

Assessment of Land use/land cover change mapping in Bangui city using Remote Sensing and GIS techniques

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ABSTRACT:

The security instability in the Central African Republic (CAR) forces the civilian population to flee the provinces to seek refuge in Bangui city, or in other countries. Human activity, which is very beneficial in the context of urbanization, is the main driving force of change in the city of Bangui, but also has a negative effect on the geoenvironment. Multispectral images data Landsat TM5, Landsat 7 ETM+ and Landsat-8 OLI of the years 1986, 2003 and 2020 was used to investigate Land use land cover (LULC) change of the city of Bangui. Maximum Likelihood (ML) classification algorithm was used to produce the map land use/land cover change detection in the study area. In Bangui city, four major classes have been identified, including vegetation, built-up, bare soil / rock and water. The analyses of the classified maps showed that Bangui city has been changed between 1986 and 2020, exceedingly area increased for built up (145.81%), vegetation (5.59%) and water (3.46%), it has however decreased for bare soil/ rock (40.60%). The overall accuracies and overall Kappa statistics achieved were 92.5%, 82.5% and 87.5%, and 0.90, 0.87 and 0.83 for 1986, 1999 and 2018 images, respectively.

1. INTRODUCTION

Land use/land cover change detection is considered to be the most effective remote sensing tool of the past to study the different phenomena related to the development of urbanization or the change of a region (Lambin, 1997). Several authors have used the different methods of remote sensing and GIS to evaluate the evolution of urbanization, the change of an area or the impact of Land use land cover on the geoenvironmental (Duncan 1993; Chen 2002; Twumasii and Merem 2005; Zhao et al., 2005; Xu, 2007; AfiFy 2011; Devan et al., 2012; Xindong et al. 2014; Hegazy and Kaloop, 2015; Sinha et al., 2016; İslam et al., 2017;; Sérgio and Mace, 2019; Ma et al., 2019; Jazouli et al., 2019). Land Use Land Cover changes analysis are considered as the main mores of environmental change at all spatial and temporal scales (Hurni et al., 2005; Ebrahim and Mohamed, 2017; Gashaw et al., 2018). The research based on Land use land cover in ecosystem changed was studied by several authors such as (Lambin et al., 2003; Balthazar et al., 2015; Paudyal et al., 2019) The Central African Republic (CAR) is a country located in the center of Africa. This landlocked country has 16 provinces, the largest city is Bangui, capital of Central African Republic. The security instability that reigns in the country is considered as the cause of several mutinies and war. This security problem forces the civilian population to flee the provinces to seek refuge in other countries or to the Central African capital. This rural exodus has allowed the city of Bangui to grow in terms of urbanization. Human activity is seen as the main driver of change, which is

very beneficial in the context of modernization, industrialization and global integration. But it also has a detrimental effect on the geo-environmental (King et al., 2005). The present work focuses solely on the methods of supervised classification to evaluate the Land use land cover of the city of Bangui from 1986 until 2017. Because it should be noted that so far no scientific article has been made in this area on the CAR in general and the City of Bangui in particular, hence the need for this study.

1.1 Study area

The Central African Republic's capital is Bangui. It is the largest city in the Central African Republic. The population of the agglomeration is estimated at about 1,145,280 inhabitants, a quarter of that of the country, it extends to the neighboring communes of Bégoua in the north and Bimbo in the east. Bangui is located between 4 ° 21 '41 "North Latitude, 18 ° 33' 19" East Longitude.

Bangui has a tropical savannah climate with dry winter (Geiger, Rudolf, 1954). The average annual temperature is 25.9 ° and the average annual rainfall is 1,525 mm, the dry season is limited to the three winter months from December to February, the period of highest rainfall lasts from May to October, the average rainfall is then above 145 mm monthly. Bangui is an autonomous commune, which does not belong to any of the 16 prefectures or economic prefectures.

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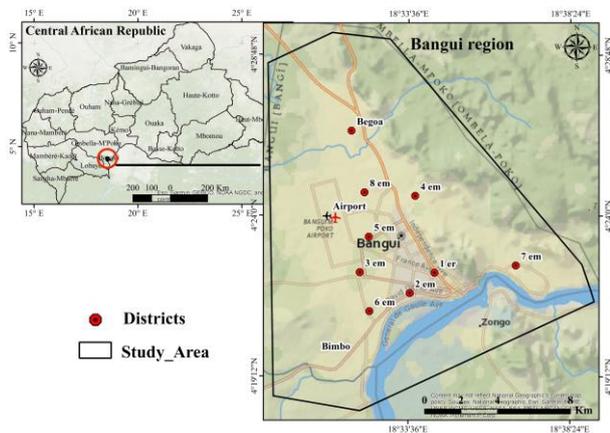


Figure 1. Localization of the study area.

2. MATERIAL AND METHOD

2.1 Materials

For this research, we used three Landsat images (Path/Row 181/057): Landsat TM5 for 1986, Landsat 7 ETM+ for 2003 and Landsat 8 OLI for 2017 years. These scenes were acquired from the freely available Landsat archive of United States Geological Survey (USGS) (<http://earthexplorer.usgs.gov/>). These Landsat images were already georeferenced to the Universal Transverse Mercator (UTM) map projection zone 34N with WGS84 datum and ellipsoid. The Landsat TM5 and Landsat7 ETM+ images were geometrically corrected using GCPs (ground control points). ENVI 5.3, Erdas imagine 14 and Arcgis software were used in this study. Table 1 shows the details of images using in this study.

	Path/Row	Data of acquisition	Source
Landsat TM5	181/057	16/01/1986	USGS
Landsat 7 ETM+	181/057	07/01/2003	USGS
Landsat-8 OLI	181/057	30/01/2020	USGS

Table 1. Details of images using in this research

2.2 Methods

The methodology used in this research is subdivided into three steps Pre-processing, processing and Post-processing.

2.2.1 Pre-processing

Pre-processing is one of the important steps in research using Remote Sensing. Download images must be pre-processed either automatically by the company or by user. The objective of this step is to establish direct linkage between data and biophysical phenomena (Singh, 1989). In the case this research, we have 3 steps with regard to Pre-processing.

2.2.1.1 Geometric correction

The geo-referencing, it is the process of removing the effects of geometric distortion in the raw image and placing the image in

a geographic coordinate system defined by using control points ENVI software was using in this step.

2.2.1.2 Radiometric calibration and Atmospheric correction

This step includes eliminating the atmospheric effects that cause irregular and false perceptions in the information, and correcting or eliminating reflections that do not fully represent objects from the radiation perceived by the sensors. For atmospheric correction, (Fast Line-of sight Atmospheric Analysis of Spectral Hypercubes (FLAASH)) were performed (ENVI module, 2009).

2.2.1.3 Image Enhancement

The aim is to further improve visual interpretation. Contrast extension convolution Edge enhancement in ERDAS IMAGINE software (version 2014) was use.

2.2.2 Processing

This step is based on the supervised classification - Maximum Likelihood (ML) method was produce the maps of land use/land cover change detection in study area. The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The likelihood Lk is defined as the posterior probability of a pixel belonging to class k.

$$Lk = P(k/X) = P(k) * P(X/k) / P(i) * P(X/i)$$

Where P(k) : prior probability of class k

P(X/k) : conditional probability to observe X from class k, or probability density function.

For this processus, the spectral signature of each pixel gets matched with the training signatures and the image is classified accordingly was performed (Japan Association of Remote Sensing, 1996)

2.2.3 Post-processing

In this step, we used ArcGIS software package to calculate area change between the results of the classifications obtained. Erdas software was used also to calculate Accuracy and statistical kappa. Based in the method using by Islam et al. (2017). The magnitude change of this study area was calculate using the equation (2):

$$\text{Magnitude} = \text{magnitude of the new year} / \text{magnitude of the previous year} \quad (2)$$

The Percentage change and Annual rate were obtained using equation (3) and (4):

$$\text{Percentage Change} = \text{Magnitude of Change} * 100 / \text{Base Year} \quad (3)$$

$$\text{Annual Rate Change} = \text{Final Year} - \text{Initial Year} / \text{Interval of Years} \quad (4)$$

3. RESULTS AND DISCUSSION

3.1 Land use land cover identification from 1986-2017

The Landsat images classified obtained after the Pre-processing of the different periods of 1986, 1999 and 2017 are showing in Fig.2. The aerial distribution of various land use land cover classes for the year 1986, 1999, and 2018 in between different time frames are shown in Table 1. During the classification, four (4) category of classes of land use land cover were obtained in the study including: (1) Built up, (2) Vegetation, (3) Bare soil/ rock and (4) water.

LULC Class	Land use/cover for 1986		
	Count	Area (km ²)	%
Built Up	39234	35.31	14.16
Vegetation	70252	63.23	25.36
Barren Land	151908	136.72	54.83
Water	15634	14.07	5.64
Total	277028	249.33	100
Land use/cover for 2003			
	Count	Area (km ²)	%
Built Up	46224	41.60	16.69
Vegetation	82639	74.37	29.83
Barren Land	132609	119.35	47.87
Water	15556	14.00	5.62
Total	277028	249.32	100
Land use/cover for 2020			
	Count	Area (km ²)	%
Built Up	96443	86.80	34.81
Vegetation	74178	66.76	26.78
Barren Land	90232	81.21	32.57
Water	16175	14.55	5.84
Total	277028	249.32	100

Table 2. Land use/ cover distribution of Bangui from 1986 - 2017.

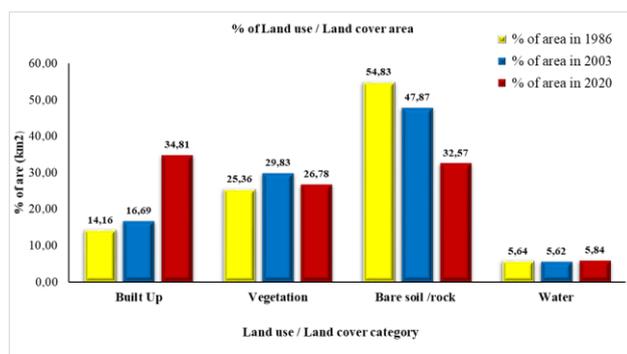


Figure 2. Special distribution of Land use land cover in Bangui from 1986-2017.

3.2 Land use/land cover classified of Bangui in 1986

In order to know the relationships between the different images, it is necessary to present the classification result period by period. To do this, we will start with the result of the Landsat TM5 image obtained in 1986. In this period 4 different categories of land use have been classified (Fig.3). The largest area (km²) was occupied by Bare soil / rock (136. 72 or 54.83%), followed by vegetation (63.23 or 25.36%), after Built up (35.31 or 14.16%) and finally the water (14.07 or 5.64%) table1.

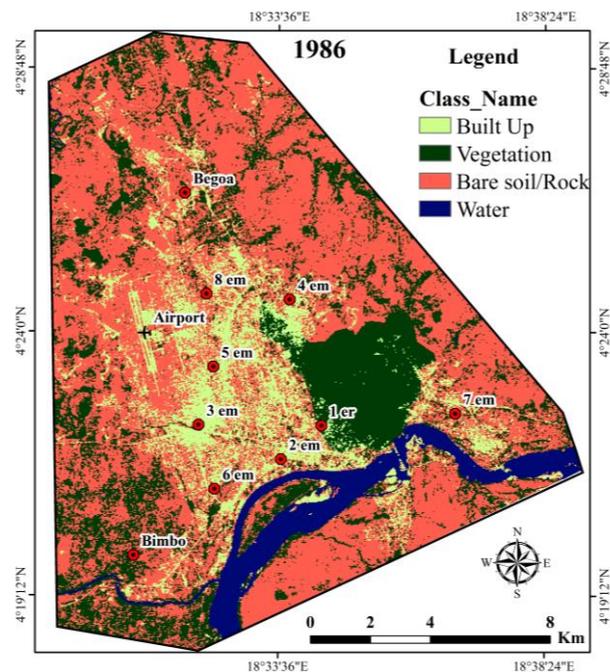


Figure 3. Land use land cover map of Bangui 1986.

3.3 Land use land cover of Bangui in 2003

As in 1986, the classification obtained from Landsat 7 ETM+ of the year 2003 also includes 4 large classes (Figure 4). Depending on the size of different classes, we found that there is a small change in the surface area of these classes. But the largest area (km²) is still occupied by the bare soil / rock (119.15 or 47.87%), after comes the Vegetation (74.37, or 29.83%) then the Built up (41.60 or 16.69 %) and finally the Water (14 or 5.62%) table1.

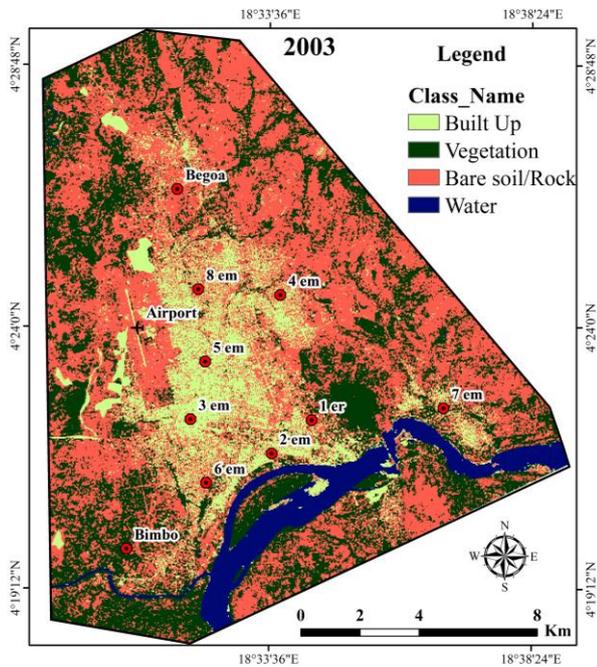


Figure 4. Land use land cover map of Bangui 2003.

3.4 Land use land cover pattern of Bangui in 2020

The year is marked by political stability in the Central African Republic. This stability is characterized above all by a migration of the population to the capital Bangui. This migration also has an effect on urbanization. As for the years 1986 and 1999, we obtained 4 major class categories after the Landsat 8 OLI classification (Fig.5). During this period, we noticed an increase in the area occupied by the Built up (86.80 or 34.45%), Bare soil / rock (81.21 km², or 32.57%), the Vegetation (66.76 or 26.78%) and the Water (14.55 km², or 5.84%) Table1.

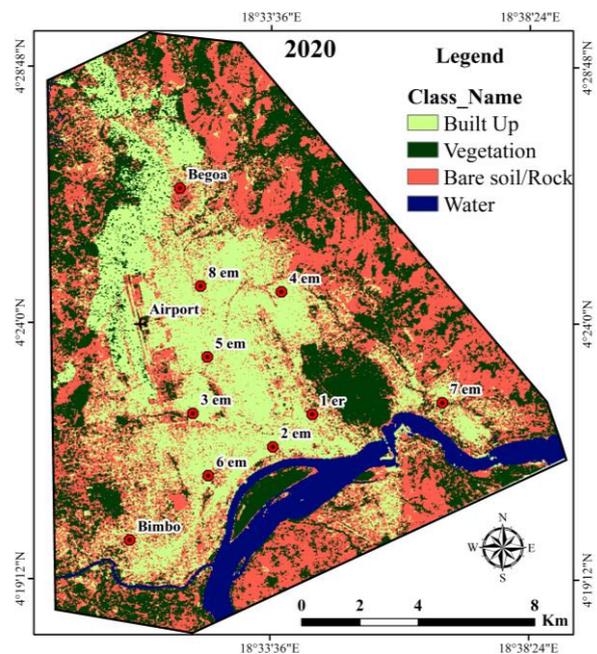


Figure 5. Land use land cover map of Bangui 2020.

3.5 Land use/cover change assessment of Bangui in the period of 1986 – 2020

The Figure 6 and Table 2 present the results of the different changes in class categories during the period 1986-2020. We used the formula (1) presented in the methodology to evaluate the change in the case of this research. We found low and high proportions of changes between the years 1986-20120 (Table 2) (Figure 6). The result shows that between 1986-2003, there was a small increase of Built up (+ 17.82%), a sharp increase in vegetation (+ 17.62%) and a decrease of Bare soil (-12.70%) and that of Water (-0.5%). Between 2003-2020, we saw a strong increase of Built up (+ 108.64%), and that of Water (+ 3.98%), and decrease in the area of Bare soil / rock (-31.96%) and that vegetation (-10.24%). Finally, the scenarios between 1986-2020 shows a very good change between the different classes: The Built Up increased by + 145,81%, for a rate of (166.09), the vegetation also increased by 5.59% or a rate of (11.40) and a slight increase in water of 3.46%, or a rate of 1.57. By cons bare soil / rock recorded a sharp drop of -40.60% for a rate of (179.06).

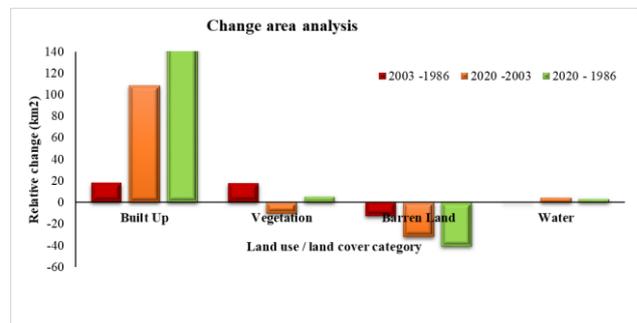


Figure 4. Assesment Change in land use land cover in Bangui during 1986 – 2020.

LULC Class	2003 -1986		
	Area (km ²)	Change area	Rate
Built Up	6,29	17,82	48,39
Vegetation	11,15	17,63	85,76
Barren Land	-17,37	-12,70	-133,61
Water	-0,07	-0,50	-0,54
	2020 - 2003		
	Area (km ²)	Change area	Rate
Built Up	45,20	108,64	603,57
Vegetation	-7,61	-10,24	-56,88
Barren Land	-38,14	-31,96	-177,54
Water	0,56	3,98	22,11
	2020 - 1986		
	Area (km ²)	Change area	Rate
Built Up	51,49	145,81	166,09
Vegetation	3,53	5,59	11,40
Barren Land	-55,51	-40,60	-179,06
Water	0,49	3,46	1,57

Table 3. Land use/cover change assessment of Bangui in the period of 1986 - 2020.

3.6 Accuracy Assessments and Kappa statistics

Accuracy given a set of data points from repeated measurements of the same quantity, the set can be said to be precise if the values are close to each other, while the set can be said to be accurate if their average is close to the true value of the quantity being measured. An accuracy assessment for the supervised land use classification was done using ERDAS IMAGINE software (version 2014). From the classifier 54 points were generated randomly for 1987, 2003 and 2020 supervised images. The accuracy assessments for both images are shown in Table 3. Cohen's kappa coefficient (κ) or kappa statistic is a statistic which measures inter-rater agreement for qualitative (categorical) items (Landis and Koch, 1977; Islam et al., 2017). The highest accuracy was for 1987 year (92.50%) and the lowest for 1999 year (82.50%). The overall accuracies and overall Kappa statistics achieved were 92.5 %, 82.5 and 87.5 %, and 0.90, 0.87 and 0.83 for 1986, 2003 and 2020 images respectively.

LULC Class	1986		2003		2020	
	PC	UA	PC	UA	PC	UA
Built up	100.0	100	88.8	80.0	81.8	90.0
Vegetation	76.9	100	88.8	80.0	76.8	100
Bare soil/rock	100.0	70.0	70.0	70.0	100.0	70.
Water	100.0	100	91.9	100.	100.0	90.
Overall Accuracy	92.50		82.50		87.50	
Overall Kappa	0.90		0.77		0.83	

PC: Producer's Accuracy;
UA: User's Accuracy.

Table 4. Summary of classification accuracies (%)

This present study demonstrates the Assessment of land use land cover change of Capital of Central African Republic (CAR). This research illustrates how LULC change between 1986 and 2020 in Bangui city. The methodology and the different processes adopting were allowed to correlate the different classes obtaining from satellite images. The increase in the population of Bangui corresponds more to an increase of Built up obtained in this study. The absence of previous work in this area has not allowed us to discuss the result obtained and the work that has already been done. But this research will be a starting point for future research in CAR in general and especially in large cities in particular.

4. CONCLUSION

The present study evaluates the Landsat image potential for land use land cover of the city of Bangui during 1986-2020. During this research, we can conclude that: firstly, there is a lack of previous local work on Bangui City and secondly, the use of different Landsat images shows very important and reliable results and this can be studied also on a large scale. According to the results obtained, most of the city of Bangui is dominated by a Bare soil/ rock. And during the period 1986-2020, there is an increase of Built up of over 145% and that of

Vegetation by 5%. This means that bare soil / rock has become Built up and vegetation. In Addition, Although Accuracy and Kappa statistics shows satisfactory results but there are still some problems to correct. We recommended that a very precise study be done in the said domain using several types of images or several periods or other methods to improve this result. The local authorities should encourage studies of this kind to contribute to the development of research in the Central African Republic. Because we must remember that this is the first time that a study of this kind has been made in this locality.

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