Analysis and prediction of land cover change of a biosphere reserve using geospatial tools: A case study of Omo Biosphere, Nigeria

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Abstract: A land cover change analysis has been previously performed on Omo biosphere reserve in Nigeria, but with a simplistic method, which could lead to wrong management decisions in the biosphere reserve. This study assesses the land cover change of Omo biosphere reserve using a supervised maximum likelihood classification method. The analysis was carried out using 2000 and 2015 Landsat images. The images were classified with overall accuracy and kappa coefficient of 86.5% and 0.75 for 2000, 86% and 0.79 for 2015 respectively. The result reveals that undisturbed/natural forests have reduced significantly while disturbed/plantation forests, degraded forests/farmland, settlement/bare ground increased over the 15-year period. The 8% annual increase in the settlement suggests that changes in the other land cover classes of the biosphere reserve could be attributed to population growth around the biosphere reserve. Using Omo biosphere reserve, this study justifies the need for regular assessment of biosphere reserves for adequate management plan and appropriate decision to be taken. Consequently, such assessment will help to ensure the sustainable function of the biosphere reserve. If no attention is given to stop the trend of deforestation in this biosphere reserve, there is an indication of complete loss of natural forests.

Keywords: biosphere reserve; gis and remote sensing techniques; landsat images; supervised classification

Introduction

Biosphere reserves have been explored to address challenges facing biodiversity conservation over the last few decades. Biosphere reserves are areas where potential innovative ideas are being experimented and implemented for sustainable development [1]. These reserves are designated by the United Nations Educational, Scientific and Cultural Organization (UNESCO) under the Man and the Biosphere Programmes (MAB) launched in 1971. The fundamental concept behind the MAB is to improve the relationship between human and his environment for sustainable development, using biosphere reserves for biodiversity conservation and for sustainable development [2]. The roles of the biosphere reserves will consequently help to reduce biodiversity loss, improve the well-being of local people and enhance environmental sustainability. Additionally, as a network of environmental sites of importance, containing one or more protected areas, biosphere reserves were selected and established for their provision of scientific research while contributing to sustainable development both locally and internationally.
There has been a remarkable increase in the number of biosphere reserves designated since inception, from 58 sites in 1976 to 669 sites in 2016. Coetzer et al. [3] suggest the need for continuous evaluation of the biosphere reserves to ensure they maintain the requirement that qualifies them for the initial designation as well as to assess how close they are to the model envisioned by UNESCO-MAB. This assessment is necessary to ensure that the designated biosphere reserves are not just a bureaucratic label but are contributing to sustainable development. Some studies have assessed the status of the biosphere reserves by detecting changes in their land cover using geospatial technologies [3-5].

The term land cover explains the different features present on a land surface of the earth such as trees, bare ground or buildings [6-7]. Changes in land cover have been one of the most important factors of global change influencing ecological systems [8]. For policy makers to be adequately equipped to make informed decisions on land resources, the spatial dimension of land cover must be known at all times [9]. Geographical Information Systems (GIS) and remote sensing have proved to be a more useful and a more accurate tool than the in-situ measurement for assessing land cover change [10-11]. This tool helps to provide timely information on the spatial distribution of land over a large area [12].

Previous studies have effectively demonstrated the application of GIS and remote sensing techniques in analysing land cover change of biosphere reserves in different countries [4-5, 13-15]. A study by Chima and Adedire [16] attempted to apply the same techniques to analyse land cover change of Omo biosphere reserve, the only biosphere reserve in Nigeria. The study created a land cover map, calculated the extent and rate of change between 1987 and 2011, which was purported to inform the decision on sustainable management of the reserve. However, this attempt has been found to be ineffective for this type of analysis because the method of image classification employed was unsupervised classification. Unsupervised classification uses a computer algorithm to assign pixels into classes based on clusters present in the image values. A major drawback of this approach is that the land cover class classified is not always the same as the land cover class on the ground, and also the spectral cluster will be different on different dates of imagery, resulting in significant misclassification errors [17-18]. This claim was supported by Hasmadi et al. [19] in evaluating the accuracy of supervised and unsupervised classification methods for land cover analysis, the result of the study shows that supervised classification is more accurate than unsupervised classification. Consequently, using the result of the study by Chima and Adedire [16] for any decision on Omo biosphere reserve could lead to wrong management decisions. Therefore, there is a need to take prompt action in addressing this shortcoming.

This study adopts a supervised image classification method to analyse the land cover change of Omo biosphere reserve between 2000 and 2015. The major aim of this study is to provide information on the land cover of Omo biosphere reserve. To achieve this aim, a land cover map will be created using maximum likelihood classifier; the extent and the rate of land cover change that has occurred will be computed. This study potentially will contribute to making successful plans for sustainable management of the biosphere reserve and biodiversity conservation simultaneously. Although this study adopted a recommended methodology and achieved its objectives, there were few unavoidable limitations. For example, there is paucity of suitable freely available cloud-free multispectral imagery of the study area. The organisation of this write-up includes; the introduction, followed by an explanation of procedures used and presentation of what the study found out with a full interpretation of the results. Finally, a logical conclusion and relevant recommendations were presented.

Data and Methods

Study Area

Omo forest reserve was designated as a biosphere reserve by the UNESCO MAB programme in 1977 [20]. This reserve derives its name from river Omo that traverses it, located between Latitude 6^{o} 35' to 7 ^{o} 05' N and Longitude 4 ^{o} 19' to 4 ^{o} 40' E. Omo biosphere reserve is about 80km east of Ijebu-Ode and 180km of north-east of Lagos, Nigeria [21]. The total land area of the reserve is 130,600 hectares, which includes a core area of 800 hectares, a buffer zone of 14,200 hectares and a transition area of 115,600 hectares [20]. The altitude ranges between 15m and 150m above the sea level, mainly dominated by an undulating topography of up to 15% slope. The mean annual rainfall reaches up to 175mm, with mean relative humidity of about 80% and mean daily temperature of 26.4^{o}C. Tropical humid forests are the main forest ecosystem present, comprising several habitats with major habitat in the north and south of this reserve covered with dry evergreen mixed deciduous forests and wet evergreen forests respectively. The moist lowland evergreen forest of the reserve consists of tree species such as *Strombosia pustoulate, Octolobus angustatus,* while the dry evergreen mixed deciduous forest of the reserve consists of tree species such *Spondianthus preussii*, *Anthonotha macrophylla*, with *Pinus caribaea* and *Gmelina arborea* as the major plantation species [20].

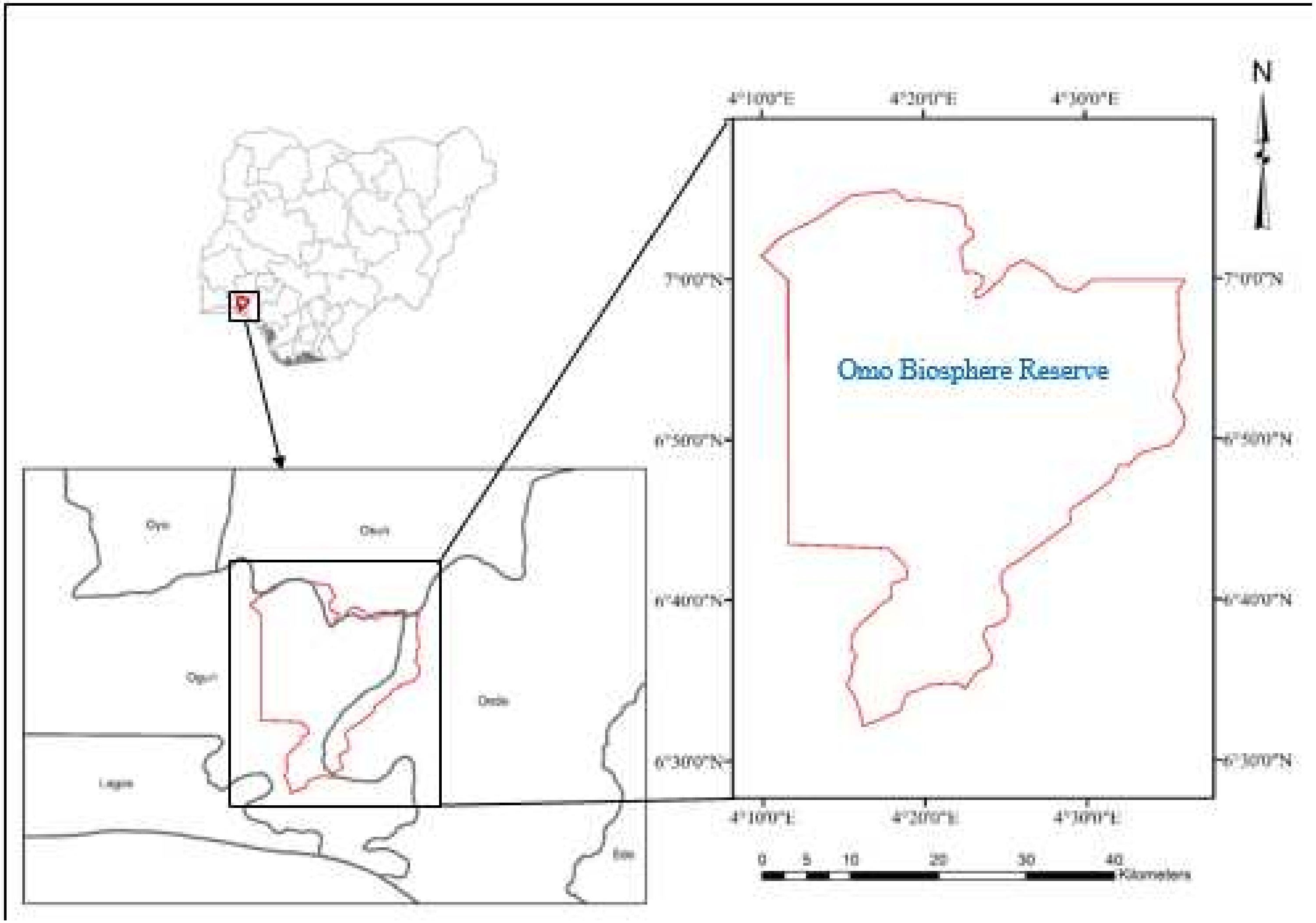

Figure 1: Location of Omo Biosphere Reserve in Nigeria

Data acquisition

Landsat level 1T (terrain corrected) satellite images were used for this study. These images were downloaded from the United State Geological Survey (USGS) archives using the USGS Earth Explorer (http://earthexplorer.usgs.gov/). Comprehensive characteristics of the image and the source are shown in Table 1. Landsat image is widely used for land cover change analysis due to its long-term continuous data archive, repetitive observation, its medium spatial and spectral resolution [22]. The 2000 image was from the Landsat 7 ETM+ sensor while the 2015 image was from the Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS). The two images (2000 and 2015) were images of the same season to minimise the influence of seasonal changes in the forests, and thus, on the images. Both images were the best available scene taken from path 190 and row 55 of the WRS-2 Worldwide Reference System.

Image pre-processing

The images were pre-processed because effective image pre-processing is critical to successful land cover change analysis [23]. Xie et al. [24] explain that operations such as radiometric, geometric and atmospheric corrections are necessary to rectify distortion or degradation of an image for a more accurate representation of the original scene needed for qualitative analysis such as land cover analysis. The images used for this study are Landsat Level-1T Standard data, implying that the images have undergone standard levels correction which includes geometric correction using a cubic convolution method and removal of image defects such as striping. However, there is a need to perform radiometric and atmospheric corrections on the images before further analysis because the calibrated digital numbers (DN) in the raw image need to be converted at-surface reflectance and then atmospheric correction.

Table 1: Properties of Images Used

Properties	2000	2015
Landsat	7	8
Scene ID	LE71900552000046EDC00	LC81900552015351LGN00
Acquisition Date	2/15/2000	12/17/2015
Path	190	190
Row	055	055
Sensor	ETM+	OLI & TIRS
Number of Bands	8	11
Spatial Resolution	30 m (60 m- thermal, 15 m pan)	30 m (100 m- thermal, 15 m pan)
Spectral Range	0.45 µm -12.36 µm	0.435 - 12.51 µm
Temporal Resolution	16 days	16 days
Swath Width	185 km	185 km

Alternatively, *Landsat 7 ETM+ Imagery tool* in ERDAS Imagine was used to calculate the at-sensor reflectance for the Landsat 7 ETM+ image (2000 image) to save time and effort since few details such as solar elevation and solar distance are known. However, ERDAS Imagine software does not have such tool for Landsat 8 OLI image, therefore the conversion of the Landsat 8 OLI image (2015 image) from at-sensor radiance to at-sensor reflectance was done using ENVI software. For atmospheric correction, a COST model was made for the Landsat 7 image using the COST formula to remove additive atmospheric influences. *Dark Object Subtraction tool* in ENVI software was used to calculate the TOA reflectance for Landsat 8 image. Atmospheric correction helps to remove any external influence such as radiation which does not carry any information about the surface being examined.

Image Subsetting

Image subsetting is done to reduce the spatial extent of the images to the area of study. Because the Landsat images cover an area of approximately 185x185 kilometres, it is important to subset them to the area of interest or the study area to reduce the data volume of the images for efficient computer processing. The two images were subsetted using the *create subset image tool* in ERDAS Imagine software. A Shapefile of the study area was digitised on a thematic map that had been georeferenced to the same coordinate system as the images. It was necessary to ensure that both the Shapefile of the study area and the satellite images have the same geographical projection so that it will overlap perfectly.

Image classification

Image classification involves categorising pixels that have a similar combination of spectral reflectance in an image into land cover classes [24]. There are two primary methods used for digital image classification, namely; unsupervised image classification and supervised image classification. The unsupervised classification does not utilise training sites but uses a computer clustering algorithm to group image pixels into different classes known as spectral classes [25]. On the other hand, supervised classification utilises representative samples sites known as training sites to describe various land cover class present in an area [26]. The method of image classification employed for this study is supervised classification using Maximum Likelihood Classifier. Maximum likelihood classifier is one of the most commonly used supervised classification algorithm [27] and one good reason that Reis [28] suggested for its wide application was it gives a very high classification accuracy results. Using this method, training samples need to be generated for each land cover class. Training samples were determined based on personal experience, previous knowledge of the study area as well as an initial unsupervised classification carried out using the *Iterative Self-Organizing Data Analysis Techniques* or ISODATA method. The reason for the initial unsupervised classification is to help identify the most common separable spectral classes and ensure they are adequately represented during the supervised classification. More than 100 training points were gathered for each of the images with an average of 25 points per class. A supervised method of classification was used, and a maximum likelihood parametric rule was selected as the decision rule.

Several studies have achieved success and accurate image classification using the Maximum Likelihood Classifier. A good example is a study conducted by Coetzer et al. [3] to detect changes in land cover of the Kruger to Canyons biosphere reserve in South Africa. However, a large number of computations are required to classify each pixel and the use of only spectral information to classify each pixel are some of the drawbacks of using this classifier [6]. It is worth mentioning that Object-Based Image Analysis (OBIA) is another method of image classification that has proven to yield a higher classification accuracy [29-30]. OBIA uses image objects rather than pixels to classify image, thereby, using spatial, spectral, textural and contextual information [31]. Chmielewski et al. [32] demonstrated Land cover change analysis of biosphere reserve using Object-Based Image Analysis (OBIA), analysing land cover and landscape diversity in the West Polesie Biosphere reserve. The object-based approach is beyond the scope of this study because the approach requires very high spatial resolution imagery for fine details. Therefore, OBIA is recommended for more detailed local studies with a Very High Resolution (VHR) or aerial imagery in the future.

Accuracy Assessment

Assessing the accuracy of an image classification is important to ascertain the quality of information that could be derived from the classified image [33]. One of the widely used methods of assessing classification accuracy is the preparation of a contingency table or error/confusion matrix which is done by comparing the classified images with ground validation data class-by-class [6]. Two hundred random points were generated using the '*create random points tool'* in Erdas Imagine and converted to KML file in ArcMap. The file was imported into Google Earth to record the land cover class of each point, denoting each with value number. The validated values are then recorded in the attribute table followed by extraction of classified values to point using the 'extract values to points' tool in ArcMap. An error matrix was prepared using the classified values and validated values. Producer's accuracy/error of omission, user's accuracy/error of commission, overall accuracy and kappa coefficient were calculated. Producer's accuracy represents the percentage of a particular land cover class that is correctly represented on the classified map, calculated by dividing the number of correctly classified pixel in each class by the total referenced number in that class. User's accuracy represents the percentage that a pixel classified into a given land cover class represent that land cover class on ground, calculated by dividing the number of correctly classified pixel in each class by total classified number in that class. Overall accuracy is the average of individual class accuracies expressed in percentage. Overall accuracy only incorporates the data along the diagonal and does not consider the non-diagonal data. On the other hand, kappa coefficient combines both the diagonal and non-diagonal data which makes it a widely used method of assessing classification accuracy [18].

Change Detection Analysis

Change detection analysis explains and quantifies the changes between images of the same area at a different period [34]. In this study, the area of land cover class, statistical change in area and the rate of change was computed. The absolute change was computed to determine the changes in area in hectares of each land cover class and the direction of change; that is if it increases (positive) or decreases (negative). The annual equivalent rate of change was calculated from the relative change. The statistical computation was done using Microsoft Excel. To understand in details, the changes that occurred in the land cover of Omo biosphere reserve, a cross-tabulation statistics was computed. Cross tabulation statistic helps to compare the two classified images to determine the area of one land cover class that remain the same over time and the area of land cover that changes to other land cover class.

Results

Image Classification

The image classification was done to generate a classified image showing the spatial distribution of the land cover class within the study area on each of the two imagery dates as shown in Figure 2. Four land cover classes were identified: the undisturbed/natural forests, disturbed/plantation forests, degraded forests/farmland and settlement/bare ground. From the classified image presented in Figure 2, the undisturbed/natural forests in the northern part of the reserve in 2000 has become fragmented in 2015, leaving scattered patches of undisturbed/natural forests. In addition, most of the degraded forests/farmland in 2000 became settlement/bare ground in 2015. The tract of disturbed/plantation forests at the centre remains almost unchanged except for the increase towards the north-western and southern part of the biosphere reserve. There appears to be more presence of degraded forests/farmland almost around the corner of the biosphere reserve. The area covered by each of the land cover class in each of the years under study is revealed in Figure 3. The chart shows an increase in area covered by all the land cover classes of the biosphere reserve except the undisturbed/natural forests.

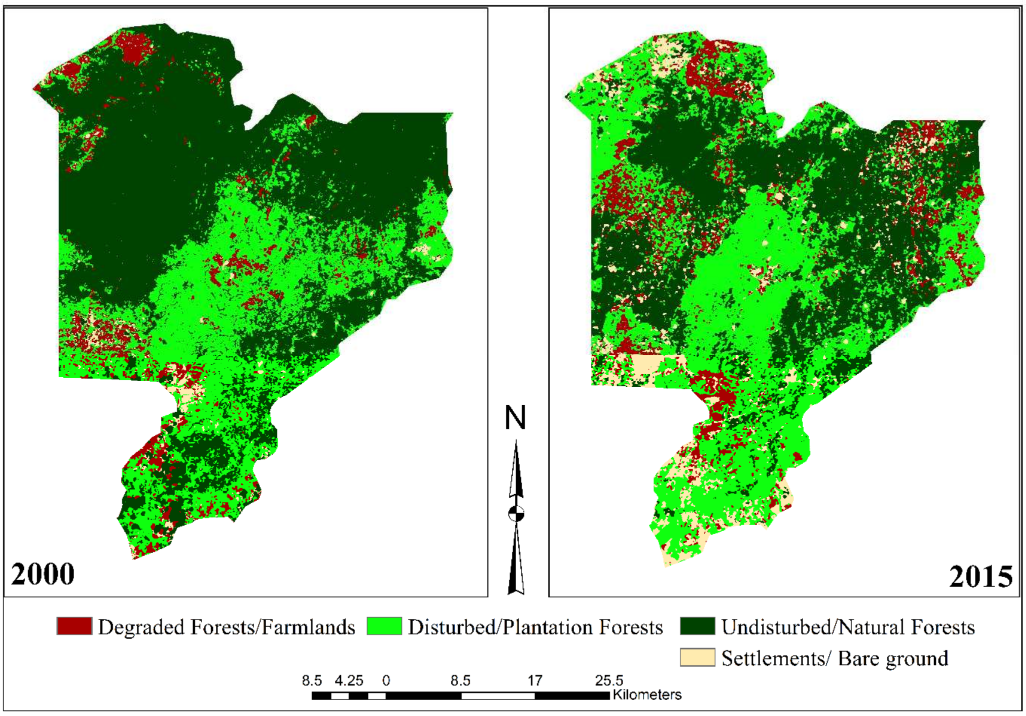

Figure 2: Classified images of Omo biosphere reserve for 2000 and 2015

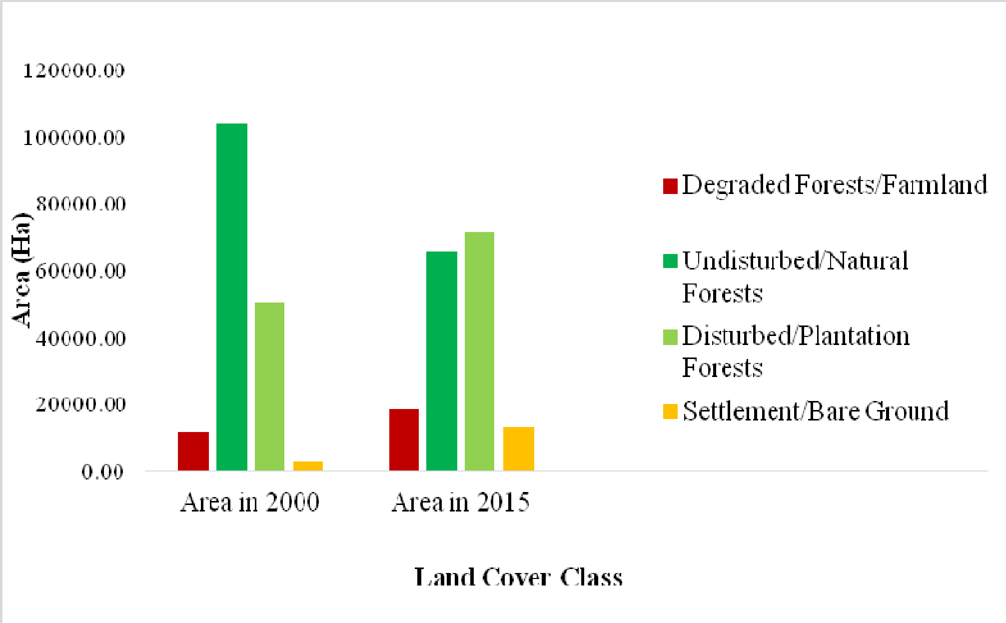

Figure 3: Area of land cover class of Omo biosphere reserve for 2000 and 2015

Accuracy assessment

The classified images were assessed to determine their accuracies to ensure that an accepted accuracy level was met before further analysis. Table 2 presents the result of accuracy assessment for the 2000 classified image, and this showed a user's accuracy ranged from 83% to 100 %, producer's accuracy ranged from 79% to 100% with the overall accuracy of 86.5% and a kappa of 0.75. For the image 2015, as summarised in Table 3, the user's accuracy ranged from 79% to 89 %, producer's accuracy ranged from 73% to 94%, and the overall accuracy was 87.5% with a kappa of 0.79. An overall accuracy score of 85% and above for a classified image is considered excellent. Therefore, the overall accuracy scores of 86.5% and 86.0% for 2000 and 2015 images show almost perfectly classified images.

Change detection

Following the methodology adopted, the results revealed that undisturbed/natural forests which covered 99,808 ± 8,982 hectares in 2000 had significantly reduced to 65,851 ± 7,902 hectares 2015, depicting about 20.2% decrease in natural forest class of the total land area. The disturbed/plantation forests increase from 51,607 ± 10,837 hectares in 2000 to 71,152 ± 9,249 hectares in 2015, adding 12% of plantation forests to the total land cover area. The area covered by degraded forests/farmland and settlement/bare ground also increased by 4% from 11,051 ± 1,547 hectares in 2000 to 18,269 ± 4,932 hectares in 2015 and increase by 6% from 2,835 ± 0.00 hectares in 2000 to 13,055 ± 783 hectares in 2015 respectively.

A transition matrix was generated to calculate and examine the shift among classes through the off-diagonal of the transition matrix. Table 5 shows the summary of land cover conversion of Omo biosphere reserve between 2000 and 2015 in percentage. The diagonal values in the table show the land cover that remains unchanged during the period, which is a total area of 50,747.91 hectares. The fixed land cover represents 30.15% of the study area. The most significant conversion is the 35,252.19 hectares' conversion of undisturbed/natural forests to disturbed/plantation forests, representing 20.94% of the total land area. 4,037.04 hectares of the area previously occupied by plantation representing 2.40% of the total area has been fully laid bare because of felling without replacing activities going on in the reserve. Other disturbances recorded in the undisturbed/natural forests are the 11,254.50 hectares (6.69%) and 4,316.40 hectares (2.56%) conversion to degraded forests/farmland and settlement/bare ground respectively between the two-year period. The disturbed/plantation forests dominated by Teak and Gmelina exotic tree species experienced a notable increase from 51,607 hectares in 2000 to 71,152 hectares in 2015. Furthermore, 3,595.81 hectares (2.14%) of the degraded forests/farmland in 2000 became settlement/bare ground 15 years later.

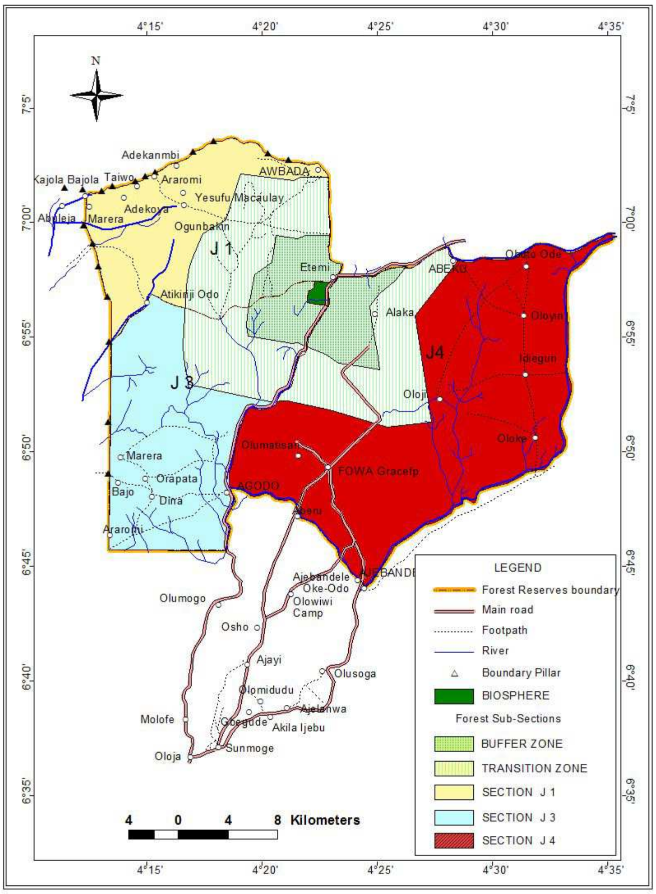

Figure 4: Map of enclaves in Omo biosphere reserve [35]

Table 2: Error matrix of land cover change for 2000

		Classified image					Producer's Accuracy (%)
		Disturbed/Plantation Forests	Undisturbed/Natural Forests	Settlement/Bare Ground	Degraded Forests/Farmland	Total	
Reference Data	Disturbed/Plantation Forests	52	13	0	1	66	79
	Undisturbed/Natural Forests	10	107	0	1	118	91
	Settlement/Bare Ground	0	0	2	0	2	100
	Degraded Forests/Farmland	1	1	0	12	14	86
	Total	63	121	2	14	200	
User's Accuracy (%)		83	88	100	86		

Overall Accuracy: 86.5%
Kappa Coefficient: 0.75

Table 3: Error matrix of land cover change for 2015

		Classified Image 2015					Producer's Accuracy (%)
		Disturbed/Plantation Forests	Undisturbed/Natural Forests	Settlement/Bare Ground	Degraded Forests/Farmland	Total	
Reference Data	Disturbed/Plantation Forests	85	8	0	5	98	87
	Undisturbed/Natural Forests	7	52	0	0	59	88
	Settlement/Bare Ground	1	0	16	0	17	94
	Degraded Forests/Farmland	2	3	2	19	26	73
	Total	95	63	18	24	200	
User's Accuracy (%)		89	83	89	79		

Overall Accuracy: 86.0%
Kappa Coefficient: 0.79

Table 4: Extent and rate of land cover change in Omo biosphere reserve between 2000 and 2015

Land Cover Types	Area in 2000		Area in 2015		Absolute change in 2000 - 2015		Relative change in 2000 - 2015	
	Ha	%	Ha	%	Ha	%	%	% per year
Degraded Forests/Farmland	11051 ± 1547	6.6	18269 ± 4932	10.9	7217	4.3	65	4
Undisturbed/Natural Forests	99808 ± 8982	59.3	65851 ± 7902	39.1	-33957	-20.2	-34	-2
Disturbed/Plantation Forests	51607 ± 10837	30.7	71152 ± 9249	42.3	19546	11.6	38	3
Settlement/Bare Ground	5860 ± 0.0	3.5	13055 ± 783	7.8	7195	4.3	123	8

Table 5: Cross tabulation matrix of Omo biosphere reserve for 2000 and 2015 in percentage

		2015				Total Area (%)
		Degraded Forests/Farmland	Undisturbed/Natural Forests	Disturbed/Plantation Forests	Settlement/Bare ground	
2000	Degraded Forests/Farmland	1.56	0.62	2.43	2.14	6.75
	Undisturbed/Natural Forests	6.69	31.47	20.94	2.56	29.95
	Disturbed/Plantation Forests	1.82	7.01	18.72	2.40	61.66
	Settlement/ Bare ground	0.77	1.43	0.22	0.64	3.05
Total Area (%)		10.83	40.53	42.31	7.74	100.00

Grey cell means permanence while others indicate transition

Discussion

Image classification

The importance of a good image classification is not only limited to helping generate credible land cover change values statistically but also provide a visual understanding of where in the geographical location the changes are happening, making this approach of analysis land cover change more appreciated. The distribution of communities within Omo biosphere reserve provides an insight to why some parts of the reserve had undergone such degree of disturbance and degradation than other parts as shown in Figure 4. A concentration of enclaves was noticed in the north-western part of the reserve where there was a massive conversion of undisturbed/natural forests to other land cover classes between 2000 and 2015. The conversion can be attributed to the influence of human activities on the changes in land cover of the biosphere reserve. According to Price [36], the people living in and around a biosphere reserve have a participating role in ensuring the management, conservation and protection of the biosphere reserve. By contrast, the inhabitants of Omo biosphere reserve seems to be playing a destructive role. One major reason for this could be the ineffectiveness of the management to enlighten the inhabitants, getting them involved in their role while supporting them to derive their livelihood sustainably within the biosphere reserve.

Accuracy Assessment

The reasonable overall accuracy of the image classification can be attributed to a very high total number of correctly classified pixel. However, considering the percentage accuracy of each land cover class, the disturbed/plantation forests in 2000 image has a relatively low percentage accuracy. The relatively low percentage accuracy can be explained by the fact that some of the pixels representing the land cover classes were misclassified for undisturbed/natural forests, and this is due to the closeness in the spectral signature of the two land cover classes. Also, due to some haze-affected area of 2015 image, the 2015 image after the pre-processing operation was not as clear and not as sharp as the 2000 image which may be responsible for the general less percentage accuracy values of the image. The presence of haze in the atmosphere is known to degrade the quality of satellite images. Nonetheless, the range of the classification accuracy was found to be consistent with the range reported in other studies [37-38]. Additionally, according to the kappa coefficient, the accuracy has a substantial agreement between the two dates which means it can be considered a satisfactory accuracy level [39].

Change Detection

The spatiotemporal analysis of land cover change in Omo biosphere reserve using the supervised method of image classification reveals some interesting changes, extents and trends in the year 2000 to 2015 period. Islam and Ahmed [40] explained that land cover changes are precarious issues that have a notable impact on human life and biodiversity. Serra et al. [41] provide a further explanation that reduction in some of the land cover classes such forests may lead to loss of biodiversity and loss of resistant to natural hazards. To determine the extent of changes in the land cover of Omo biosphere reserve, the absolute change in area between 2000 and 2015 were calculated and the relative percentage change in area to detect the rate of change. Also, error margin estimates on the areas were incorporated using the percentage accuracies of individual land cover classes. These are summarised in Table 4. The degraded forests/farmland, disturbed/plantation forests and settlement/bare ground increased in area between the fifteen years' period while the undisturbed/natural forests experienced a tremendous decrease in the area covered. It is expected that the degraded forests/farmland, disturbed/plantation forests and settlement/bare ground will increase with the 20.2% loss in the undisturbed /natural forests area. However, what is striking in the result is the 8% annual increase in the land cover area of settlement/bare ground as compared to 4% and 3% annual increment for degraded forests/farmland and disturbed/plantation forests respectively. Perhaps the reason could be due to more roads being constructed for evacuation of timbers and more influx of settlers to either engage in farming activities or illegal loggings. UNESCO [1] reported that about 6,000 people were living within the biosphere reserve when it was designated in 1977. In 1992, the population increased to about 20,000 inhabitants [35], representing approximately 16% average annual population growth within the biosphere reserve.

The result reveals an extensive loss of undisturbed/natural forests in the biosphere reserve which was anticipated because an estimate by UNESCO-MAB [42] had earlier reported that about 65 tree species, totalling more than 35,775 logs are removed from the reserve every year. The reason for this can be related to the general high deforestation rate of 3.5% annually going on in Nigeria as reported by FAO [43]. From the result of this study, one major driver that could be responsible for the land cover change in the study area may be increasing demand for forest products. The increasing demand for forest products is perhaps due to proximity to the major cities such as Lagos where demand for timber products is high both for local use and international export. Loss of forests in

Nigeria has been mostly attributed to the influence of human activities, including illegal logging and clearance for farming activities [38].

Conclusions

The suggestions made by some studies on the regular assessment of biosphere reserves to ensure the biophysical features is maintained for continuous provision of the roles they were designated for has been verified valuable. This study used a supervised method of image classification to detect the changes and the trend in the land cover of Omo biosphere reserve between 2000 and 2015. The study showed a tremendous decline in the area covered with undisturbed/natural forests, indicating a high level of deforestation in the reserve. As a result, such loss will have a great consequence on biodiversity and on other roles provided by the biosphere reserve. Furthermore, this study reveals a population growth in Omo biosphere reserve which could be a key factor for the land cover changes. Therefore, using these findings, the next most important needed knowledge is to examine the roles and the degree of participation of local communities in sustainable management of Omo biosphere reserve. Understanding the roles of communities in biosphere reserve conservation will help to identify options to increase and maximise their involvement because community participation is one of the key strategies to biodiversity and natural resources conservation.

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