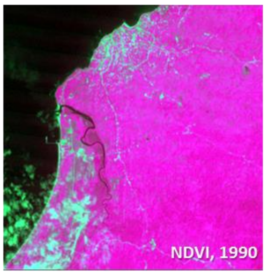

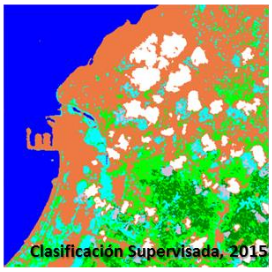

MAPPING AND EVALUATING LAND-COVER AND LAND COVER CHANGE IN THE RIO CAMPO NATURAL RESERVE, EQUATORIAL GUINEA

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Introduction

The Central African region has the second largest area of rainforest in the world with a relatively low level of deforestation (Ernst et al., 2010). In 2013, it was estimated that around 98% of Equatorial Guinea (74% classified as dense forest, 24% as mixed forest, and the remaining 2% as other) was covered by forest (WRI, 2013). The net deforestation rate estimated for Equatorial Guinea between 1990-2000 was the lowest in the Congo Basin (0.02%, Min–Max= 0.02% – 0.11%, N= 6 countries) (Ernst et al., 2012). The Rio Campo Natural Reserve is one of 13 protected areas in Equatorial Guinea. In 1991, Fa described its biological importance and since then, efforts to conserve this area have been implemented. However, there is no information related to land cover and land cover change at a local scale in the study area. The lack of basic information regarding the status and patterns of land cover change (especially forest resources) in Equatorial Guinea is highlighted by several authors (Mbomio and Ngua, 2009; FA0, 2010) and there are no known studies that evaluate land cover change in the Rio Campo Natural Reserve.

Mapping and analyzing land cover changes is essential for land and conservation planning. It can provide critical input to the decision-making process of environmental management and planning because changes in land cover could result in deforestation, increase of vulnerability to global warming (e.g., landslides, floods), and biodiversity loss, among others. Remote sensing and Geographic Information Systems (GIS) are powerful tools to acquire accurate and timely information on the spatial and temporal distribution of land cover changes. Therefore, the purpose of this study is to document changes in land cover in the Rio Campo Natural Reserve from 2001 to 2016.

Materials and methods

Study area

The Natural Reserve of Rio Campo is one of 13 protected areas of Equatorial Guinea, with an estimated area of approximately 347 km^2 (WRI, 2013). The reserve is located in the littoral zone of Equatorial Guinea. It was created through the Law 8/1988 and in the law 4/2000 it is formally recognized as a protected area. In 2003, it was declared a Ramsar site. The management plan (Mbomio and Ngua, 2009) estimates approximately 2,595 people living within the reserve (no year of reference for this estimate). The main economic activities in the reserve are agriculture, fishing, hunting, and exploitation of non-timber forest products. Mbomio and Ngua (2009) identified the lack of management programs for hunting and fishing activities, industrial forest exploitation, urban development and infrastructure as the main treats to the reserve’s biodiversity. Currently, the reserve’s management plan has been technically, but not politically, validated.

The climate of Equatorial Guinea is warm and humid with two wet and two dry seasons. The mean temperature is approximately 25 °C (Cano et al., 2006). In the littoral zone of Equatorial Guinea, annual rainfall estimates ranged from 58.8–64.4 mm from 2001 to 2016 (USGS, 2016). The Rio Campo Natural Reserve is rich in biodiversity. The vegetation community in this reserve is characterized as semi deciduous forest with extensions of dense humid tropical forest with intersperse wetlands (Fa, 1991). Ernst and others (2010) classified the dominant vegetation of the reserve as dense moist forest fragmented by roads and villages.

The Law 7/2003 of Equatorial Guinea defines a nature reserve as “a natural space created to protect ecosystems or biological elements that, due to their scarcity, fragility, and rarity should be highly valued. This decree limits all resource exploitation within a natural reserve unless this exploitation is compatible with the resources under protection. The collection of biological and geological material is prohibited except for research and educational purposes and as long as the collector has the required permits” (Mbomio and Ngua, 20009).

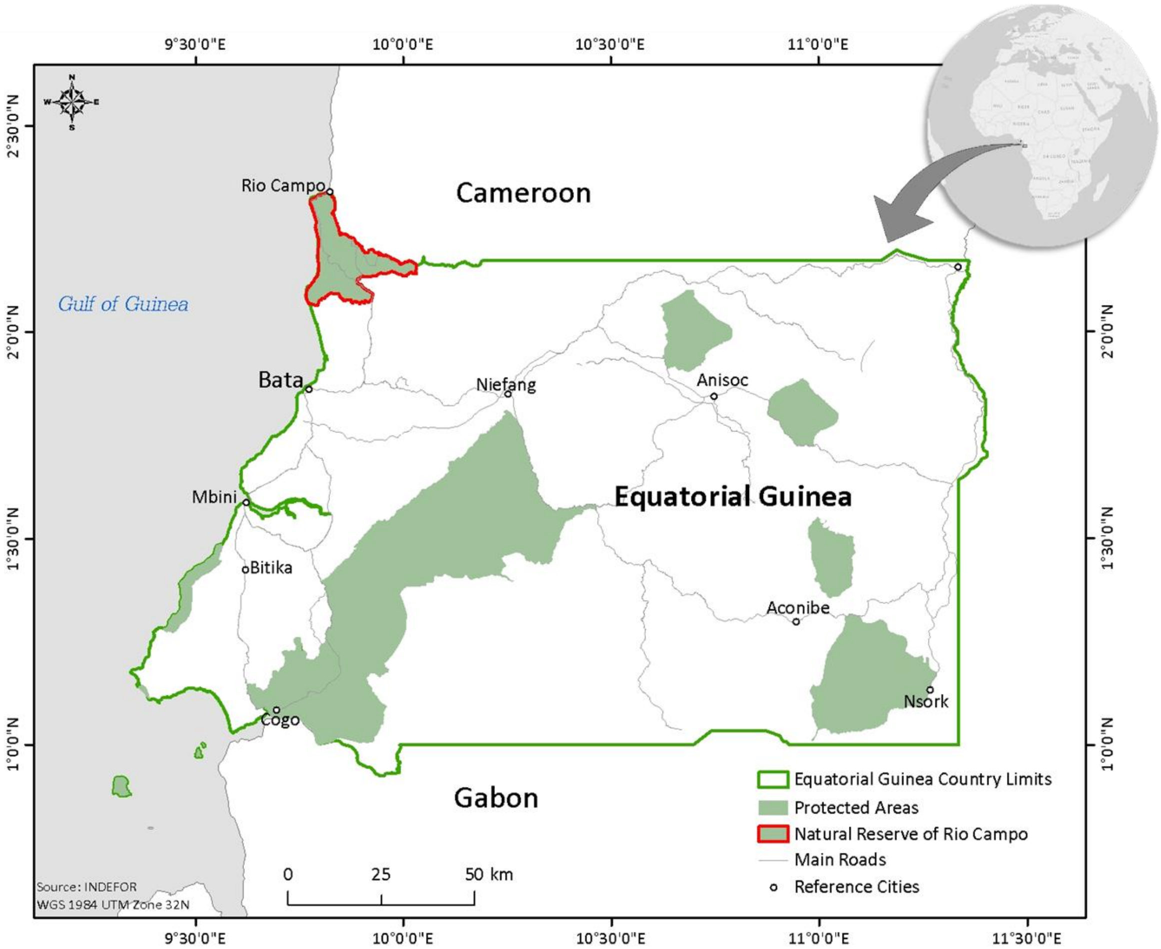

Figure 1. Location of the Rio Campo Natural Reserve within the continent of Africa (inset) and within Equatorial Guinea.

Image analysis

A number of steps were required to analyze multi-temporal Landsat scenes of the Rio Campo Natural Reserve. A general workflow of these steps is shown in Figure 2.

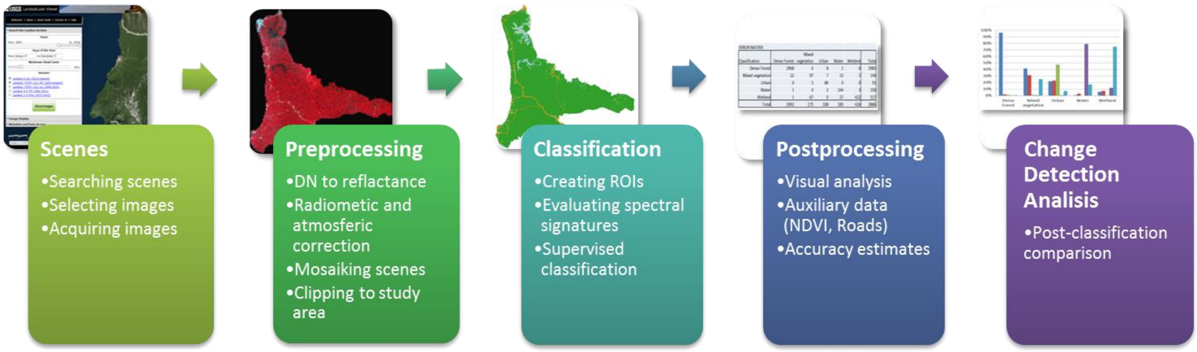

Figure 2. Workflow showing steps of forest cover change analysis

Satellite image acquisition: Because the Rio Campo Natural Reserve was recognized as a protected area in 2000 (Law 4/2000), the decision was made to analyze satellite images from the year 2000 and compare these with recent images from 2016. After exploring the scenes from the Landsat catalog, we found very few scenes with low cloud cover percentages (<20%) and therefore only one image from each time period was used to perform each classification. Because of its location, Equatorial Guinea is constantly covered by clouds, especially near its coast (Bwangoy et.al., 2010; Ernst et al., 2010), where the study area is located (Figure 1).

Scenes from 2001 and 2003 from Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and 2016 from Landsat 8 Operational Land Imager (OLI) were classified and analyzed (Table 1). Due to the presence of clouds in the 2016 Landsat 8 scene, an additional image was used to obtain information of land cover in areas with clouds and shadows. Landsat scenes were downloaded from USGS Landsat-Look Viewer[1] as Landsat Level-1 Data Products. Data processing and the analyses were conducted using ArcGIS 10.2 and QGIS projected in the WGS 1984 UTM zone 32N cartographic system. To minimize season variability, all the images used for the analysis correspond to similar months.

Table 1. Landsat scenes used in this report

Scene Identifier	**Data Acquired**
LC801860582016118LGN00	April 27, 2016
LC801860582016134LGN00	May 13, 2016
LE71860582003090ASN00	March 31, 2003
LE71860592003090ASN00	March 31, 2003
LE71860582001116EDC00	April 26, 2001
LE71860592001116EDC00	April 26, 2001

[1] http://landsatlook.usgs.gov/viewer.html

Pre-processing: Most of the images acquired had already been georeferenced by USGS, with a Standard Terrain Correction (Level 1T). Raw scene data was converted to total reflectance values and atmospheric corrections were performed. The Dark Object Subtraction Model (DOS) (Chavez, 1996) was used. The DOS model assumes no atmospheric transmittance loss, and corrects for spectral band solar irradiance and solar zenith angle. The study area is located between satellite path 186 and rows 058 and 059. Therefore, scenes were mosaicked and clipped to correspond with the reserve's area. A polygon delimitating the Rio Campo Natural Reserve was provided by INDEFOR. However, the polygon was georeferenced and modified to fit only land area (where its borders follow water features) of the reserve using high resolution imagery.

Classification and post processing procedures: The minimal distance classification was used for the supervised classification. In this method a sample is classified into the class whose known or estimated distribution most closely resembles the estimated distribution of the sample to be classified (Wacker and Landgrebe, 1972). Regions of interest (ROIs) were acquired using high resolution imagery from Google Earth for the years 2003 and 2011 or 2012 and from the Landsat images when high resolution images were not available. Spectral signatures of the pixels within a class and with respect to other classes were compared and examined. If spectral signatures between classes overlapped and land cover appeared visually similar, these classes were combined into one class (Figure 3). Five land cover types were used: dense forest, mixed vegetation, wetland, urban areas and bare soil, and water. The normalized Difference Vegetation Index (NDVI) was used to improve land cover classification results using the raster calculator tool. Once the image was classified, visual examination and comparison between land-cover classes with the original Landsat scenes, NDVI map, and Google Earth images was performed.

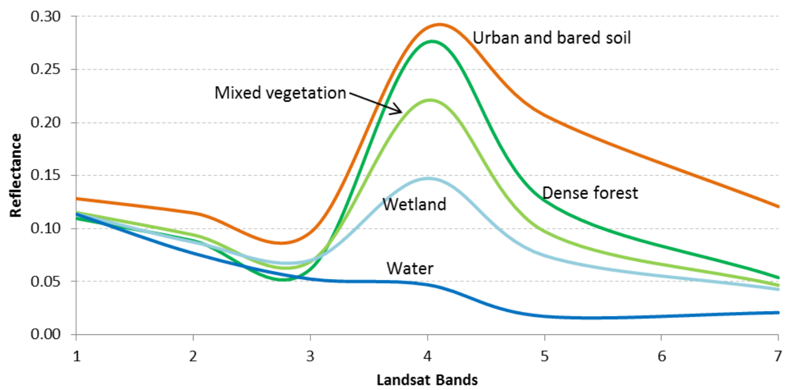

Figure 3. Spectral signatures of selected regions of interest (ROIs) used for the 2016 supervised classification.

An error matrix was used to assess classification accuracy of each of the classification maps using validation regions of interest obtained from high resolution images from Google Earth.

Accuracy is assessed by comparing a sample of reference locations to the classification thematic map. Overall, producer's (omission error), and user's (commission error) accuracy, and conditional kappa score were used to measure accuracy. Producer's accuracy measures the probability that a reference pixel was classified correctly, while user's accuracy is a measure of the probability that a pixel classified actually represents that category on the ground (Jensen, 2005). Kappa, a coefficient of agreement, accounts for the likelihood of pixels being classified correctly based on random probability (Stehman, 1997).

Change detection analysis: The post-classification comparison method was used for this analysis. This method consists of separately classifying multi-temporal scenes into classification maps, then compares the pixel by pixel difference of a reference classification against another (Mausel, et. al., 2004). The main disadvantage of this method is that it requires expertise to create the classes under study, and the final accuracy relies on the quality of the multi-temporal classified images (Mausel, et. al., 2004).

Results

Overall accuracy of the multi-temporal classifications ranged from 86.4% to 95.8%. Kappa hat classifications were 0.85 for 2001, 0.89 for 2003, and 0.89 for 2016 classifications. A kappa statistic at or above 0.8 is considered strong agreement between the reference and classified classes (Jensen, 2005). Most of the classes showed high producer's, user's and kappa accuracy estimates (Table 2). The mixed vegetation class is the only exception. Accuracy estimates for this class showed that the analysis had a lower producer's accuracy and pixels were not assigned to the correct class (46%, 63%, and 55%, respectively).

Table 2. Accuracy estimates (in percentages) for the classification maps for the 2001, 2003, and 2016 satellite images.

	2001			2003			2016		
	Producer's accuracy	User's accuracy	Kappa	Producer's accuracy	User's accuracy	Kappa	Producer's accuracy	User's accuracy	Kappa
Dense Forest	100	88	.71	99	96	.87	99	99	.98
Mixed Vegetation	46	87	.85	63	74	.73	55	69	.67
Urban and bared soil	76	100	.98	45	95	.94	83	94	.94
Wetland	92	73	.70	99	95	.94	99	81	.79
Water	65	99	.98	88	98	.98	77	96	.96

The amount of land covered by dense forest decreased from 2001 to 2016 (Table 3 and Figure 4-10). The area of all other classes used in this analysis increased. For instance, mixed vegetation had an estimated increase of 1.6 km^2 in 2003 when compared to 2001. Urban and bared soil is the class that showed the largest increase (3.4 km^2 and 2.6 km^2, respectively).

The wetland and water classes showed an increment in the amount of area from 2001 to 2016.

Table 3. Area estimates (in square kilometers) of each of the land cover classifications derived from Landsat scenes.

Class	2001	2003	2016	Difference 2003-2001	Difference 2016-2003
Dense Forest	338.6	330.2	325.5	-8.4	-4.7
Mixed Vegetation	7.6	9.3	11.1	1.6	1.9
Urban and bared soil	1.9	5.2	7.8	3.4	2.6
Wetland	5.3	8.0	7.9	2.7	-0.1
Water	0.8	1.5	1.7	0.7	0.2

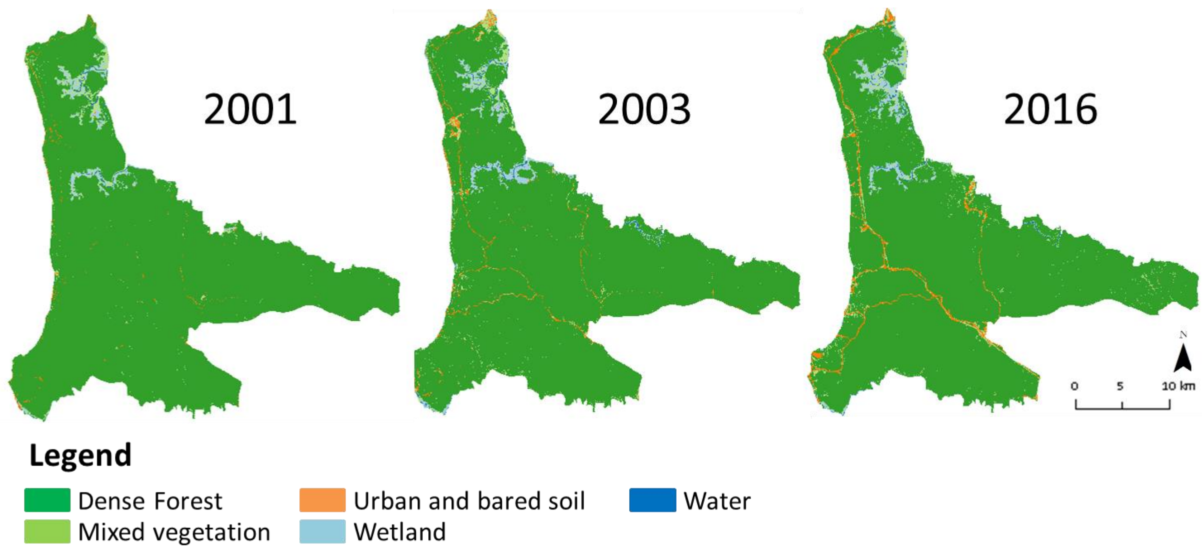

Figure 4. Supervised classification results for the 2001, 2003, and 2016 scenes of the Natural Reserve of Rio Campo.

The urban and bare soil class increased due to new developments, especially in the Rio Campo village. Figures 5 and 10 show how the expansion of the constructed portion of Rio Campo was expanded from 2001 to 2003. Other examples of development in villages can be found in the Mideast (Figure 6) and Mid-south (Figure 7) portion of the reserve. In these areas, the road system was already in place in 2003, however, since then, the classification and scenes from 2016 showed that there has been a considerable expansion of town centers.

There is also an increase in the extension of the road systems in the study area (Figures 8-9). This may also contribute to the increase in area of the urban and bare soil's class. Power lines and their related pathways are also more evident in the newest image (2016) when compared with the reference ones (2001 and 2003).

The mixed vegetation class extension showed an increasing pattern from 2001 to 2016. Some areas that were previously classified as dense forest (2001) were classified as mixed vegetation class in the classification of the recent scenes (2016). These areas are mainly associated to human settlements and the road and power line systems (Figures 6-9).

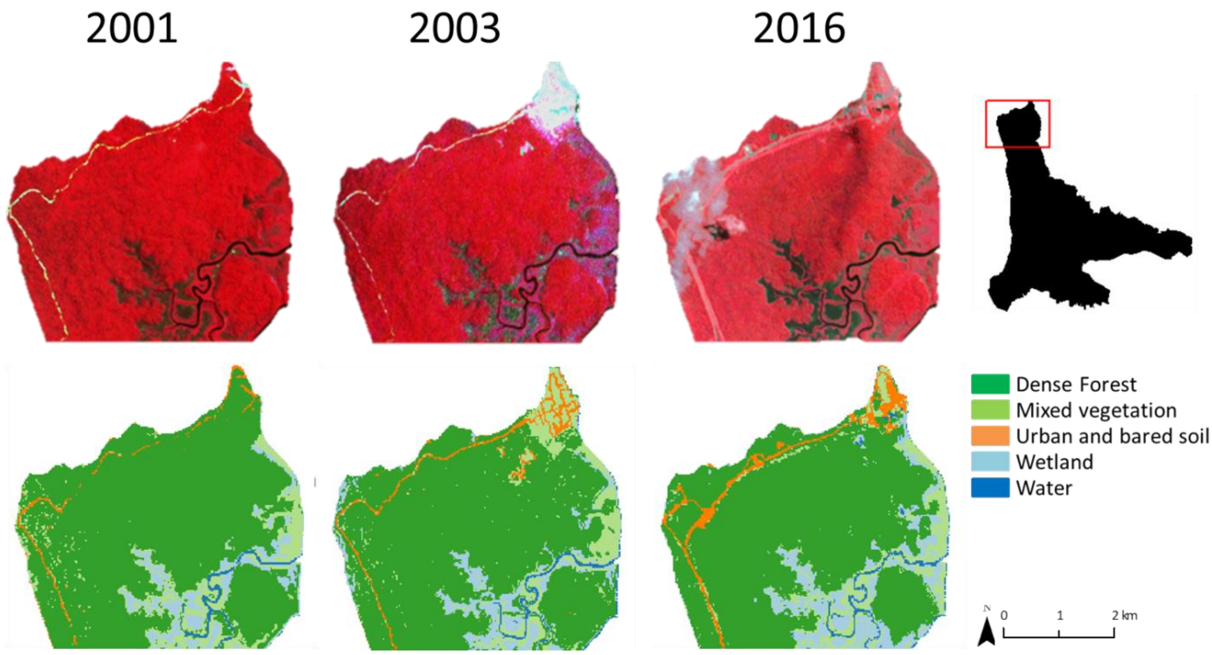

Figure 5. Northern region of Rio Campo Natural Reserve. Villages within this view are Rio Campo and Edyabe. Upper panel: color-infrared color composite. Lower panel: Results of applying minimum distance to means classification algorithm to the multi-temporal Landsat images.

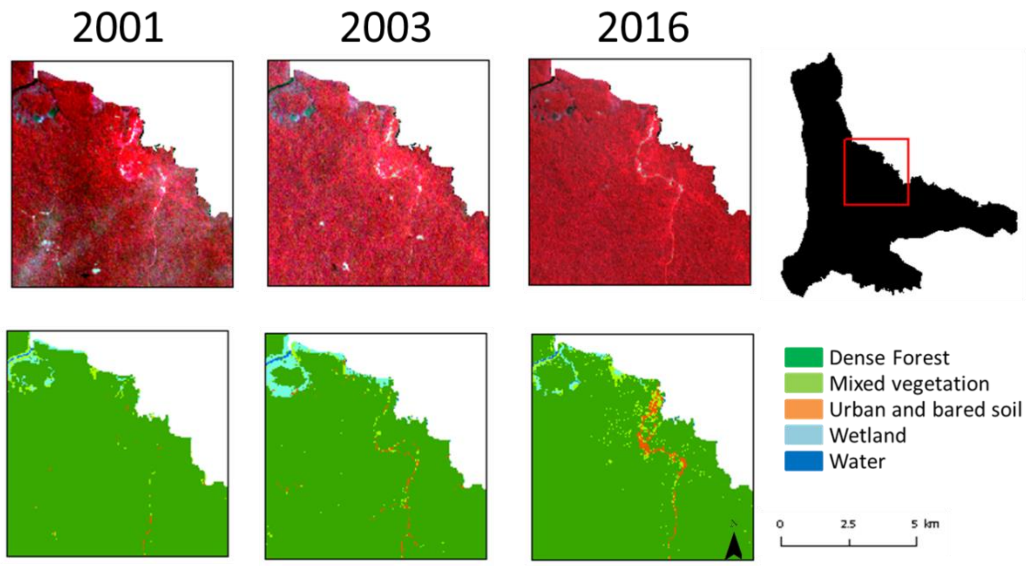

Figure 6. Mideast region of Rio Campo Natural Reserve. The villages within this view are, from north to south: Puesto de aduana, Yengue, Bilan (Cdo.), and Ncoho Mecak (Esasun). Upper panel: color-infrared color composite. Lower panel: Results of applying minimum distance to means classification algorithm to the multi-temporal Landsat images.

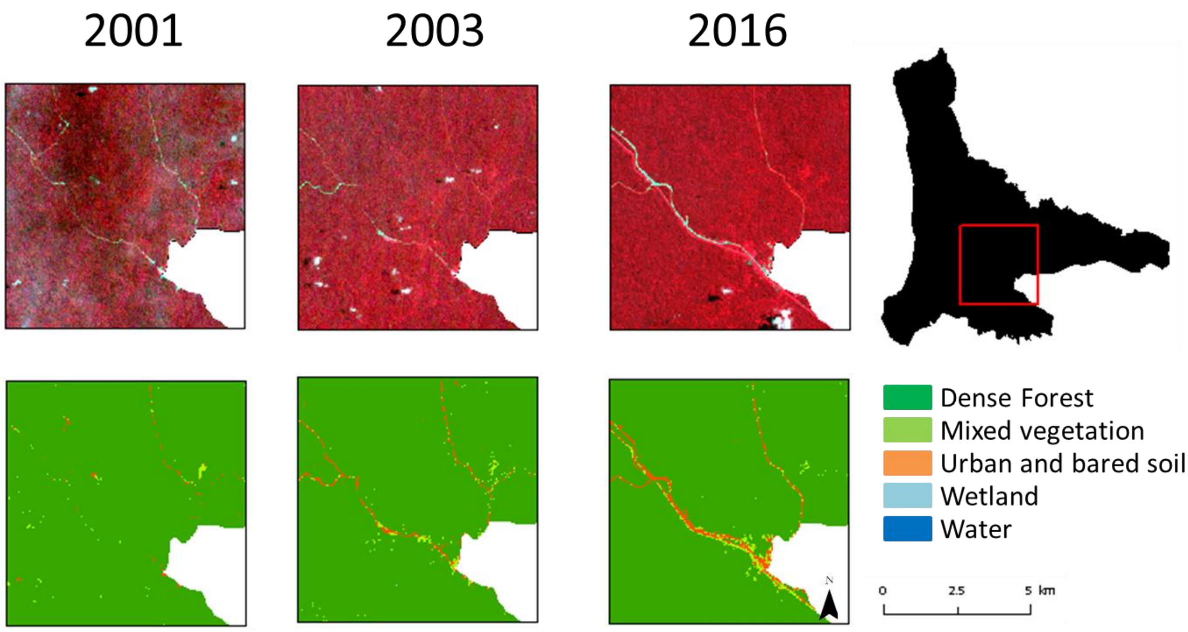

Figure 7. Mid-south region of Rio Campo Natural Reserve. The village of Bongoro is located within this view. Upper panel: color-infrared color composite. Lower panel: Results of applying minimum distance to means classification algorithm to the multi-temporal Landsat images.

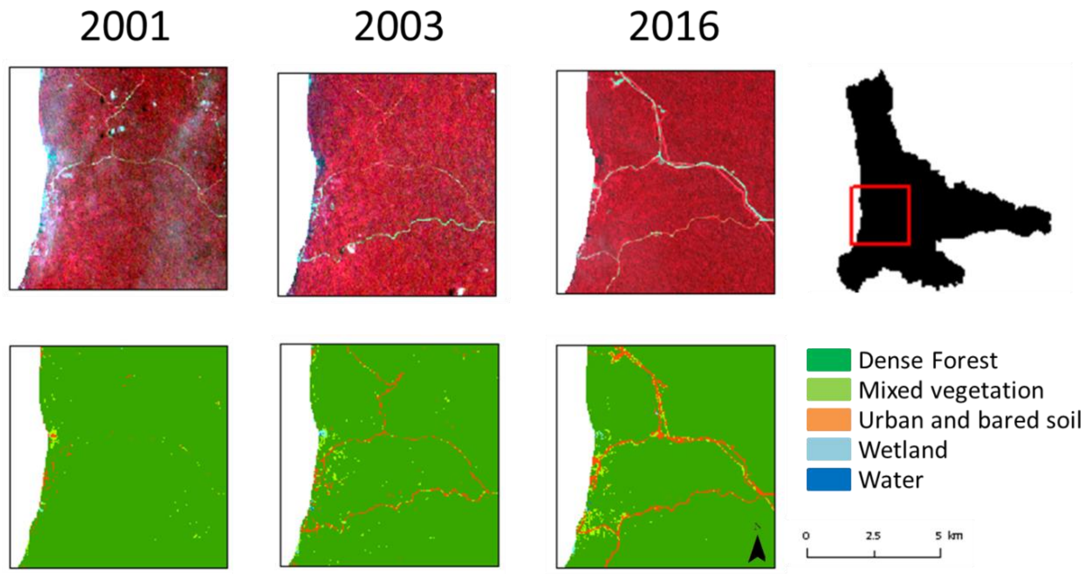

Figure 8. Midwest region of Rio Campo Natural Reserve. In most cases a village is found at the end of each road. The villages, from north to south, are: Machawa, Besu, Mary, Nguanamanga, Mahoco, Evongo-Divolo. Upper panel: color-infrared color composite. Lower panel: Results of applying minimum distance to means classification algorithm to the multi-temporal Landsat images.

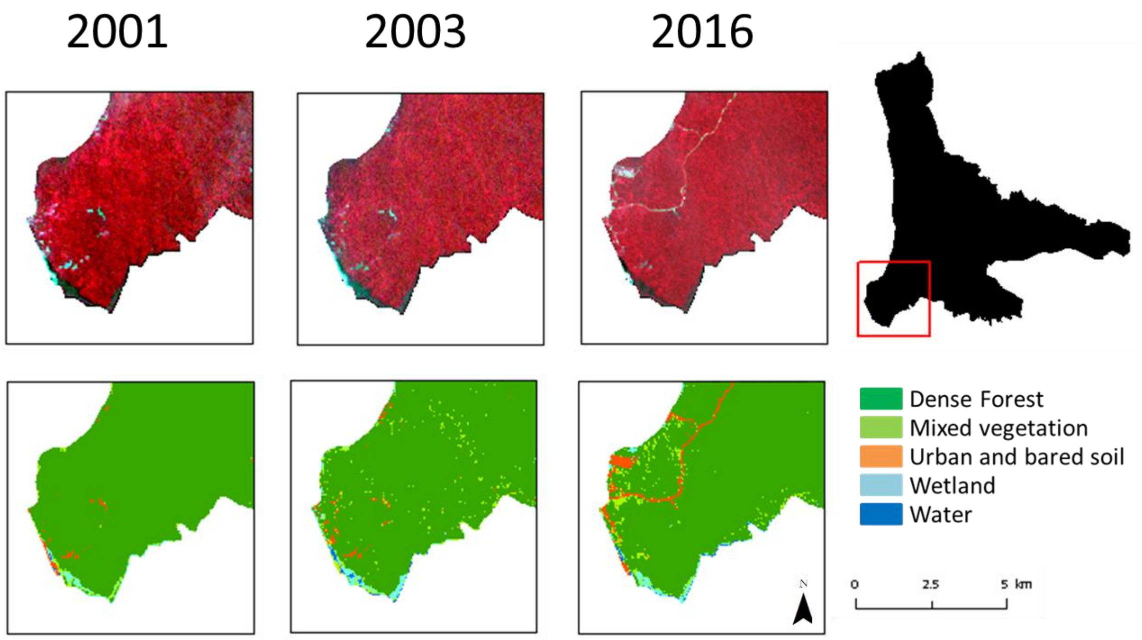

Figure 9. Southwest region of Rio Campo Natural Reserve. In most cases a village is found at the end of each road. The villages, from north to south, are: Combue and Mbonda. Upper panel: color-infrared color composite. Lower panel: Results of applying minimum distance to means classification algorithm to the multi-temporal Landsat images.

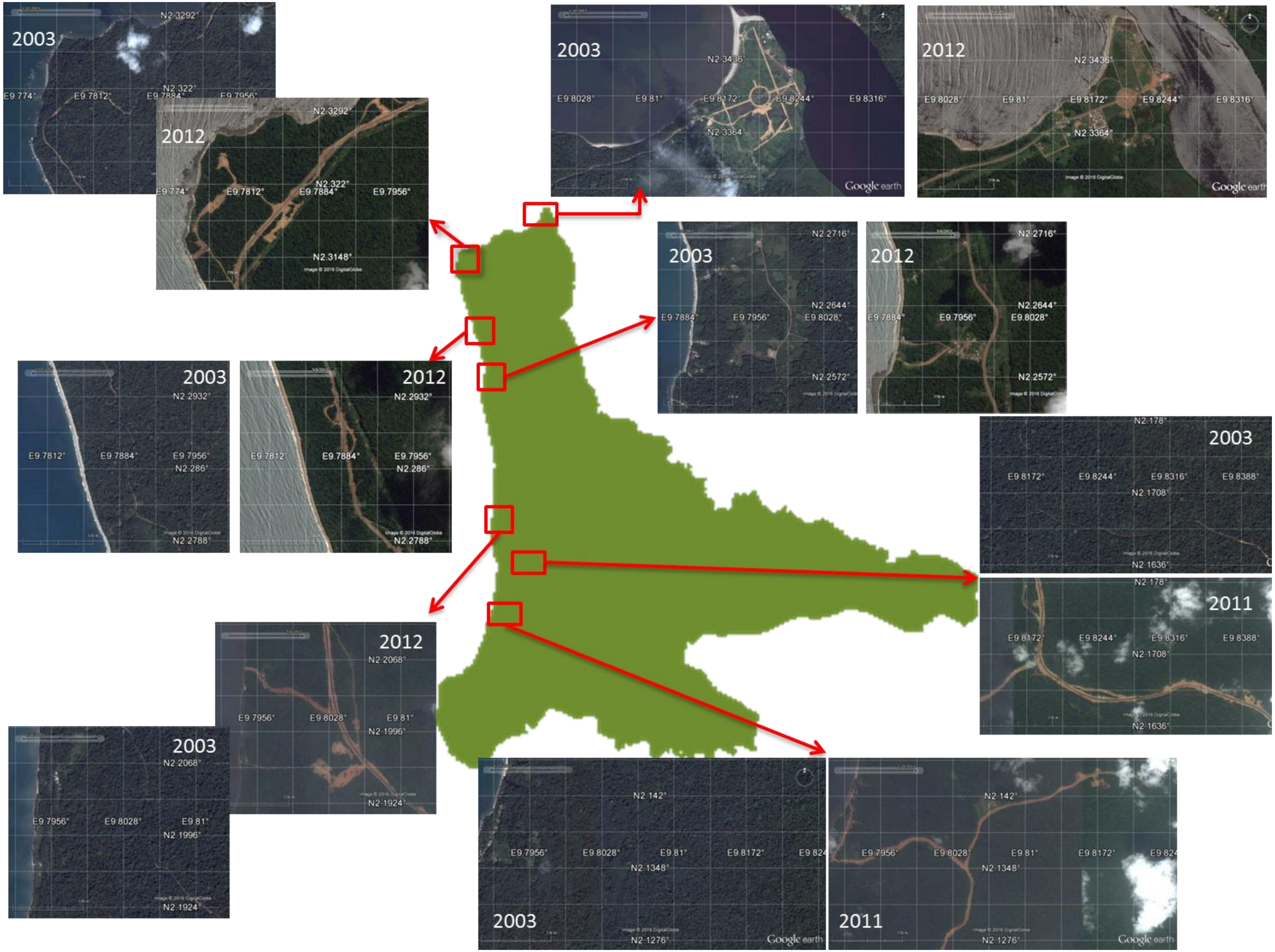

Figure 10. Selected image comparison between high resolution satellite images from 2003, and 2011 or 2012 (based on availability). Source: Google Earth

Discussion

Remote sensing and GIS analyses allowed us to detect changes in land cover, quantify these changes and identify land cover classes and areas most affected. Patterns observed in our analysis are comparable to other studies and areas (Mayaux et al., 2013; Ernst et al., 2010; Mokpidie et al., 2014), where urban and agricultural land use types are increasing at the expense of dense forest cover.

Studies in the region have identified population growth, agricultural expansion, infrastructure improvement and expansion of marketing opportunities as main drivers of land cover change (Ernst et al., 2010; Laporte et al., 1998; Hansen et al., 2013; Mayaux et al., 2013). Thus, the increase in urban and bare soil land cover types in the Rio Campo Natural Reserve is most likely associated to human development triggered by an increase in population density. Our multi-temporal approach may shows that the direct and local drivers of forest loss are the establishment of settlements and road expansion. For instance, figures 7-10 depict the expansion and improvement of main roads in the study area. Not only are there new roads, but the existing ones were improved (e.g., from dirt to pavement). However, a causal inference regarding the relationship between these possible drivers of land cover change in the reserve will required further analysis.

The mixed vegetation class was second in area increase. The change in this class may also be associated to human settlements and road and power line systems. However, another potential factor affecting this class could be natural dynamics such as hydrological cycles that cause expansion and retraction of the area's wetland and water classes. The latter two classes also showed an increase in area during the study period that not only affected the mixed vegetation class, but also dense forest cover. The mean rainfall estimate for the littoral zone of Equatorial Guinea for 2016 (Mean=64.4, St. Dev.=38.84, N=6) is greater than the observed in 2001 (Mean=58.8, St. Dev.=47.4, N=12) and 2003 (Mean=58.9 mm, St.Dev.=38.6, N=12) (USGS, 2016) (Appendix 1). Therefore, it is important to consider not only anthropogenic drivers of forest cover change, but also ecological processes and climatological events.

Remote sensing is a practical and cost effective tool to monitor changes in land cover (Ernst et al., 2010; Mayaux et al., 2013; Mokpidie et al., 2014). Our study can be used to guide the management and decision-making process of natural resources in the reserve. However, further work is needed to increase the accuracy of our results. For example, the classification algorithm for the mixed vegetation class was between 30 and 54% less accurate than the most accurate class (i.e., dense forest). The classes used for this analysis were selected based on previous studies in Equatorial Guinea (WRI, 2013). Nevertheless, the mixed vegetation class is comprised of miscellaneous vegetation types (e.g., grass cover, secondary forest) that may have a different spectral signature and require further classification at a finer scale. Further studies will also require a ground-truthing component and auxiliary information (e.g., soil and topography layers) to improve image classification. To identify the factors that influence forest cover loss in the area, it is vital to implement programs that systematically collect data on population size and growth, socio-economic activities, and strengthen the already existing geographic and cartography departments of INDEFOR. This should include continued capacity building and upgrading software and hardware capabilities.

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Appendix

Year round rainfall estimate (mm) for the littoral zone of Equatorial Guinea. Satellite data for this study corresponds with March and April (graded zone). Source: USGS FEWS, 2016.