the soil material, vegetation and water whilst land use refers to the utilization of land resources by humans. Changes in land covers due to excessive human activities, however, often reflect the most significant impact on the environment.

According to Ringrose *et al*. (1997), the LULC change in Africa particularly in forest landscapes is currently accelerating and causing widespread deforestation, degradation and other environmental problems since the changing pattern of LULC reflects the changing ecological, economic and social conditions. Monitoring such changes is important for coordinated actions especially at the national and international levels (Bernard and Wilkinson, 1997) to help develop management interventions that are scientifically based and cost-effective. The major drivers of forest degradation and LULC changes in developing countries are inappropriate agricultural practices on farmland(s) adjoining forest areas (Angelsen and Kaimowitz, 2001), misuse of forest resources due to the ineffective forest management policies and conventional logging operations using unplanned-selective logging method (Rosyadi *et al*., 2004; Boltz *et al*., 2003). However, the most important cause of deforestation and forest degradation comes from illegal logging and trade (Atmopawiro, 2004), which leads to overexploitation and wanton destruction of forest resources and hinders sustainable forest management (Marfo, 2010).

Ghana had an extensive forest estate consisting of 266 forest reserves established in the early 1920s. Of these, 216 reserves are located within the high forest zone, occupying about 1.63 million ha (Tropenbos International, 2009) and 6.8% of the total land area of Ghana. The forest estate, however, had been subjected to various impacts and pressures including population and economic growth. The quest to satisfy the increasing demand for timber for domestic consumption and the export markets resulted in high rate of deforestation and forest degradation. The major causes of forest destruction in the high forests zone were timber exploitation (both legal and illegal), clearance for agriculture using shifting cultivation/traditional slash-and-burn practice and fodder development

(Boakye *et al*., 2008) and from mining and recurrent wildfires (FAO, 2010). These anthropogenic activities were further exacerbated by the increasing population growth, climate variability and climate change to exert severe pressure on the natural environment; culminating in forest vegetation modifications and rendered the forest productive systems at risks (FAO, 2011). An assessment of the forest estate in 2010 by the Global Forest Resources Assessment (GFRA) revealed that Ghana lost about 2% (135000 ha) of forests annually between 1990 and 2000 compared to the estimated regional deforestation rate of only 0.8% for Africa (FAO, 2010). Such high rates of forest destruction in the country led to the initiation of the Sustainable Forest Management (SFM) concept to address the many problems relating to deforestation, especially those in developing countries.

The Bounfum Forest Reserve in Ghana is one of the 216 forest reserves managed for protection and timber production (Marfo, 2010) and was gazetted in the 1920s. Since then the reserve has been subjected to wanton deforestation and degradation mainly from illegal farming activities and other land uses such as settlements and burial sites. These activities destroy large hectares of forestland annually. Researchers have advocated for an intensive and extensive monitoring of the Ghana's forest landscapes to apprise policies for their sustainable management (Tachie-Obeng, 2009; Koranteng and Zawila-Nieddzwiecki, 2015). However, knowledge on the status of the reserved areas is inconclusive, particularly regarding the detection and interpretation of the spatial and temporal extent and patterns of vegetation modifications.

The application of geospatial technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) have provided some of the most accurate, economical and efficient means of measuring the extent and pattern of changes in landscape conditions over a period of time (Miller *et al*., 1998). Geospatial techniques have been used extensively in the tropics for generating valuable information on the forest cover, vegetation type and land use changes at large spatial scales (Zoungrana *et al*., 2015; Forkuor *et al*., 2017; Grecchi *et al*., 2017). The use of geospatial technology in the current study is justified by the advancement in the technology to improve the efficiency and accuracy of LULC mapping at the landscape scale. Thus, integrating these techniques provides an effective tool for monitoring and evaluating land use/cover changes at varied scales (Zoungrana *et al*., 2015).

The study, therefore, adopted remote sensing and GIS techniques to appraise and map the extent and pattern of deforestation and degradation in the reserve as well as determine the major drivers of change in the Bounfum forest reserve. Such information will be useful to predict possible changes that might occur in future and serve as baseline information for sustainable management of the forest reserve.

2. Materials and Methods

2.1 Study Area Description

The Bounfum forest reserve derives its name from River Bounfum, which flows through it. The reserve is included in the Agogo range of the Juaso Forest District and falls within Mampong and Juaso political districts. It lies within longitudes 1˚ 2´ 30´´ W and 1˚ 12´ 30´´ W and latitudes 6˚ 47´ 30´´ N and 7˚ 00´ 30´´ N (Figure 1). The land is generally undulating with elevation varying from about 400 to 1500 metres above mean sea level. Several streams derive their sources from the reserve with the major ones being Ongwam, Kotobon, Pame, and Bounfum after which the reserve had been named (FRMP, 1975).

The area experiences bimodal rainfall pattern with peak periods occurring in May-June and September-October (minor). Long drier spells are observed from December to February. The relative humidity (RH) varies from 90 % to 75% at 1500 hours under high forest condition, where the factors affecting RH tend to be stable (FRMP, 1975). The rocks belong to the Voltaian system with sandstones, which are conspicuously flat-bedded as the predominant rocks. The soils are light, sandy and generally porous with variable depth. There are also deep, rich, alluvial soils found alongside the streams and under high forest whilst pan formations are found in the soils of the grassland areas (FRMP, 1975).

2.2 Data Acquisition

The data used were mainly satellite-captured images. The study spans three different year periods (thus, 1986, 2002 and 2014). The Thematic Mapper (TM) onboard the Landsat 5 earth observation satellite captured the 1986 image on January 11, 1986. For 2002, the data comprised the Enhanced Thematic Mapper plus (ETM+) captured image of February 24, 2002. Again, the Operational Land Imager (OLI) of the Landsat 8 captured the data for 2014 on February 21, 2014 (Table 1). The imagery was obtained from the USGS Global Visualization Viewer (GLOVIS). The satellite imagery was preprocessed using ERDAS Imagine software (2011 version) whilst ArcGIS (version 10.4) was later used for further data processing and analysis.

2.3 Satellite Data Preprocessing

Prior to digital classification, the images were preprocessed so that errors due to the geometry of the earth, radiometry and atmospheric effects can be removed to improve the image quality (Figure 2). In the current study, the geometric correction was not applied to the satellite imagery because the data were already georeferenced to the UTM Coordinate System Zone 30N. The histograms of the satellite scenes were computed and assessed to determine the distribution of the digital numbers (DNs) of pixels. The pixel DNs were then converted into terrain radiance using the parameters from the Landsat metadata file. The Bounfum Forest Reserve shapefile was also georeferenced to the same UTM coordinate system to facilitate data combination in the ArcGIS software (v 10.4) environment.

The satellite data used for the study had cloud cover of less than 10%. However, they were removed using the techniques proposed by Martinuzzi *et al*. (2007). Atmospheric correction was done by the Dark-Object Subtraction (DOS) technique in the ArcGIS 10.4 package to enhance the image quality prior to classification. The DOS being an image-based technique does not require in-situ measurement during the acquisition of satellite images (Chavez, 1996). The technique assumes that there is a high probability that there are at least few pixels within an image which should be black (0% reflectance), for example, areas of shadow caused by topography or clouds in the image where the pixels should be completely dark. Ideally, an imaging system should not detect radiance at these shadow locations, and a DN value of zero should be assigned to them.

However, because of the atmospheric scattering effect, these shadowed areas will not be completely dark and the sensor records a non-zero DN at these locations. Thus, the DN values at these locations were assumed the haze values and had to be subtracted from the particular band to account for atmospheric scattering effect. Chavez (1996) also noted that there are only a few objects on the Earth's surface that are completely dark and so an assumption needs to be made that these objects have at least one-percent of reflectance. Therefore assuming that there are some dark objects whose reflectance are around zero, then the minimum DN value needs to be subtracted from all the pixels so that atmospheric effect can be removed from the entire image (Sobrino *et al.,* 2004).

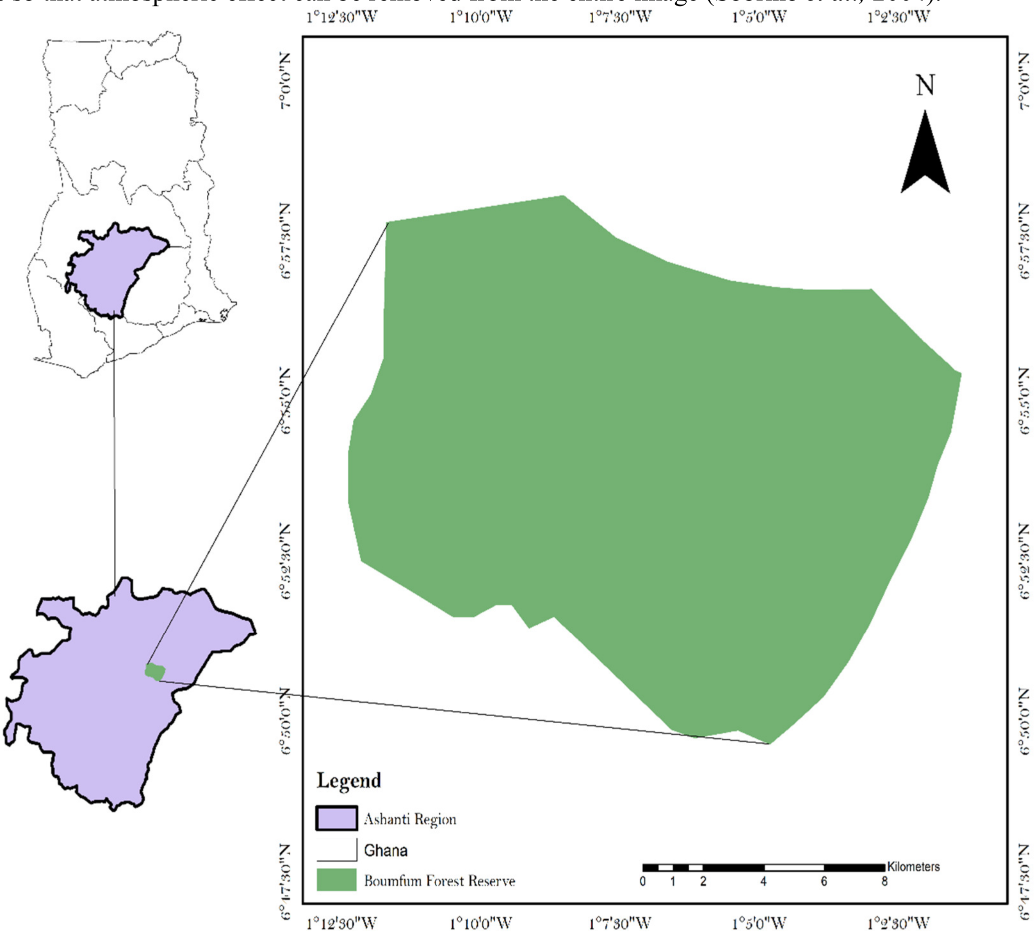

Figure 1. A map of Ghana showing the location of the Bounfum forest reserve

Table 1: Description of the satellite images used in this study

Date of image acquisition	Land sensor	Spatial resolution
11/01/1986	TM 5	30 m
24/02/2002	ETM+ 7	30 m
21/02/2014	OLI-TIRS 8	30 m

2.4 Classification of Satellite Image Data

In this study, the supervised classification that employs a statistically based maximum likelihood classification (MLC) algorithm was applied in the classification of the image data. The MLC algorithm quantitatively classifies every pixel by evaluating both the variance and covariance of the categorical spectral response pattern (Lillesand, 2008). With supervised classification technique, the analyst defines training areas to train the algorithm, which then classifies pixels based on their likelihood to belong to the defined land cover class. Thus a set of ground data (training data) were collected using polygons at certain locations (training areas) for the land cover categories: shrub/grassland, open forest, farmlands, closed forest and bare/built-up areas. Then areas of interest (AOIs) were created at the training sites where training data were collected. The land cover classes were separated using their spectral response on the current image. The spectral differences between pairs of defined land cover classes were assessed with the ROI Separability tool, which showed high values of separability between the areas of interest (from 1.99 to 2.00). These AOI polygons were then converted into parametric files (statistical parameters of the pixels) representing the spectral signatures of the training data.

Based on the statistical parameters of the specified classes from the training data, the maximum likelihood classification method calculates the likelihood of which every pixel in the image belongs to the respective land cover classes. Every pixel was then assigned to the land cover class with the highest likelihood based on the assumption that similar features with similar spectral signature have a normal distribution and their statistical probability can be computed. The areas (ha) of the detected land cover classes; Shrub/Grassland, Open Forest, Farmlands, Closed Forest and Bare/Built-up were then computed in ArcGIS (v 10.4) by a count of pixels from the digital map and compared to determine the extent of change in the LULC classes for the period of observation.

2.5 Post Classification Accuracy Assessment

The post-classification accuracy assessment was performed on the classified images. During the accuracy, stratified random sampling method could be used to generate reference points for the whole of the study area (Jensen, 1996). In our study, the accuracy assessment was done by selecting the known location of each of the observable land cover classes on the preprocessed but unclassified images. These known locations of perceived land cover classes are known as the ground truth points. The truth points were selected just after the image processing and the extraction of the ROI. Care was taken while selecting the truth point in order that the training sample locations are avoided. This helps increase the accuracy by reducing biases. Overall, a total of 443, 406 and 316 points were collected randomly from the 1986, 2002 and 2014 imageries, respectively. An error matrix was produced for each image. Indicators of accuracy such as the overall accuracy, the user's accuracy, producer's accuracy, and kappa coefficients were calculated.

Kappa Coefficient was calculated using;

$$\widehat{K} = \frac{N\sum_{i=1}^{r}(X_{ii}) - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} * X_{+i})}$$

Where:

K is Kappa coefficient; N = total number of correctly predicted pixels: Xii is the sum of the correctly classified pixels; Khat >80% represent strong agreement and good accuracy, 40% - 80% is middle, <40% is poor (Cheng-Chien, 2015). This has been one of the major problems of remote sensing (Jensen, 1996). To determine the accuracy of classification for these images, stratified random sampling method (Jensen, 1996) could be used to generate reference points for the whole of the study area.

2.6 Post Classification Change Detection

After the final maps had been reclassified and improved through change rationality test, post-classification change detection was performed to detect the land use/land cover changes (LULCC) in a similar manner as used by Singh (1989). Two maps were paired at a time to calculate their categorical change using the 'Tabulate Area function in ArcGIS (version 10.4). For instance, the map of 1986 was paired with that of 2002 to determine how much of an area of a class in 1986 map had changed in the 2002 map.

2.7 Landscape Metrics

Fragmentation of the Bounfum forest reserve along a time series was quantified using the Fragstats (v4.7). A series of landscape indices were deemed necessary to understand the objectives of this paper. This included number of patches (Turner, 1989), patch density (McGarigal and Marks, 1995; Saura and Martinez-Millan, 2001), mean patch perimeter/area ratio (Krummel *et al*., 1987), DIVISION, largest patch index (Saura and Martinez-Millan, 2001) etc. A four-neighbour rule was used in this analysis. The patch density equals the number of patches in the landscape, divided by total landscape area; an indicator that allows comparison between landscapes of varying areas. Figure 2 summarises the methods used in the study in a flow chart.

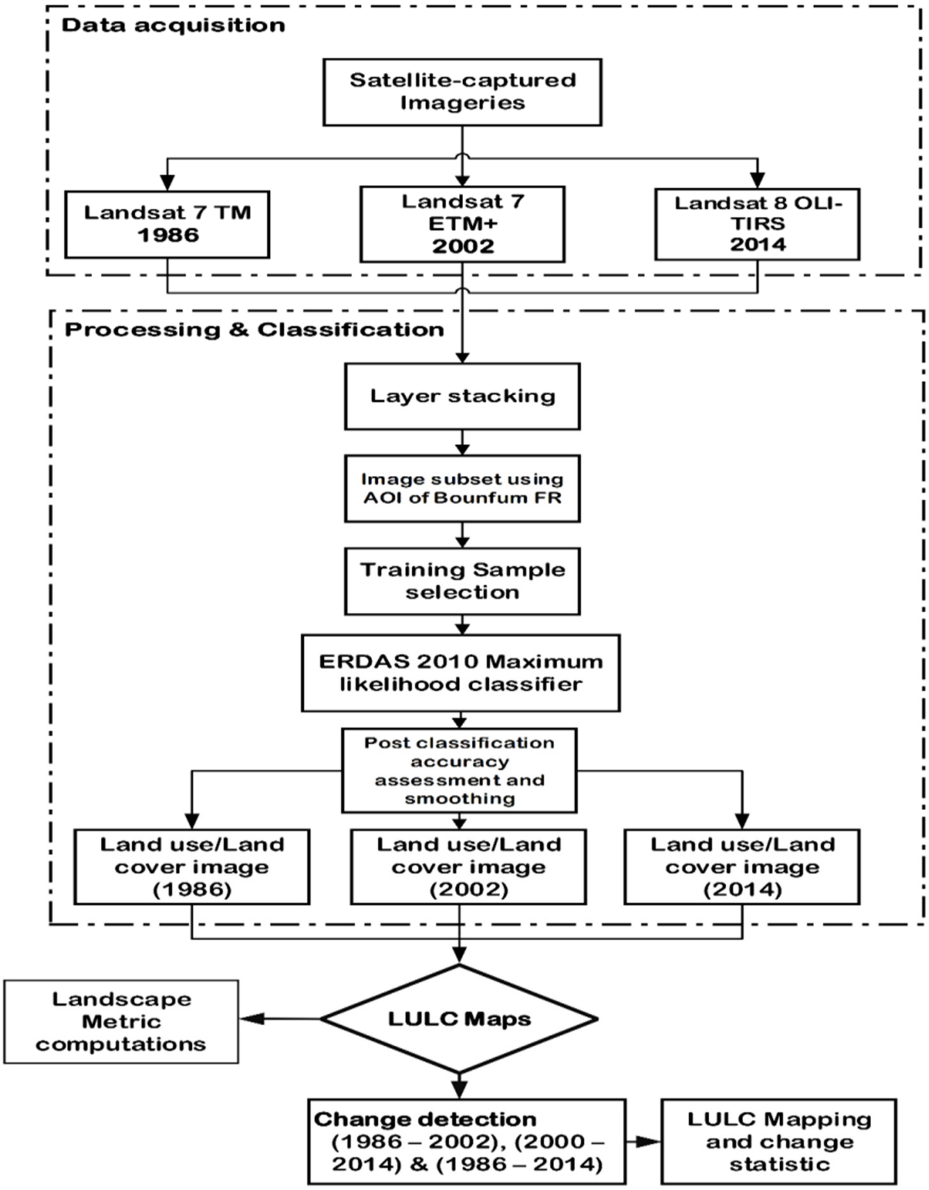

Figure 2. A flowchart of methods used in the study

3. Results

3.1 Validation of Land Cover Maps

The classified images were validated by performing accuracy assessment. The assessment report obtained has been summarised in Table 2. The overall classification accuracy was 81.0%, 77.8% and 84.5%, respectively for 2014, 2002 and 1986. Again, the Kappa's statistic of 0.75, 0.72 and 0.80 was computed for 2014, 2002 and 1986, respectively. Based on the interpretation criteria by Cheng-Chien (2015), the classified images are robust enough to make deductions and further analysis.

Table 2. Accuracy assessments

	1986		**2002**		**2014**	
	PA	UA	PA	UA	PA	UA
Shrub/Grassland	85.8	100.0	89.8	83.0	83.3	92.6
Closed Forest	100.0	55.9	67.8	68.5	50.0	100.0
Open Forest	82.5	90.8	72.2	66.9	94.5	76.5
Farmland	82.6	91.0	71.0	80.0	83.3	71.4
Bare/Built-up	-	-	93.3	98.8	65.5	90.5
Overall accuracy	84.5		77.8		81.0	
Kappa (Khat)	0.83		0.72		0.75	

PA: Producer Accuracy; UA = User Accuracy

3.2 Analysis of the LULC Dynamics of the Bounfum Forest Reserve from 1986 to 2014

3.2.1 General Statistics and Spatial Distribution of LULC

Figure 3 is a thematic map of the Bounfum forest reserve obtained after classifying into five different land cover themes viz: closed forest, open forest, bare/built-up, farmland and shrubs/grassland. The area statistics are summarised in Table 3 and 4. In 1986, the closed forest cover occupied the highest proportion of the forest reserve (16131.20 ha, 74.3%) and its patches were mostly located in the northern and southern parts of the Bounfum Forest Reserve. However, in 2002, it reduced significantly by 10482.40 ha at 4.1% per annum to 5648.76 ha (26.0%). The closed forest patches were concentrated in the northwestern and southern part of the image. This forest type, in 2014, had decreased by 5307.50 ha to 430.2 ha (1.6%). Similarly, the open forest, which initially occupied 198021 ha, representing 9.1% of the forest reserve in 1986 had increased to 12086.60 ha (55.7%) in 2014 by 10106.40 ha at a rate of 31.9% per annum. Again, in 2014, the open forest cover type increased significantly to 12775.7 ha at 0.5% yearly. The shrubs/grassland were mostly patches located mainly around the western part of the reserve. In 1986, the shrubs/grassland cover type was about 1308.50 ha, which represented 6.0% of the forest reserve. However, by 2002, the shrubs/grassland had increased to 1588.10 ha (7.3%) at a rate of 1.3% per annum. Its patches were scattered within the entire scene.

Conversely, the shrubs/grassland recorded the same increasing growth at a rate of 6.6% per annum to 2841.26 ha (13.1%) from 2002 to 2014. Farmland, on the other hand, occupied an area of 2240.10 ha (10.3%) in 1986 and were scattered in smaller patches within the forest. By 2002, the farmland cover class had decreased to 2088.8 ha (9.6%) at a rate of 0.4% per annum and was mainly found around the western, southern and along the northern part of the reserve. The farmland, in 2014, extended its spatial boundaries to cover about 4059.28 ha (18.7%) and was scattered along the entire scene of the image. Interestingly, there was no built-up area in the forest in 1986. However, the bare/built-up had been introduced in the 1989 image, which occupied 268.02 ha (1.2%) of the entire Bounfum Forest Reserve. The bare/built-up area grew significantly to 1689.4 ha (7.8%) in 2014 at 44.2% per annum.

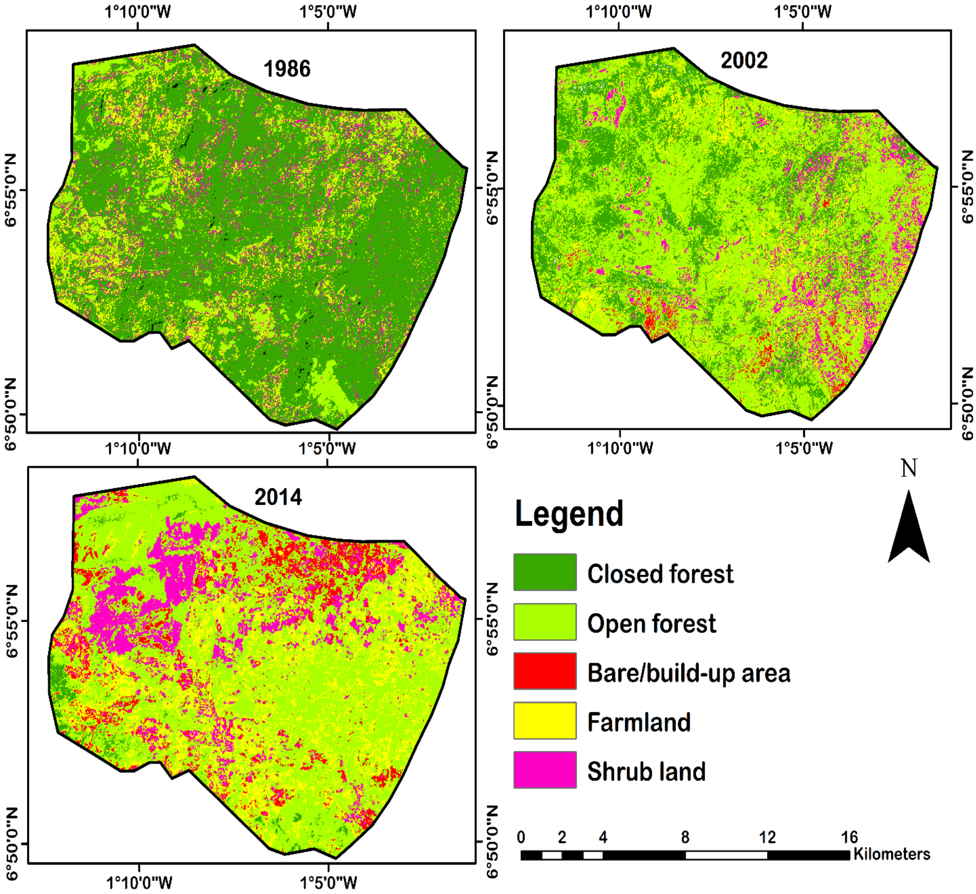

Figure 3. Spatial representation of land cover types of the Bounfum forest reserve in 1986, 2002, and 2014

Table 3. The area statistics of land use/land cover types obtained for the classified image data

LULC	**1986**		**2002**		**2014**	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Closed forest	16131.19	74.3	5648.76	26.0	341.25	1.6
Open forest	1980.21	9.1	12086.6	55.7	12775.67	58.9
Bare/built-up	0	0.0	268.02	1.2	1689.35	7.8
Farmland	2240.1	10.3	2088.76	9.6	4059.28	18.7
Shrub land	1308.52	6.0	1588.1	7.3	2841.26	13.1
Unclassified	48.76	0.2	28.54	0.1	1.97	0.0
Total	21708.78	100.0	21708.78	100.0	21708.78	100.0

Table 4. Land use/ land cover (LULC) change statistics

	1986 - 2002			**2002 - 2014**			**1986 - 2014**		
LULC	Area (ha)	%	%/year	Area (ha)		%/year	Area (ha)	%	%/year
CF	-10482.4	-65.0	-4.1	-5307.5	-94.0	-7.8	-15789.9	-97.9	-3.5
OP	10106.4	510.4	31.9	689.1	5.7	0.5	10795.5	545.2	19.5
BB	268.0	0	0	1421.3	530.3	44.2	1689.3	0	0
FL	-151.3	-6.8	-0.4	1970.5	94.3	7.9	1819.2	81.2	2.9
SG	279.6	21.4	1.3	1253.2	78.9	6.6	1532.7	117.1	4.2
UC	-20.2	-41.5	-2.6	-26.6	-93.1	-7.8	-46.8	-96.0	-3.4

(**LULC** = Land use/land cover, **CF** = Closed forest, **OP** = Open forest, **BB** = Bare/built-up land, **FL** = Farmland, **SG** = Shrubland/grassland, **UC** = Unclassified)

3.2.2 LULC Change Trajectory Analysis

Figure 4 shows the direction of land use/land cover changes that occurred from 1986 to 2014. The direction of change was computed on a pixel-by-pixel basis. The conversion statistics are shown in Table 5 and 6. The positive and negative indicators on Figure 4 depict the recovery and decline of the closed forest cover, respectively. Overall, between 1986 and 2014, the open forest, farmland, bare/built-up and shrub land have taken a significant portion of the original 76.2% of closed forest that existed in 1986 by 45.5%, 5.4%, 15.3% and 10.1% respectively. There was no significant recovery (0.8 %) of the closed forest since only 0.7% of the open forest, farmland and shrub land were recovered. It is imperative to report that only 0.9% of the closed forest did not experience any change (thus, a no change forestland).

Table 5. Transition matrix of LULC change trajectory (%)

				2002		
		Closed forest	Open forest	B/Built-up	Farmland	Shrubland
1986	Closed forest	**19.2**	39.2	0.9	7.9	5.3
	Open forest	2.4	**5.1**	0.1	0.8	0.9
	Bare/Built-up	0.0	0	**0**	0	0
	Farmland	3.0	6.1	0.2	**1.1**	0.8
	Shrub land	1.7	4.0	0.1	0.6	**0.6**
				2014		
2002	Closed forest	**0.9**	15.6	1.8	3.8	4.4
	Open forest	0.5	**31.1**	4.5	11.7	6.9
	Bare/Built-up	0.0	0.1	**0**	0.4	0.1
	Farmland	0.2	6.6	0.7	**1.8**	1.3
	Shrub land	0.0	4.3	0.9	1.8	**0.7**
				2014		
1986	Closed forest	**0.9**	45.5	5.4	15.3	10.1
	Open forest	0.3	**5.1**	1.5	1.5	1.4
	Bare/Built-up	0.0	0	**0**	0	0
	Farmland	0.5	6.8	0.9	**2.3**	1.5
	Shrub land	0	0.6	0.1	0.2	**0.1**

Table 6. Summary statistics of LULC change trajectory analysis

	Decline (-)	**Recovery (+)**	**Net change**	**Unchanged**
1986 – 2002	53.4%	7.1%	46.3%	19.2%
2002 – 2014	25.6%	0.7%	24.9%	0.9%
1986 – 2014	76.2%	0.8%	75.5%	0.9%

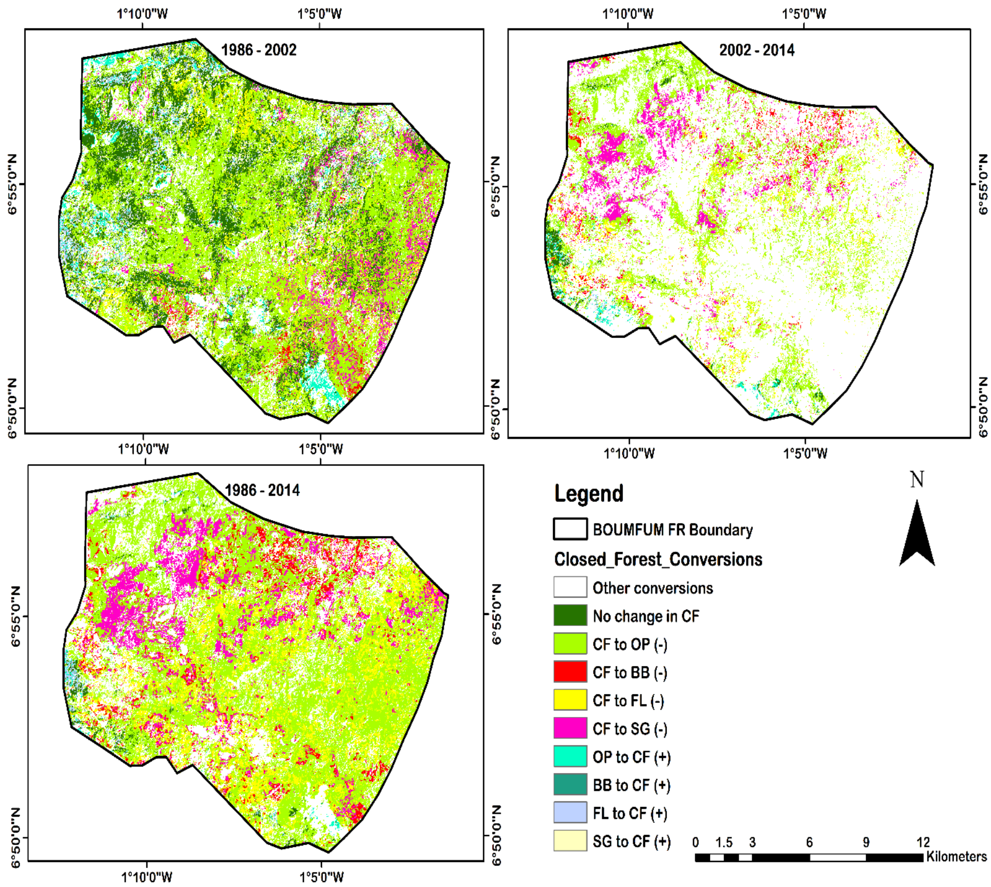

Figure 4. Spatial representation of closed forest conversion trajectory (**CF** = closed Forest, **OP** = Open forest, **FL** = farmland, **SG** = shrubland/grassland, **BB** = Bare/Built-up land)

Similarly, considering periods from 1986 to 2002, the open forests, bare/built-up areas, farm land and shrub land had collectively taken up 54.4% of the closed forest cover, which represents 39.2%, 0.9%, 7.9% and 5.3%, respectively. Additionally, an increase of 7.1% was observed during this period, whereas about 19.2% experienced no change. However, by 2014, the 26.3% of the closed forests that existed in 2002 had declined by 25.6%; thus, 15.6% to open forest, 1.8% to the bare/built-up area, 3.8% to farmlands, and 4.4% to shrub/grassland. A limited recovery (0.7%) was observed within the closed forest cover.

3.2.3 Forest Degradation Analysis

The landscape indices were used to define and ascertain the degree to which the forest has degraded judging from the decline in the acreage of its cover observed in Table 3. The results achieved for some selected indices that are believed to explain the degree of forest degradation through forest fragmentation are summarised in Table 7. The selected metrics include number of patches (NP), patch density (PD), largest patch index (LPI), mean perimeter/area ratio (PERM/AREA), COHESION and DIVISION. The number of patches of the closed forest decreased from 745 in 1986 to 486 in 2014. The patch densities obtained for the closed forest were greater than one.

Table 7. Selected landscape metrics of the forest types observed from 1986 to 2014

	1986		**2002**		**2014**	
Metrics	CF	OP	CF	OP	CF	OP
Number of Patches	745	2673	5155	2258	486	1304
Patch density (/ha)	3.44	12.34	23.78	10.42	1.34	0.10
Largest Patch Index (LPI)	71.39	1.15	3.68	49.35	0.54	54.43
Mean Perimeter/Area ratio (m/m^2)	1113.12	1086.25	119.23	1118.44	1118.19	1076.50
DIVISION	0.49	1.00	1.00	0.76	1.0	0.70

CF = Closed forest; OP = Open forest

4. Discussion

The information extracted from LULC maps indicate that Bounfum Forest Reserve has gone through changes over 28 years; from 1986 to 2014. A critical examination of this information evidently showed that there are significant changes in the land cover status of the Bounfum Forest Reserve. The decreasing trends of closed forest coupled with subsequent increments in open forest, farmland, shrubs/grassland and bare/built-up areas could be due to population expansion, rapid urbanization of the districts, admitted farms extension and illegal farming in the Bounfum Forest Reserve. This supports Harris and Miller (1984) assertion that the influence of human activities is altering the natural landscapes by changing the abundance and spatial pattern of the forest ecosystem. This finding is also consistent with that of Adubofour (2011). Though Lambin *et al.* (2001) reported that population growth cannot be considered as the sole and major cause of land use/land cover change, yet it constituted one of the determinants of the changes in the Bounfum forest reserve.

Based on the knowledge of the land use practices at the reserve gained through field validation survey, a number of explanations can be put forward for the observed changes in land cover status identified in the different images. It was evident that most of the areas that had experienced a decrease in forest cover from 1986 to 2014 were located in the southeastern part of the reserve. Currently, these locations are gradually concentrated with built-up/settlements. Thus, with the influx of humans, several areas of vegetation were cleared for agriculture and settlements in the reserve. Generally, for closed forest cover, increases in the number of patches and patch density as well as a decrease of LPI are indications of landscape fragmentation over the period under consideration (Saura and Martinez-Millan, 2001). Our results showed that the Bounfum forest reserve had gone through a series of fragmentation. Typically, whilst some researchers found an increasing trend in fragmentation in similar studies (Bracchetti *et al.,* 2012; Cakir *et al.,* 2008) in line with our current study, others observed a reduction in fragmentation regardless of the gain or loss of forests (Geri *et al.,* 2010; Keles *et al.,* 2008). The differences between fragmentation of the forest and the landscape could be because landscape results are strongly conditioned by the extension and changes in mixed shrubs.

5. Conclusion

We performed a remote sensing based study to assess the extent of deforestation and fragmentation of the Bounfum forest reserve between 1986 and 2014. By 2014, the major land uses/land cover types found in the reserve were open forest (58.9%), farmlands (18.7%), shrub land/grassland (13.1%), bare/built-up (7.8%) and closed forest (1.6%). As a percentage of the spatial extent observed in 1986, the closed forest areas experienced an annual decline of 563.90 ha (3.5%) with only some marginal recovery (0.7%) whilst the open forest cover and farm lands increased by 19.5% (385.60 ha) and 2.9% (65.00 ha) per annum within the 28-year period. These figures clearly indicate that the Bounfum forest reserve has undergone massive deforestation and forest degradation. The decreasing trend of closed forests coupled with subsequent increments in the open forests, farmlands and other land cover types could be attributed to anthropogenic activities such as population growth culminating in increasing demand for settlements, rapid urbanization within the districts, illegal logging and farming activities and expansion of admitted farms in the reserve.

Strengthening the sustainable forest management efforts such as collaborative forest management and reforestation programmes is required to ensure the conservation of Bounfum forest reserve for the present and future generations. This work may assist in policy reforms within the forestry and land-use planning and management sectors, the adoption of sustainable land use practices, the rehabilitation of damaged forest ecosystems, monitoring of environmental quality and promote the reduction of social costs and uncertainty in the selection of land-use strategies.

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