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Research Paper

Assessment of vegetation dynamics using remote sensing and GIS: A case of Bosomtwe Range Forest Reserve, Ghana

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ABSTRACT

Changing conditions owing to increasing forest fragmentation make land cover and change detection analysis an extremely important consideration for sustainable forest management. This study applied supervised classification using maximum-likelihood algorithm in Quantum GIS to detect land use land cover changes in the Bosomtwe Range Forest Reserve, Ghana from 1991, 2002 and 2017 using Landsat 4 – TM, Landsat 7 – ETM and Sentinel-2 satellite imageries respectively. Based on the results of the study, it is concluded that land use/cover of Bosomtwe Range Forest Reserve have undergone remarkable changes for over the period of 26 years. The current status of forest cover is estimated to be 2995.45 ± 401.86 ha and 2090.03 ± 412.78 ha of closed and opened forest canopy respectively. Conversely, built-up areas (1531.68 ± 487.13 ha) remains virtually high (20%) though it shows a decrease in comparison to the same area in 2002. The land use land cover change map clearly identified probable areas of forest depletion especially in the north eastern and western portions of the reserve. It is recommended that potential spatial drivers of change should be identified to generate suitable image for change modelling of the reserve, coupled with earmarking of degraded areas for reforestation projects to improve upon the forest cover.

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1. Introduction

The world's forest cover is estimated to be around 31% of the total land surface area (FAO, 2010) providing multiple functions ranging from habitat provision to about 75% of terrestrial biodiversity, protection of waterbodies to regulation of climate change (FAO, 2014). In addition, forest ecosystem is one of the terrestrial biomes known to have high carbon density and often widely regarded as potential carbon sink (Halliday et al., 2003) and reported estimates of about 80% terrestrial aboveground carbon and 70% of soil organic carbon are contained in forest biomes (Batjes, 1996; Jobbagy and Jackson, 2000). Also, forests provide a wide array of products and services that promote the social and economic growth of developing and developed countries and are

particularly important for rural communities whose lives are intrinsically connected (Köhl et al., 2015).

On the other hand, global rate of forest area loss has been declining since 2010 to 3.3 million hectares or 0.08% per annum, accounting for half the rate in the 1990s (FAO, 2015). Moreover, temperate and boreal forests are more stable while in the tropics, rates of deforestation are slowing (Keenan et al., 2015). There has also been extensive acknowledgement of the importance of forest area reservation (Federici et al., 2015) as multifunctional forest management through reducing emissions from deforestation and forest degradation and also highlighting the role of conservation, sustainable management of forests and enhancement of forest carbon stocks (REDD+). This could as well provide benefits to countries trading in carbon credits in international market systems whilst protecting biological resources simultaneously.

Tropical deforestation in Ghana has become a topic of pronounced interest among researchers, policy makers and development practitioners in the turn of the twentieth century. Besides that, the country's total forest area of 9,195,137 (FAO, 2010) had gone through varying rates of deforestation over the 25-year

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period between 1990 and 2010 (Marfo, 2010) and an estimate of 135,000 ha per annum (representing 2% of the total forest area) of forest cover loss in closed and opened forest lands has been recorded (FAO, 2010).

Similar to the vegetation in Sub-Saharan Africa, conversion of large forest areas in Ghana is significantly attributed to human-induced activities (Boakyee et al., 2008). In addition to agricultural intensification and extensification, reported annual fires have also altered the composition and structure of most forest lands and are now being dominated by *Panicum maximum* (Hawthorne and Abu-Juan, 1995). Further to this, institutional deficiencies coupled with severe logging injuries to residual trees resulted in poor recovery and understocking of productive forests between 1990 and 2000 (Boakyee et al., 2008). However, massive plantation models were implemented to halt the dwindled supply of timber and enhancement of forest ecosystems nationwide in 2001 (Ghana Forestry Commission, 2008).

Analysis of land use and land cover changes (LULC) has become essential for sustainable forest management and it is critical for understanding the interactions and patterns of anthropogenic activities within a temporal scale. This could serve as a powerful decision making tool necessary for improved forest management (Seif and Mokarram, 2012; Lu et al., 2004).

Bosomtwe Range Forest Reserve (BRFR) was considered for change detection because of the forest's proximity to the 'Bosomtwe' Lake situated in the Ashanti Region of Ghana. It is one of six meteoritic global lakes. Also, the overlapping southernmost section of the Lake with northern part of the reserve creates a combination of forests, wetland and mountain ecosystem. Recently, the World Network of Biosphere Reserves under the Man and Biosphere Programme designated the Lake as a globally significant hotspot to reconcile the conservation of biodiversity with sustainable use of natural resources (Abreu et al., 2016). Furthermore, Lake 'Bosomtwe' is rich in aquatic biodiversity of national and global significance, but has become particularly vulnerable due to intense human pressures. Existing traditional norms and ethics have contributed significantly to ensuring sustainable fish production of the lake. However, confined contamination and the degradation of the vegetation in the catchment areas are destabilizing the veracity of the lake. Increasing demand for resources due to rising population as the situation currently is envisaged to have detrimental effects on the available resources (Abreu et al., 2016) as well. Nevertheless, it is highly envisioned that sustainable management of the reserve could secondarily offer protection for the Lake and increase forest cover in the catchment areas.

Currently, knowledge on the ecological status of the BRFR is inconclusive and the present study sought to assess the ecological integrity of the reserve along a spatio-temporal sequence using remote sensing and geographic information system (GIS). The specific objectives were to: (1) identify and delineate different LULC categories and pattern of land-use change in BRFR from 1991 to 2017 and (2) assess the health of the forest vegetation using normalized difference vegetation index (NDVI).

Further to this, knowledge of vegetation mapping is important for evaluating land use and land cover changes and has been applied to assess health of forest, grassland, agricultural resources and water bodies (Ahmad, 2012) over the last decades. For this reason, remote sensing has been widely used to assess LULC with varying techniques and data sets (Butt et al., 2015) over a period of time and regarded as a cost effective and efficient tool for monitoring of forest resources (Miller et al., 1998). Information from this study could provide a systematic contribution to the sustainable management of the forest resources, conservation of the 'Bosomtwe' Lake and its catchment areas, and make significant steps towards the realization of the Sustainable Development Goals (goal 15) by 2020.

2. Materials and methods

2.1. Description of study area

Bosomtwe Range Forest Reserve is under the jurisdiction of the Bekwai Forest District in the Ashanti Region and has a working forest management unit number of 40. The forest falls within the moist semi-deciduous southeast forest zone of Ghana and it is characterized by plant species of the Celtis-Triplochiton Association (Hall and Swaine, 1981). The area experiences bimodal rainfall pattern with an average annual rainfall of 1600–1800 mm (major rainy season starts from March to mid-August and minor season starts from mid-August to November). Usually, deciduous trees in the high forest zones blossom from April to December, followed by a period of leaf shedding. Annual bushfires are prevalent in drier seasons. The area has mean annual temperature of 26 °C with variations in mean monthly temperature ranging between 32 °C in March and 20 °C in August. The reserve covers a total land area of 79 km² (7900 ha) and located within latitudes 6°16'0"N and 6°26'0" N and longitudes 1°22'20" W and 1°28'0" W (See Fig. 1). Two main soil types are found in the area: Gleyic Allisols covering about 55% of the area from north to north-western parts and Ferric Acrisols, covering from the south to south-eastern part of the forest reserve (Abreu et al., 2016). Indigenous tree species include *Terminalia Spp Ceiba pentandra*, *Celtis mildbraedii*, *Triplochiton scleroxylon*, and *Ficus Spp*. Last commercial logging in the reserve was 1986. Majority of the inhabitants depend on farming as their source of livelihood. The farming system is mostly shifting cultivation with slash and burn as a means of land preparation. The major agricultural land uses are cocoa farming, food crop farming, and bush fallow (Abreu et al., 2016).

2.2. Satellite image data acquisition

The study used data from the USGS-GloVis platform. Image data for 1991 and 2002 were downloaded from Landsat 4 (thematic mapper) and Landsat 7 (enhanced thematic mapper) platforms respectively. However, the 2017 image scene was acquired from the Sentinel satellite platform (Copernicus). High resolution imagery provided by the Worldview-3 satellite platform was used for the accuracy assessment. This platform is capable of discerning objects on earth's surface as small as 31 cm (panchromatic band), 1.24 m multispectral resolution, 3.7 m short-wave infrared resolution and offer precise views for change detection and image analysis. Table 1 shows specifications of the satellite data used for the study.

2.3. Image preprocessing and enhancement

Image preprocessing represents a useful calibration procedure as it enables the recorded pixel values to be corrected and establish a significant relationship between the acquired data and the biophysical phenomena (Coppin et al., 2004). Atmospheric corrections were done by the zero brightness method (using the dark object subtraction algorithm in the semi-automatic classification plugin) and further geo-referencing, mosaicking and sub-setting the image on the basis of area of interest in Quantum GIS software (Las Palmas version 2.18.1). Clouds and cloud shadows were masked (using band-math algorithm) and nearest neighborhood resampling technique was applied to the images to provide a better pixel matching.

2.3.1. Normalized difference vegetation index (NDVI) and change detection

Several vegetation indices have been developed for the assessment of forest vegetation, however, NDVI remains one of the most

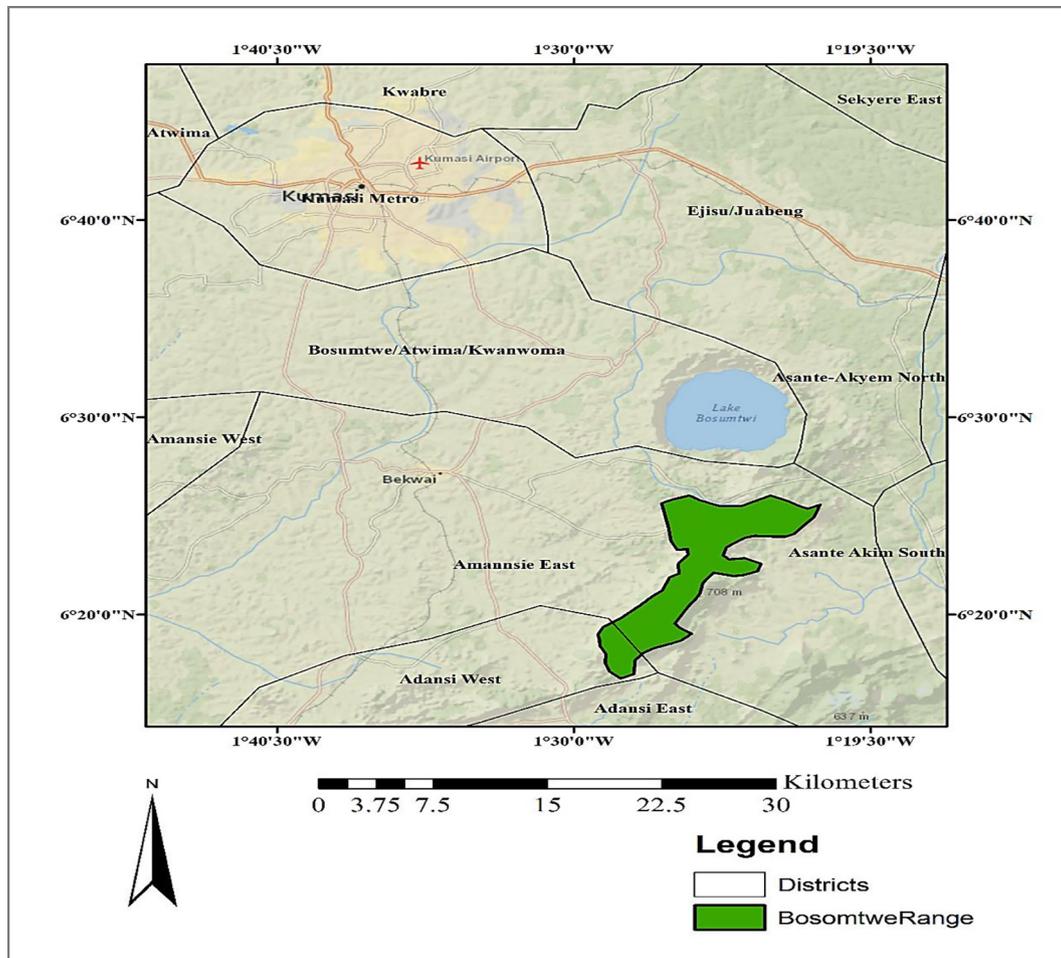


Fig. 1. Study area map showing BRFR and Lake Bosomtwe.

Table 1
Satellite data specifications.

Data/Sensor Platform	Date of Acquisition	Spatial Resolution (m)	Source
Landsat 4 TM	01/01/1991	30	USGS-GloVis
Landsat 7 ETM	15/01/2002	30	USGS-GloVis
Sentinel 2A	27/01/2017	10	Copernicus (ESA)
Worldview-3	1/02/2017	0.31	DigitalGlobe

ESA = European Space Agency, USGS-GloVis = United States Geological Survey-Global Visualization Viewer.

widely applied index by researchers to understand and characterize vegetation dynamics (Myeong et al., 2006). Theoretically, NDVI threshold value ranges between -1 and +1. Measured values range from -0.35 (water) through zero (soil) to 0.6 (dense vegetation). The more positive the NDVI, the more green the vegetation there is within a pixel. This study utilized the red (R) and near-infrared (NIR) bands in the Landsat and Sentinel images to compute the NDVI for the various years with the expression:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

The algebra based approach by image differencing was considered suitable for vegetation change along a temporal sequence. Threshold values for change were selected using standard deviations from a class mean until the resulting image was satisfactory (Chuvieco and Heute, 2009). Values of zero (0) represent no differ-

ence between images at different time periods and the more change, the farther the value diverges from zero (>0). A post classification using the combine function in ArcGIS-10.2 was done to detect and compare the changes in land cover classes from 1991 to 2017 while also delineating the spatial pattern of change.

2.4. Land cover land-use classification

Prior to the classification, all features were extracted to pre-determine land cover classes. Four (4) land cover classes were visually obtained and characterized into: (1) Closed forest canopy (forest area with a canopy exceeding 60%); (2) Opened/sparse forest canopy (forest area with a canopy cover between 10 and 60%); (3) Built-up/bare landscapes and (4) Dense grass/herbaceous cover (includes grass and shrub lands and also represents landscape that is potentially suitable for agricultural purposes). Trees were defined as “woody perennial plants with a single stem or in case of coppice, with several stems and having minimum height at maturity of 5–7 m and with definite crown (FAO, 1998). Training data were obtained first by generating 300 systematic sample points spaced with a uniform distance of 20 m from each other on each preprocessed image using vector plugin in QGIS. A circular buffer of an area of 1000 m² was created around each sample point. Plots were delineated to extract feature information for the cover classes. Systematic sampling design was used to select samples for the training data because this design-based probabilistic technique is statistically sound, uncertainties could be estimated, and spatial variability is covered as well as class distribution of the

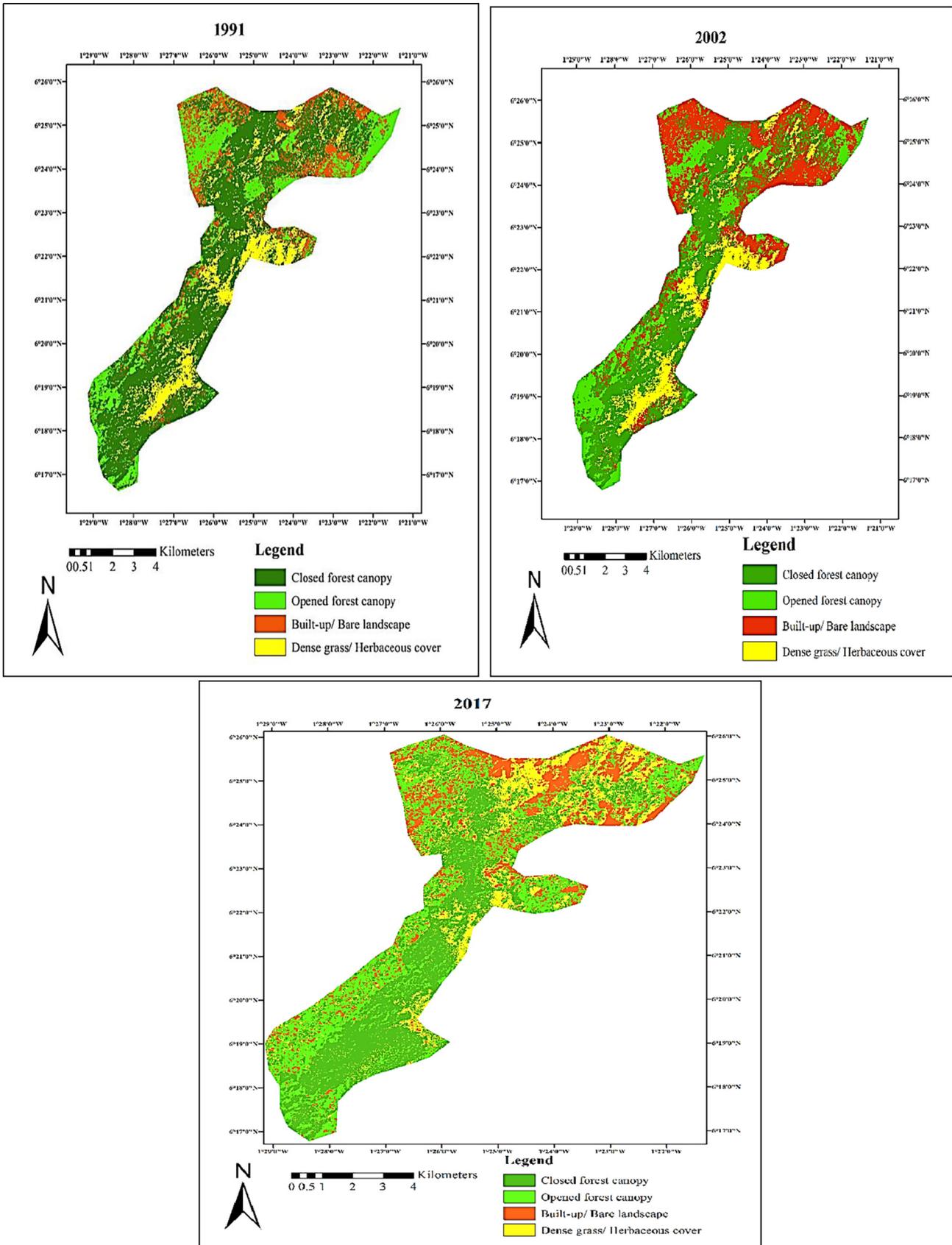


Fig. 2. Classified maps of BRFR (1991-Landsat 4TM, 2002-Landsat 7ETM and 2017-Sentinel 2A).

samples follow the proportion of land cover. To avoid bias in the classification, graphical evaluation of the extracted training data was done in feature space to explore the number of references, distribution of spectral values and the dissimilarity of the spectral distribution for each class and feature (Fuchs et al., 2009). A supervised classification was done using the Maximum Likelihood Algorithm (MLA). MLA is the most widely used algorithm for classification (Manandhar et al., 2009) based on statistical sampling by using probability density function to assign pixels to predefined set of land cover classes.

2.5. Classification accuracy assessment

Accuracy assessment of the thematic maps produced was to determine the quality of information derived from the data (Owojori and Xie, 2005). Two hundred systematic validation points representing plot centers and with a fixed distance of 20 m from each other were generated on a high resolution satellite imagery provided by Worldview-3 satellite platform. Points were re-grouped into square clusters to generate 50 sample points. Each sample point was then assigned to the corresponding land cover class. A stratified confusion matrix (Olofsson et al., 2014) was built to compare the true classes with the mapped classes. Summary statistics such as the overall accuracy, user and producer accuracies as well as error of commission and omission were computed. Kappa's test was also performed to measure the extent of the overall classification accuracy (Viera and Garrett, 2005) as specified by the expression:

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

where

Table 2
Area (hectares) estimates of LULC of BRFR from 1991 to 2017.

Land cover classes	Year		2002		2017	
	Area (Ha)	Area (%)	Area	Area (%)	Area	Area (%)
CFC	3885.24 (418.59)	51.39	3153.31 (395.46)	41.84	2995.45 (401.86)	39.58
OFC	1621.99 (337.63)	21.46	1410.69 (288.49)	18.72	2090.03 (412.78)	27.62
BUBL	1259.87 (340.48)	16.67	2021.74 (493.05)	26.83	1531.68 (487.13)	20.24
DGHC	792.14 (321.91)	10.48	950.52 (423.79)	12.61	950.70 (377.49)	12.56
Total	7559.24	100.00	7536.26	100.00	7567.86	100.00

CFC = closed forest canopy, OFC = opened forest canopy, BUBL = built-up/bare landscape, DGHC = dense grass/herbaceous cover. Values in parenthesis are the standard error of the proportion cover estimates in absolute terms.

Table 3
Summary of accuracy statistics using error matrix.

	Land cover classes	Reference				Total	CA	EC
		CFC	OFC	BUBL	DGHC			
Classified Map	CFC	18	2	1	1	22	0.818	0.182
	OFC	2	12	1	1	16	0.750	0.250
	BUBL	1	0	4	1	6	0.667	0.333
	DGHC	1	1	2	2	6	0.333	0.667
	Total	22	15	8	5	50		
	PA	0.818	0.800	0.500	0.400			
EO	0.182	0.200	0.500	0.600				
OA = 0.72 (0.33)								
Kappa value = 0.59								

CFC = closed forest canopy, OFC = opened forest canopy, BUBL = built-up/bare landscape, DGHC = dense grass/herbaceous cover. OA = overall accuracy, CA = consumer accuracy, PA = producer accuracy, EC = error of commission, EO = error of omission. Value in parenthesis is the standard error of the estimated overall accuracy in absolute terms.

\hat{K} is Kappa coefficient; N = Total number of correctly predicted pixels; $\hat{K} > 80\%$ represent strong agreement and good accuracy. 40–80% is middle, <40% is poor (Gwet, 2002). The error matrix was used to estimate the unbiased proportion of area of the land cover classes. Estimates were reported together with their absolute standard errors.

3. Results and discussion

3.1. Analysis of LULC dynamics in Bosomtwe Range forest reserve

The classified map of BRFR is shown in Fig. 2. The overall classification accuracy was 72% (0.72 ± 0.33) and Kappa value of 59% (0.59). The accuracy results is summarized in Table 3. The error matrix was used to estimate the unbiased proportion (area in hectares) of the land cover classes and the classification results presented in Table 2.

In 1991, 51% of the total forest area was covered by closed forest canopy (3885.24 ± 418.59 ha), opened forest canopy accounted for 21% (1621.99 ± 337.63 ha), built-up areas (1259.87 ± 340.48 ha) representing 17% of the total forest area. Herbaceous cover was the least (11%) having an area of 792.14 ± 321.91 ha.

Nevertheless, there was a major decline in forest area in 2002 and more notably, with increasing areas of built-up (2021.74 ± 493.05 ha) representing 27%. Closed forest cover decreased further to 41% (3153.31 ± 395.46 ha) in 2002 and opened forest cover also depreciated to 19% (1410.69 ± 288.49 ha) of the total forest area.

However, built-up areas decreased in 2017 (1531.68 ± 487.13 ha) accounting for 20% of the total forest area. Simultaneously, there was a positive increase (20%) in opened forest areas (2090.03 ± 412.78 ha). Though, closed forest cover continued to decrease (2995.45 ± 401.86 ha).

The comparison of each class of 1991, 2002 and 2017 showed that there has been a remarkable change in land use and land cover of the BRFR during the last 26 years. Much of the changes is directly correlated to anthropogenic factors especially, conversion of large forest areas to agriculture, illegal logging and fuelwood collection (Boakye et al., 2008). This therefore buttresses the claim

by Wang et al. (2008), that economic forces are direct stimuli to anthropogenic change of land.

The increase in vegetation cover from 2002 to 2017 could be significantly associated with the national forest plantation development programme (NFPDP) launched by the Ghana government in 2001 to foster the development of a sustainable forest resource

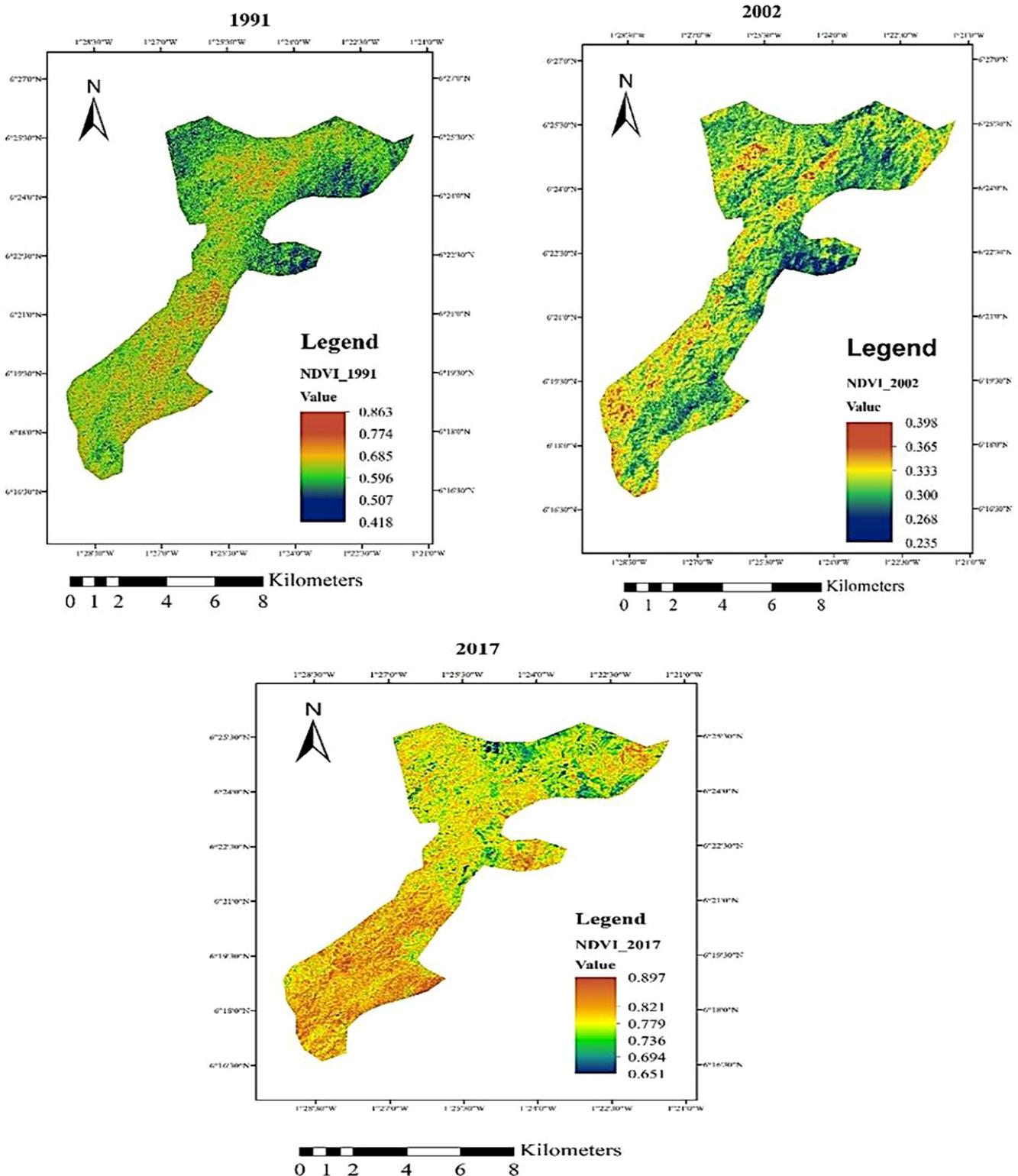


Fig. 3. Aggregate NDVI map showing vegetation covers and other LULC types.

base that will satisfy future demand for industrial timber and enhance environmental quality. The success of the NFPDP culminated in a total of 12,314.8 ha of degraded forest lands restored under the various components in high forest and transition zones. Both indigenous species including *Mansonia altissima*, *Terminalia superba*, Mahogany, *Ceiba pentandra*, and *Triplochiton scleroxylon* and the exotics (*Tectona grandis*, *Cedrela odorata* and *Eucalyptus camaldulensis*) were planted (Ghana Forestry Commission, 2008). Furthermore, the strategical plantation policy formulations and institutional reforms in the 2012 Ghana Forest and Wildlife Policy, demanded the maintenance and rehabilitation of existing forest plantations as well as enrichment planting of under-stocked forest

reserves with high value indigenous and recommended exotic timber species over the next 25 years. This further reinforces that plantation forestry development in Ghana is the most promising option to reduce deforestation and ensure the availability of forest products to meet social, economic and environmental objectives (FAO, 2010).

3.2. NDVI and change detection of BRFR from 1991 to 2017

The estimated NDVI of the forest area in 1991 was 0.65. However, the index decreased in 2002 (0.31). A sharp increase in NDVI (0.80) in 2017 was observed (Fig. 3). The decrease in NDVI in 2002

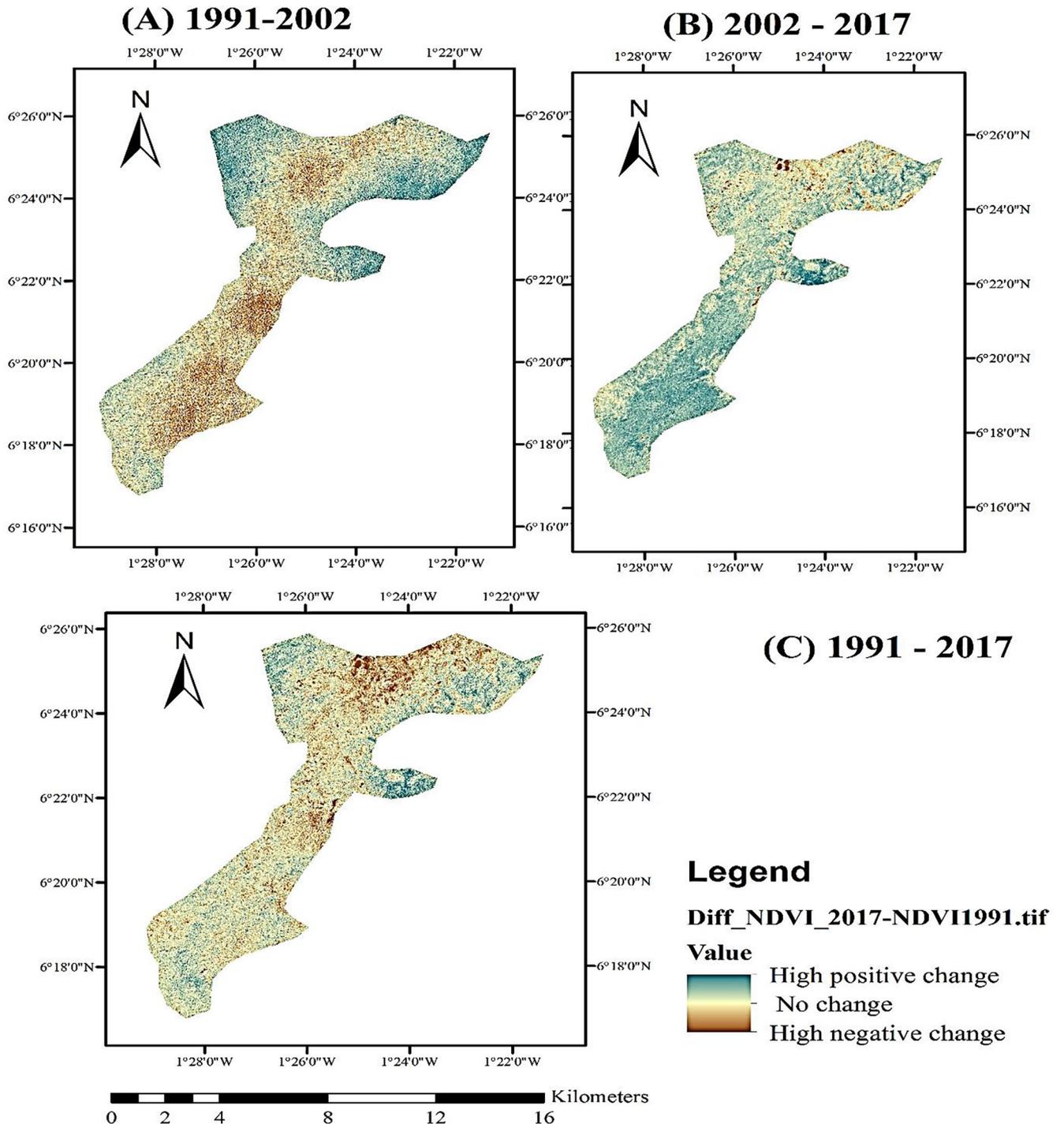


Fig. 4. Visualization of areas of change in BRFR from 1991 to 2017.

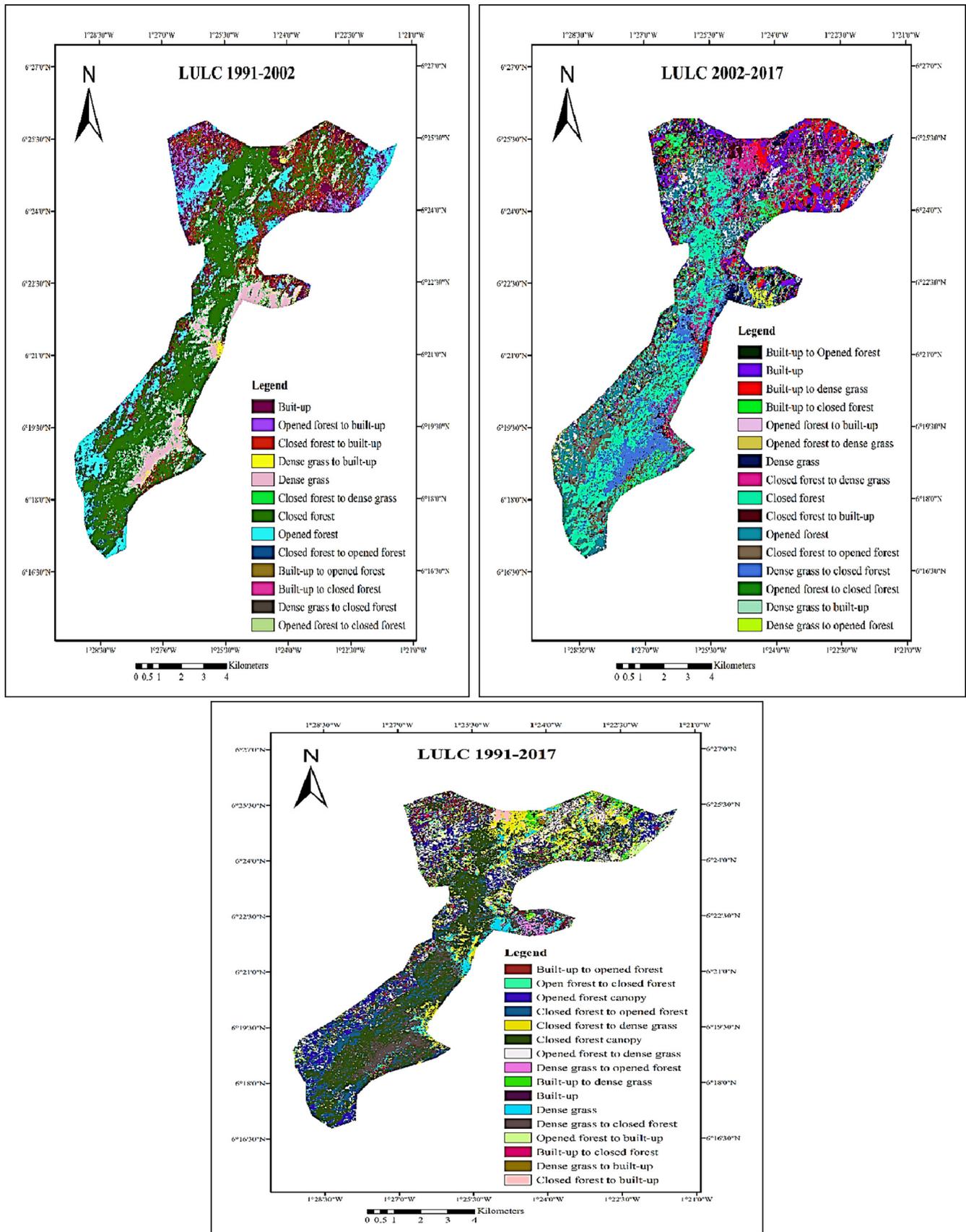


Fig. 5. Major land use conversions in BRFR from 1991 to 2017.

Table 4

Cross-tabulation of LULC classes between 1991 and 2002 (area in hectares).

Year	Land cover classes	Year 1991				Total
		CFC	OFC	BUBL	DGHC	
2002	CFC	2803.23	283.03	12.15	54.90	3153.31
	OFC	157.14	929.34	275.97	48.24	1410.69
	BUBL	617.04	305.64	851.20	247.86	2021.74
	DGHC	307.83	103.98	120.54	441.14	950.52
	Total	3885.24	1621.99	1259.87	792.14	

CFC = closed forest canopy, OFC = opened forest canopy, BUBL = built-up/bare landscape, DGHC = dense grass/herbaceous cover.

Table 5

Cross-tabulation of LULC classes between 2002 and 2017 (area in hectares).

Year	Land cover classes	Year 2002				Total
		CFC	OFC	BUBL	DGHC	
2017	CFC	1669.74	147.14	803.93	344.64	2995.45
	OFC	689.28	776.24	499.99	124.52	2090.03
	BUBL	256.47	352.79	693.62	228.80	1531.68
	DGHC	537.81	134.54	24.20	252.56	950.70
	Total	3153.31	1410.69	2021.74	950.52	

CFC = closed forest canopy, OFC = opened forest canopy, BUBL = built-up/bare landscape, DGHC = dense grass/herbaceous cover.

could be attributed to anthropogenic activities in and around the reserve and fringed communities (such as illegal logging, extensive land clearing for agriculture, human settlement) that destroy vegetation cover (Boakye et al., 2008). Larger values of NDVI represent forest areas because of the greater green biomass of trees or other vegetation and crop types.

Quantification of differences in vegetation in the study area was visualized in image differencing using NDVI for the three dates (1991, 2002 and 2017). Darkish-brown areas indicated a high negative change, thus reducing of vegetation cover in larger areas of the reserve from 1991 to 2002. However, a high positive change (deep blue) signifying increase in vegetation cover was seen in larger portions of the reserve from 2002 to 2017. Light-colored depicted areas with no change (Fig. 4).

Changed detection map was produced for the different years and the spatial pattern of change determined by overlaying the classified maps (Fig. 5) in addition to the cross-tabulation matrix (Table 4) between 1991 and 2002 and from 2002 to 2017.

Out of the 3885.24 ha of closed forest canopy area in 1991, 2803.23 ha remained closed forest in 2002, but 617.04 ha was converted to built-up areas and 157.14 ha also changed to opened forests in 2002. This negative decrease in closed forest area from 1991 to 2002 could be due to human induced pressures (FAO, 2010) more specifically, illegal logging and clearing of forest lands for farming in the Bosomtwe Range Forest Reserve (Boakye et al., 2008) coupled with high prevalence of wildfires which had altered the vegetation of most forests in Ghana to *Panicum maximum* (Hawthorne and Abu-Juan, 1995). Moreover, opened forest canopy retained an area of 929.34 ha in 2002 out of the total 1621.99 ha in 1991 with larger areas being converted to bare landscapes (305.64 ha). Simultaneously, the increase in built-up areas from 1991 to 2002, was principally from conversion of opened forest areas (275.97 ha). Changing conditions due to increasing forest fragmentation make land cover and change detection analysis an extremely important consideration for management, planning and inventory mapping (Lu et al., 2004).

However, from 2002 to 2017, a significant increase in forest cover (opened forest) was recorded from 1410.69 ha to 2090.05 ha respectively (Table 5). This gain (352.79 ha) in forest

cover was largely due to decrease in built-up areas from 2021.74 ha in 2002 to 1531.68 ha in 2017. Though, opened forest cover increased within the period, areas of closed forest canopies continued to decline (2995.45 ha) with only 1669.74 ha retained in 2017. About 689 ha and 256.47 ha were converted from closed forests to opened forest and built-up areas respectively. This study reiterates the report by Oduro (2012) that, Ghana has lost significant portions of the forest cover since 1926 and the key underlying causes of deforestation and forest degradation could be attributed to population and economic growth and weak governance structures. Increased population and economic growth and development have stemmed high domestic wood consumption and demand for timber to satisfy export markets. Additionally, evolving domestic and export demand for agricultural produce such as cocoa, oil palm, cashew, and food crops have exacerbated large scale conversion of forests to agricultural uses (Oduro, 2012).

The study has highlighted the need for remote sensing in contemporary forest management. Changing conditions due to increasing forest fragmentation make land cover and change detection analysis an extremely important consideration for management, planning and inventory mapping.

4. Conclusion

Based on the results of the study, it is concluded that LULC of BRFR have undergone remarkable changes for over a period of 26 years. The current status of forest cover is approximated to be 2995.45 ± 401.86 ha and 2090.03 ± 412.78 ha of closed and opened forest canopy representing 40% and 50% of the total area of BRFR respectively. Built-up areas (20%) remains virtually high 1531.68 ± 487.13 ha though it shows a decrease in comparison to the same area in 2002. The LULC change map shows probable areas of forest depletion especially in the north eastern and western portions of the Bosomtwe Range Forest Reserve. More importantly, these areas coincide with the southernmost portion of Lake Bosomtwe and therefore, an urgent resolve is needed to safeguard this water resource from depletion in the near future. Decrease in forest cover from 1991 to 2002 and increase in 2017 further reinforces the need for reforestation and afforestation.

The study has demonstrated the role of remote sensing and GIS in monitoring of large coverage of forest area in a given region continuously over time more precisely and in cost effective manner which will be ideal for conservation planning. It is recommended that potential spatial drivers of change should be identified to generate suitable image for change modelling of the BRFR. Strict monitoring of the reserve should be further strengthened whilst at the same time, engaging in reforestation of degraded areas to improve upon the forest cover.

Conflict of interest

None.

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