Detecting Land Use Land Cover Change Impacted by Civil Crisis in Ivory Coast using Remote Sensing and GIS

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ABSTRACT---- ***Civil unrest has been identified as a powerful form of collective human dynamics, which has led to major aggressive changes in land use and land cover of societies in modern history. The District of Abidjan in Ivory Coast was faced with drastic landscape change following the civil war that started early 2000 until late 2012 that led to spontaneous inflow of people from the affected areas into the capital city for protection and survival. This paper examines the impact of over a decade civil unrest on the land use and land cover changes and its implications on infrastructure and utility service delivery in the capital city of Ivory Coast using Landsat ETM+ and Landsat 8 imageries acquired in December 2002 and April 2014. First, the two images were classified using the supervised classification scheme and the accuracy of classification assessed to examine their suitability for change detection. Thereafter, we used post-classification analysis to evaluate land use land cover changes. The classification accuracy results yielded Overall accuracy of 91.54% and 95.58%, and Kappa Coefficient 0.89 and 0.95 for 2002 and 2014 images respectively. Similar, quantitative analysis of changes expressed in land area coverage reveals a decrease in the thin forest class by 13.7% while the dense forest reduced by 17.3%. Conversely, build-up area appreciated in land coverage by 13.8%.***

Keywords — Change detection, Abidjan District, remote sensing, post-classification, Landsat.

1. INTRODUCTION

The earth surface and covers of many areas around the world are continually reshaping and changing as a result of human activities including urbanization, agriculture, infrastructural developments, economic activities, and war. This anthropogenic interference is considered the main forces behind the global climate change and their negative impact on ecological, environmental, and socioeconomic elements [1]. Today, land cover has becomes one of the most important resources of the earth that is continuously endangered. Detecting changes of this earth covers is extremely necessary to understand the relationship and interactions between human and natural phenomena. This is usually achieved by exploiting the temporal capabilities of earth observation satellite systems [1, 2].

Remote sensing has been widely accepted as a tool that provides a unique view of the earth surface. Different satellite sensors consistently generate large quantities of imagery from repeated acquisition at different spatial, spectral, and temporal resolutions which are considered key to diverse applications solve problems in environment management and conservation, forestry, hydrology, agriculture, geology, etc. since the first earth orbiting satellite was launched into space, remote sensing imageries have been in used to detect and monitor land cover changes at various scales [3], taking the advantage of uniqueness of spectral interaction with different earth features.

Land cover describes the assemblage of abiotic and biotic components on the earth's surface like water, snow, forest, grassland, and bare soil, while land use describes how the land cover is modified or put into use through human activities for the purpose of agriculture, industrialization, and other developmental purposes. Land cover changes can be detected by comparing images acquired in different dates or land cover products derived from them [2, 4]. The process identifies and examines temporal, spatial and spectral changes in pixels to evaluate changes [5]. A number of methods of change detection have been proposed and applied such as the Mixture Analysis, kernel-based BRDF model [6], Fuzzy Sets and Artificial Neural Networks - ANN [7], Integration of Multi-Source Data, et cetera. Most of these techniques have been extensively compared and reviewed [1, 3, 5, 7] .

Three categories of change detection techniques are prominent: (1) analysis of spectral type, (2) vector analysis of spectral changes and (3) time series analysis [1, 4, 8]. Time series analysis based change detection technique is utilized in this study. This technique analyzes the process and trend of changes by monitoring ground objects based on remote sensing continuous observation data to detect land use land cover (LULC) changes in the District of Abidjan, Ivory Coast. The objective of this study is to evaluate LULC changes in the study area between year 2002 and 2014 to identify the impact of the civil war experienced in the country within that period and its implications on infrastructural decay. The rest of the paper is organized into four sections. Next Section gives a general description of the study area and Landsat data sets used in this study. In Section 3 we present the methodology employed, explaining the supervised classification and post-classification change detection techniques. Data analysis, results presentation and discussion forms the focus of section 4, and finally, the paper draw its curtain in section 5 with brief conclusion

2. STUDY AREA AND DATASET

2.1 Study area

Abidjan, the capital city of Ivory Coast, lies on the Ebrie Lagoon in the South-Eastern part of the country with an estimated population of about 7.6 million people. Geographically, Abidjan is located within latitudes 5° 29´ 57´´N and 5° 12´ 29´´N and longitudes 4°9´ 12´´W to 3° 53´ 19´´W (see Fig 1). The District of Abidjan is the economic hub of Ivory Coast and covers a total land area of about 2,119 square kilometers (approximately 0.6% of the national territorial land mass). The region is a typical tropical rainforest with characteristic wet and dry seasons and average annual rainfall and temperature of about 2,000 mm and 27 °Celsius respectively.

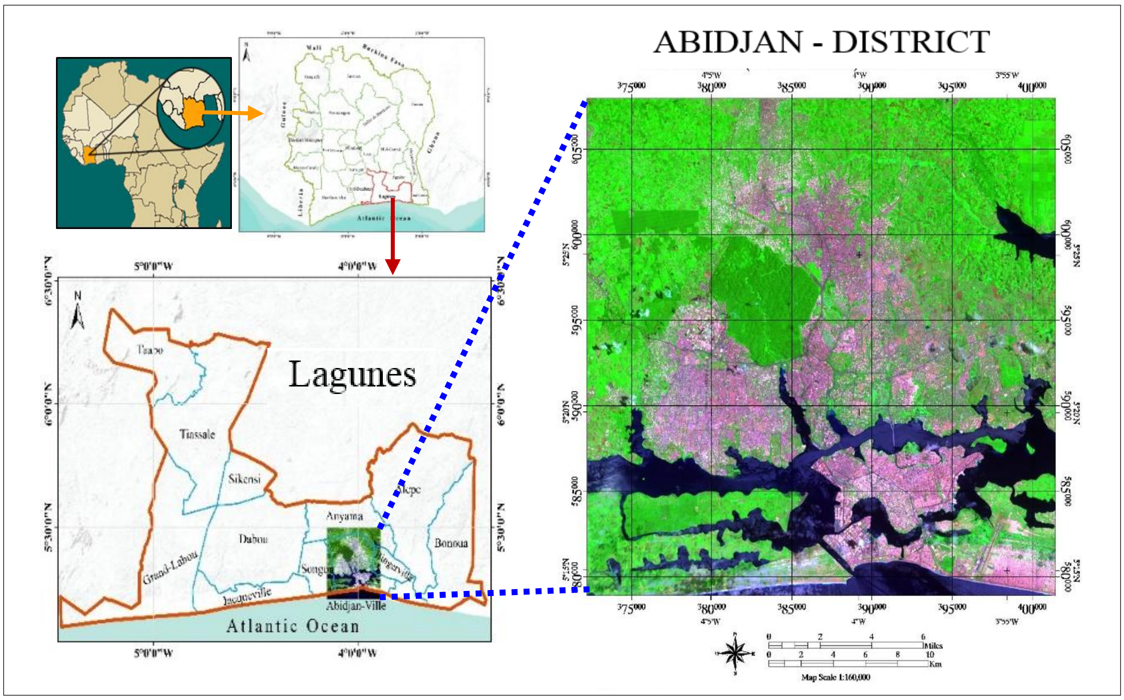


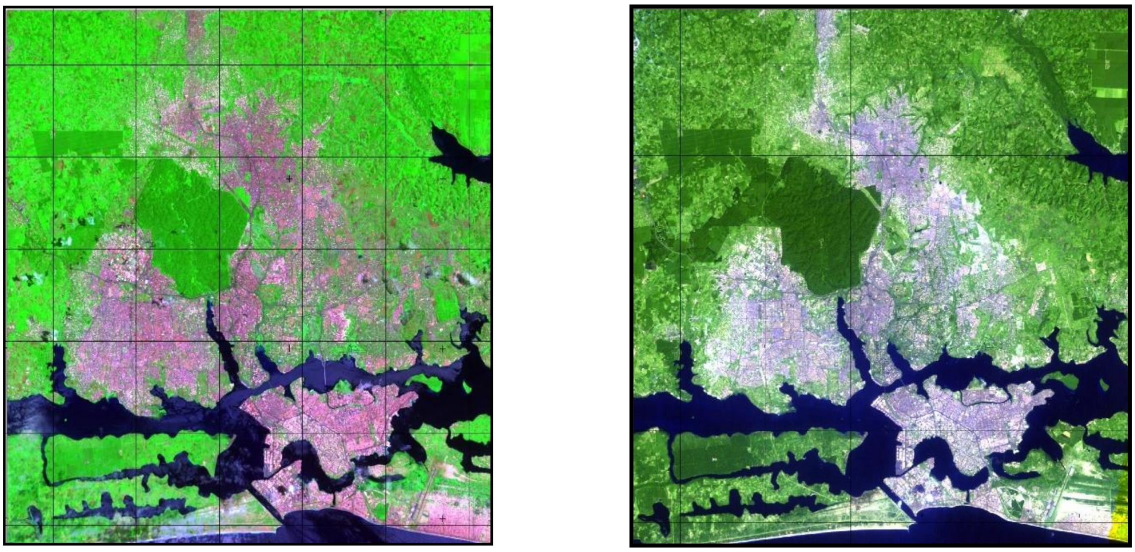
Figure 1: Map and the Landsat 8 image scene covering the study area

2.2 Dataset

Two sets of Landsat imageries (Fig. 2), Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) and Landsat 8, covering the study area were downloaded from the USGS Earth Explorer (glovis.usgs.gov), specifically for the periods of 15 November, 2002 and 18 November, 2014 (details in table1). The datasets represent pre and post war time. In order to have a fairly reliable comparison of land cover changes, remote sensing data acquired during the same time of the year, as closely as possible, and with the similar sensor were used. This will reduce the impact of sun angle and vegetation phenology differences [1, 5]. In addition to the Landsat data, vector data in shapefile was obtained from DIVA-GIS. This data was later overlaid on the classification results to show the extent of built-up area in 2014 as against 2002.

Table 1: Properties of Landsat data used

Details / Data	***Landsat ETM +***	***Landsat 8***
Scene	LE71960562002365EDC00	LC81960562014102LGN00
Acquisition date	December 31st, 2002	April 12th, 2014
Date of download	November 14th, 2014	November 18th, 2014
Downloading Source	USGS (Earth Explorer)	USGS (Earth Explorer)
Spatial Resolution	30 meters	30 meters (7 bands) - 15meter for the Panchromatic bands.
Spectral Resolution	7 bands	



a) b)

Figure 2: Landsat Images used the investigation: (a) 2014 - Landsat 8; (b) 2002 - Landsat 7 ETM+

3. METHODOLOGY

In this study, data processing and analysis operations follow these four steps discussed in their sequential order of operation. The steps are:

- Pre- processing activities.
- Data classification/creation land cover maps for 2002, and 2014.
- Accuracy assessment.
- Computation of change detection using post classification method and analysis of land cover change.

3.1 Preprocessing of Data sets

Data processing was carried out in ENVI 4.8. Fig. 3 shows the data processing workflow. Pre-processing task began with atmospheric correction using Quick Atmosphere Correction (QUAC). QUAC corrects atmospheric effects in image using parameters within the image spectra in a scene without the need for ancillary information (exelisinc.com). It is computational efficient, simple to use and yield accurate spectra collection. Thereafter the images were rectified and area of interest was subset for further processing.

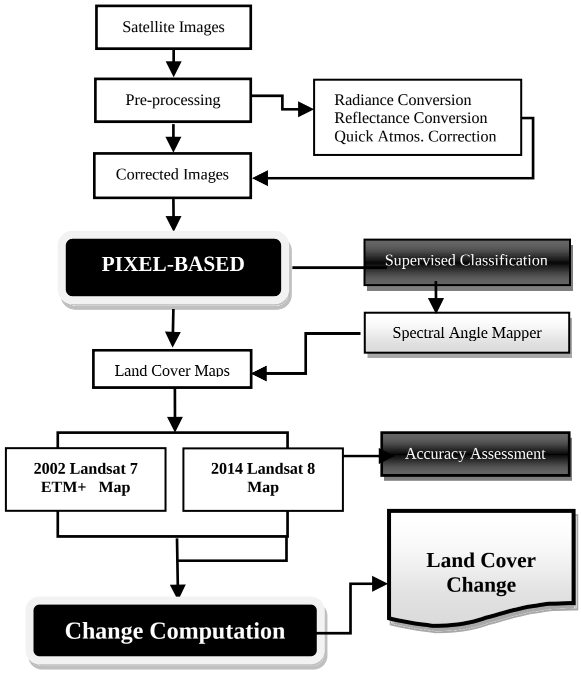


Figure 3: **Methodological work flow**

3.2 Image Classification and Accuracy Assessment

Several classification algorithms had been developed and employed to extract land cover information and monitor change. Supervised and unsupervised pixel-based classifications have been widely used and documented in the literature [1, 3, 4]. Although Maximum Likelihood Classification (MLC) have been widely used [9] spectral angle mapper (SAM) was used in this study because it can efficiently examine spectral similarity of images to their reference spectra. SAM suppresses the impacts of shade to highlight target reflectance characteristics [10] [11]. It measures similarity by using a test spectrum *t* in relation to a reference spectrum *r* using the expression in equation 1 [12]. In this study, four land cover classes: built-up area, thin forest, dense forest and water body were identified for classification. To do that, training polygons were selected and digitized on-screen as representative of each class based on terrain knowledge acquired from Google earth, RGB color composition images and elements of visual interpretation such as color, shape etc. observed on the images of the study areas. Thereafter, we assessed the accuracy of the classified map using confusion matrix.

$$x = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{(\sum_{i=1}^{nb} t_i^2)^{1/2} (\sum_{i=1}^{nb} r_i^2)^{1/2}} \right) \qquad (1)$$

Accuracy assessment involves statistical estimates obtainable from remote sensing classification output and an independent reference dataset in order to measure the probability of error for the classified map [13]. We carried out accuracy assessment for 2002 and 2014 classification maps produced from Landsat 7 ETM+ and Landsat 8 data. Due to lack of reference data for the study area as ground truth data, it was difficult to carry out accuracy assessment with independent data. Alternatively, stratified random sampling design was adopted with sample points generated and their locations chosen to represent the four land cover classes considered in the area. The two classified images were used as input data to detect the pattern of change in land use land cover within the study area.

3.3 Computing Change using post-classification comparison

Many Change Detection reviews based on Pixel-Based classification of RS data have been published [4, 7, 8]. One of the most commonly used change detection method is Post-classification [9], a method that determines the difference between independently classified images for each of the dates in question. Post-classification comparison algorithm allows the type of land cover changes that have occurred within the time frame to be recognized and quantified. The technique is selected because it minimizes the impact of geometric and radiometric differences [14] and the most suitable where data from different sensors are involved as in this case. The only drawback of the method is that the result obtained depends on the accuracy of the individual classifications, hence the need to be more careful during classification operation. Quantitative analysis of class change is presented on the percentage bar scale.

4. RESULT AND DISCUSSIONS

Image Classification

The accuracy of change detection using post-classification algorithm depends largely on how accurate the classified maps are. So, a necessary step to ensure that the results obtained are true representation of reality on ground is to assess the accuracy of LULC maps of the study area using error matrix. Figure 4 shows the result of the maps after classification with four land cover classes displayed in different colors: built-up areas in red, dense forest in dark green, thin forest in light green, and water body in blue.

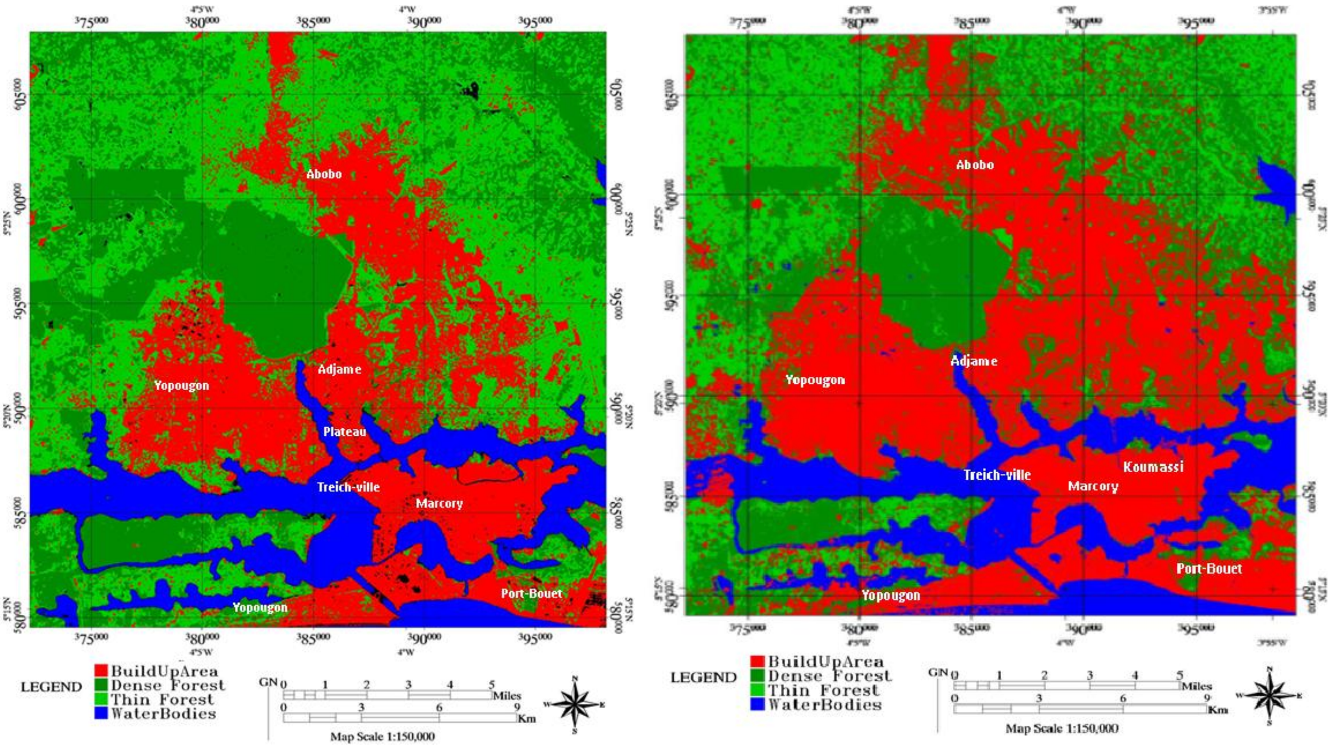


Figure 4: LULC classification results from 2002 Landsat ETM+ (left) and 2014 Landsat 8 imagery

Classification Accuracy

The classification accuracy gives satisfactory results for both maps. Tables 2 and 3 are the error matrix obtained from classification maps of 2002 and 2014. The tables present detailed of pixels correctly assigned to each class. The evaluation produced Overall accuracy of 91.54% and 95.58% and Kappa Coefficient 0.89 and 0.95 respectively for 2002 and 2014 land cover maps. The achieved accuracies are sufficiently adequate for the maps to be used for change detection.

Table 2: *Classification image of 2002*

Classes	Build-Up Area	Dense Forest	Water Bodies	Thin Forest	Total
Unclassified	0.00	0.00	0.00	0.00	0.00
Build-Up Area	95.78	0.03	0.00	7.32	20.15
Dense Forest	1.17	99.86	0.00	14.46	37.62
Water Bodies	0.00	0.00	100.00	0.00	21.39
Thin Forest	3.05	0.11	0.00	78.21	20.84
Total	100.00	100.00	100.00	100.00	100.00

***Table 3:** Classification image of 2014*

Classes	Build-Up Area	Dense Forest	Water Bodies	Thin Forest	Total
Unclassified	0.00	0.00	0.00	0.00	0.00
Build-Up Area	96.24	0.00	0.00	0.00	22.46
Dense Forest	3.11	98.07	0.00	5.27	24.79
Water Bodies	0.58	0.00	100.00	0.00	36.17
Thin Forest	0.08	1.93	0.00	94.73	16.58
Total	100.00	100.00	100.00	100.00	100.00

Land cover changes

Quantitative analysis – As mentioned earlier, quantitative analysis of changes among classes (excluding water body) are shown on statistical percentage scale (Figure 5). Between 2002 and 2014, there has been a decrease of the thin forest by 13.7% while dense forest experienced a reduction by 17.3%. Conversely, build-up area record increase expansion by 13.7%. These values are expressed in term of land coverage area. Change from dense to thin forest observed in the north-west and east predominantly are as a result of deforestation, caused by uncontrolled logging and forest clearing for cultivation [10]. In essence, it is to emphasize that not all the changes that occurred in the study area are as a result of urban sprawl. Accordingly, there had been expansion around the city's peripherals that reflects less of economic and industrial development of modern days' urban growth (detail of the implications is discussed in the next section).

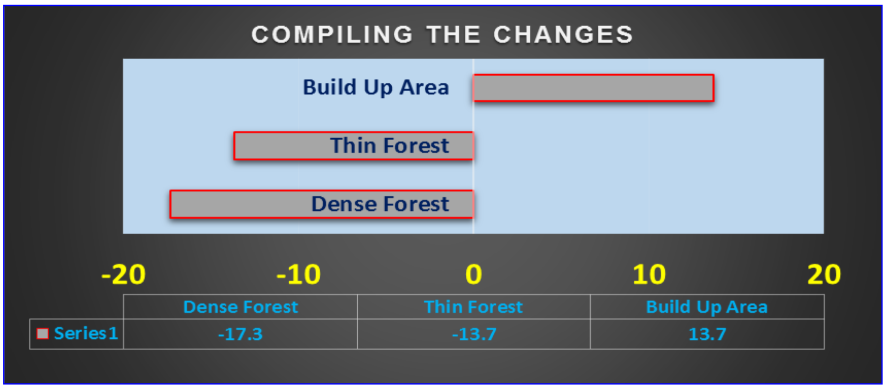


Figure 5: Percentage changes scale depicting gain and lost in land area amongst built-up area, thin and dense forests

Base-knowledge analysis

Qualitative evaluation is done through visual analysis of the two classified images of 2002 (left) and 2014 (right) in Figure 6 to decipher the change relationships within the area. Generally, urban expansion had occurred the north of the River (Ebrie Lagoon), as highlighted with different shapes and colors, contrary to the southern riverine terrain. Areas previously identified as thin forest in the city suburbin year 2002 such as east of Adjame (in black circle), Yopougon in the west (in white ellipse), and Abobo in the north have changed to built-up areas. The direction of urban growth is controlled by factors such as topography and legal restrictions, Take for instance, Banco Reserved Forest located that shares boundary with Yopougon, Abobo and Adjame maintains the existing land cover because it is reserved forest therefore no access is allowed. Likewise, hilly terrains such as are largely avoided too. In addition to the northern sprawl, areas earlier mapped as thin or dense forest in the southern part of Yopougon (across the Ebrie Lagoon) have been lost to built-up class.

The surge in population is attributed to two main reasons. One, is the massive migration of displaced people during the war seeking protection [15], and two, rural-urban migration for better life. According to the United Nation Higher Committee for Refugee (UNHCR) report in 2009, about 700,000 people, mainly from the west and northern areas, were displaced and majority of them relocated to the country's capital city perceived to be safer. In short, the 2014 census reported population of 7.5 million for Abidjan districts, that is to say, on the average, for every square kilometer there are 3,600 inhabitants. This is in shape contrast to the projected population of about 4.8 and 5.5 million for year 2015 and 2020 respectively, published by the Ministry of Economic Infrastructure [16] . The current population of Abidjan district has surpassed even the estimated figure for year 2020. This has led to serious overstretch on the existing infrastructure on different fronts.

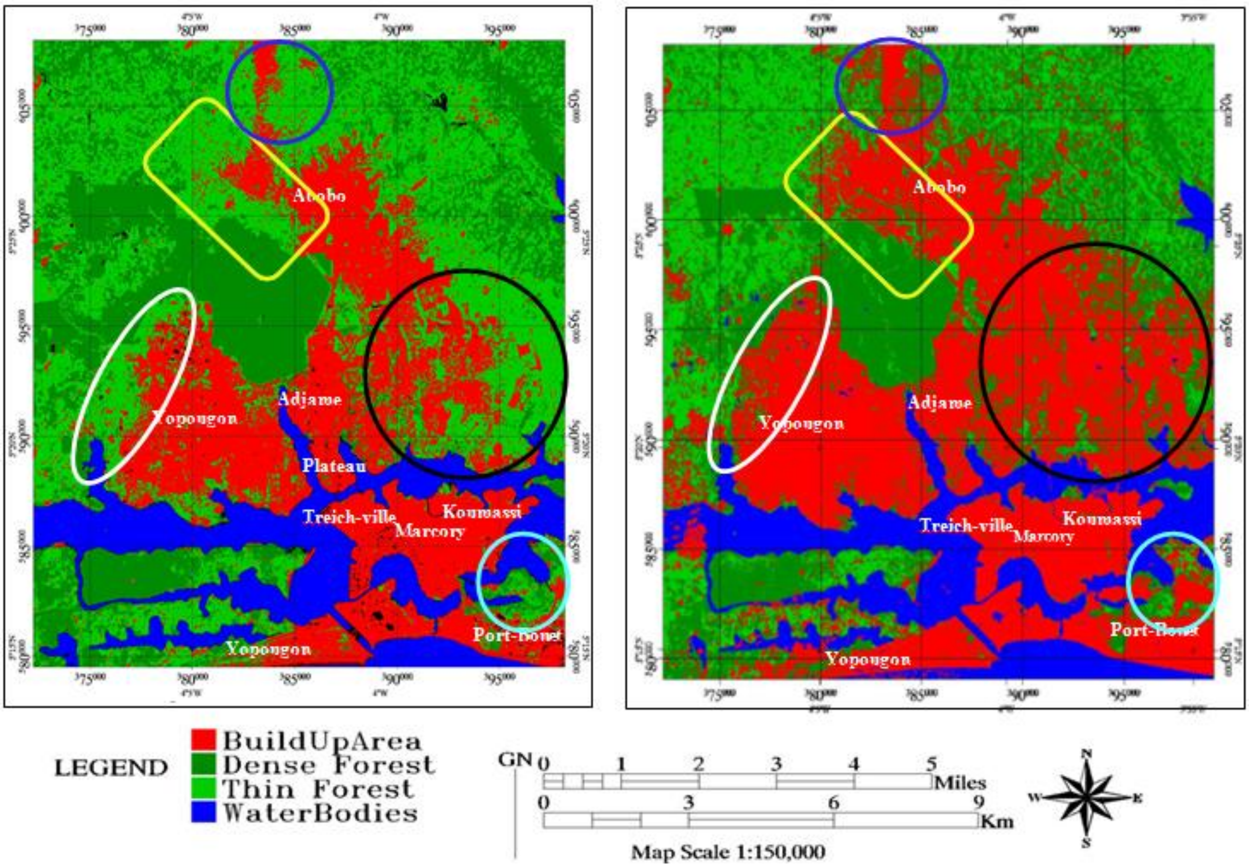


Figure 6: Comparing SAM Classification Results: (a) 2002 Landsat ETM+ **VS** (b) 2014 Landsat 8 Image

To further reinforce land use change in relation to urban expansion and coping with infrastructure, vector data of the of the Capital city, Abidjan, was overlaid classified maps. The data, which is available freely on diva-gis.org, was downloaded but only two salient points are highlighted for explanation. Development in urban setting can be viewed through the complexity the road network. Figure 7 explains urban expansion by visually correlating fitness of road network with built-up area. Plates "a,b" and "c,d" depict two different areas. Plates "a" and "c" show land cover map of 2002, while "b" and "d" are extract from 2014 land cover map. Built-up areas are presented in yellow and red colors for visual clarity. In the 2002 map (a and c), road network can be seen lying completely in a forested area whereas the road network perfectly match the built-up areas in plates b and d.

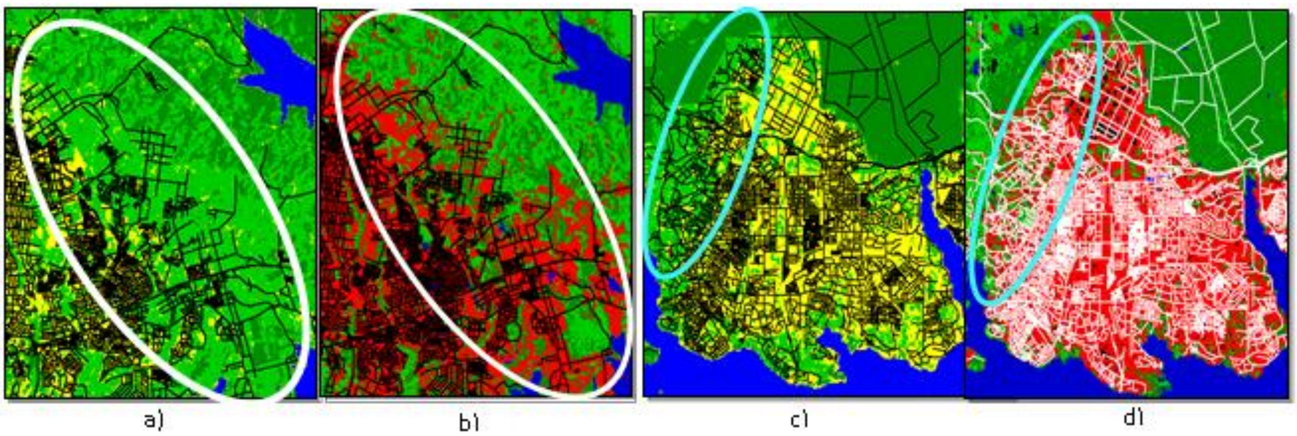


Figure 7: Shapefile Overlay to demonstrate the degree of correlation between road network and land use map: Plates a, c show land cover map of 2002, and plate b and d are extracted from 2014 map.

Implications of population growth on urban infrastructure in Abidjan district

The momentous geometric increase in population to the tune of 40% [16] has direct negative implications on the available infrastructural facilities with consequential effects on the lives of the inhabitants. Emphasized here are the three key infrastructures which are critically affected. They are water supply, electricity, and drainage system [17]. Unarguably, these utilities cannot be expected to perform beyond their design capacities, less to say of serving the current population. Water supply has been in great shortage in Abidjan district due to rural-urban migration for better lives and again influx of people displaced by civil unrest who relocate to the capital city. The coping capacity of the responsible agency has been further weakened due to inadequate funding for maintenance, system upgrading, illegal connections and available manpower [16]. In the area of power supply, incessant power interruption has been a characteristic of the capital city and its environ as a result of intense pressure on power consumption at alarming rate. This has seriously affected the day-to-day business activities and other power-dependent means of livelihood for the inhabitants. Another hardship brought the citizens by increase in population and urban expansion is flooding. City Council (Municipalities) is finding it hard dealing with the sewerage and draining systems which for most parts are not functioning again. For example in 2014, several parts of the city were temporarily flooded resulting to high numbers of casualties and damages to properties worth of millions of Dollar. As discussed earlier, funding, manpower, and absence of maintenance culture are common causes of this menace.

5. CONCLUSION

Land use land cover change detection of Abidjan District in Ivory Coast from analysis of the time series remote sensing data reveals clear indications of change in in land use/cover pattern. Areas previously covered by thin and dense forest have been converted to another use such as urban development. There was rapid expansion in urbanization within the period under consideration that not much a reflection of economic development but the aftermath of decade long civil unrest and the surge in population inflow into the capital city with consequential overstretched of the existing infrastructures, especially those discussed in this paper. The major contribution of this study is the ability to use satellite data to detect land use changes to provide link to social and environmental challenges.

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