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

M. Traore 1, *, C. P. Ndepete 2, R.L. Zaguy-Guerembo 3, A. B. Pour 4

1 University of Çukurova, Department of Geological Engineering, Sarçam, Adana, Turkey - matraba77@gmail.com
2 Bangui University, Faculty of Sciences, Department of Earth Sciences, Bangui, Central African Republic - ndpetecyrille@yahoo.fr
3 Bangui University, Department of Geography, Bangui, Central African Republic - rgzaguy@gmail.com
4 Korea Polar Research Institute (KOPRI), Songdomirae-ro, Yeonsu-gu, Incheon 21990, Republic of Korea - beiranvand.amin80@gmail.com

Commission VI, WG VI/4

KEY WORDS: Land use/Land cover, Bangui city, Remote Sensing, GIS, Classification

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; Atifi 2011; Devan et al., 2012; Xindong et al. 2014; Hegazy and Kaloop, 2015; Sinha et al., 2016; Islam et al., 2017; Sérgio and Mace, 2019; Ma et al., 2019; Jazouli et al., 2019). Land Use Land Cover changes analysis is 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 very 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 Béoua in the north and Bimbo in the east. Bangui is located between 4°21′21″ 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 °C 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.

* Corresponding author Tel: +905312945444; Email address: matraba77@gmail.com

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-1651-2020 | © Authors 2020. CC BY 4.0 License.
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 Landsat 7 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 $L_k$ is defined as the posterior probability of a pixel belonging to class $k$.

$$L_k = P(k|X) = P(k) * P(X|k) / P(i) * P(X|i)$$

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):

$$Magnitude = magnitude of the new year / magnitude of the previous year \ (2)$$

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

$$Percentage \ Change = Magnitude \ of \ Change \ * 100 / Base \ Year \ (3)$$

$$Annual \ Rate \ Change = Final \ Year - Initial \ Year / Interval \ of \ Years \ (4)$$
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  | Count | Area (km²) | %     |
|-------------|-------|------------|-------|
| 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   |

Table 2. Land use/cover distribution of 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.](image)

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. Special distribution of Land use land cover in Bangui from 1986-2017.](image)
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 km² 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.

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).

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

| LULC Class | 2003 -1986 | 2020 - 2003 | 2020 - 1986 |
|------------|------------|-------------|-------------|
|            | Area (km²) | 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       |
|            |            |              |             |
|            | Area (km²) | 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       |
|            |            |              |             |
|            | Area (km²) | 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        |
### 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 PC | 1986 UA | 2003 PC | 2003 UA | 2020 PC | 2020 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   | 70.0    |
| Water            | 100.0   | 100     | 91.9    | 100.0   | 100.0   | 90.0    |
| 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 Assement of land use land cover change of Capital of Central African Republic (CAR). This research ilustrates 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.

### REFERENCES

Aafat El Jazouli, Ahmed Barakat, Rida Khellouk, Jamila Rais, Mohamed El Baghdadi., 2019. Remote sensing and GIS techniques for prediction of land use land cover change effects on soil erosion in the high basin of the Oum Er Rbia River (Morocco). Remote Sensing Applications: Society and Environment 13. 361–374.

Afify, H.A., 2011. Evaluation of change detection techniques for monitoring land cover changes: a case study in new Burg El-Arab area. Alexandria Eng. J. 50, 187–195.

Balthazar, V., Vanacker, V., Molina, A., Lambin, E.F., 2015. Impacts of forest cover change on ecosystem services in high Andean mountains. Ecol. Ind. 48, 63 –75. https://doi.org/10.1016/j.ecolind.2014.07.043.

Chen, X., 2002. Using remote sensing and GIS to analyse land cover change and its impact on regional sustainable development. International Journal of Remote Sensing, 23(1), 107–124. Copyright © 1996 Japan Association of Remote Sensing.

Dewan, A.M.; Kabir, M.H.; Nahar, K.; Rahman, M.Z., 2012. Urbanisation and environmental degradation in Dhaka Metropolitan Area of Bangladesh. Int. J. Environ. Sustain. Dev. 11,118–147.

Duncan, J. S. D., Franklin, J.,1993. Assessing the relationship between spectral vegetation indices and shrub cover in the Jornada Basin, New Mexico. International Journal Remote Sensing 14(18): 3395–3416.

Ebrahim, E., Mohamed, A., 2017. Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. Environ. Syst. Res. 6 (4), 1 –13.

ENVIL., 2009. Atmospheric Correction Module: QUAC and FLAASH User’s Guide, Version 4. 7. ITT Visual Information Solutions, Boulder, CO.

Geiger, R., 1954. “Klassifikation der Klimate nach W. Köppen” [Classification of climates after W. Köppen], Landolt-Börnstein – Zahlenwerte und Funktionen aus Physik, Chemie, Astronomie, Geophysik und Technik, alte Serie. Berlin: Springer. 3. pp. 603–607.

Hurni, H., Kebede, T., Gete, Z., 2005. The implications of changes in population, land use, and land management for surface runoff in the Upper Nile Basin area of Ethiopia. Mt. Res. Dev. 25 (2), 147–154.
Ibrahim, R. H., Mosbeh, R. K., 2015. Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate, Egypt. International Journal of Sustainable Built Environment, 4, 117–124.

Islam K., Jashimuddin M., Nath., and Nath T. K., 2017. Land use classification and change detection by using multi-temporal remotely sensed imagery: The case of Chunati wildlife sanctuary, Bangladesh. The Egyptian Journal of Remote Sensing and Space Sciences 21 (2018) 37–47.

King, R.S.; Baker, M.E.; Whigham, D.F.; Weller, D.E.; Jordan, T.E.; Kazyak, P.F., Hurd, M.K., 2005. Spatial considerations for linking watershed land cover to ecological indicators in streams. Ecol. Appl., 15, 137–153.

Kiran, P., Himlal, B., Santosh, P., Bhandari, Anil, B., Rodney J. K., 2019. Spatial assessment of the impact of land use and land cover change on supply of ecosystem services in Phewa watershed, Nepal. Ecosystem Services 36. 100–895.

Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241.

Lin, C., Wu, C.-C., Tsogt, K., Ouyang, Y.-C., Chang, C.-I., 2015. Effects of atmospheric correction and pansharpening on LULC classification accuracy using WorldView-2 imagery. Inf. Process. Agric. 2, 25–36.

Lambin, E.F., 1997. Modelling and monitoring land-cover change processes in tropical regions. Prog. Phys. Geogr. 21, 375–393.

Landis, J.R., Koch, G.G., 1977. The measurement of observer agreement for categorical data. Biometrics, 159–174.

Temesgen, G., Taffa, T., Mekuria, A., Abeyou, W., Worqlul., 2018. Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. Science of the Total Environment 619–620. 1394–1408.

Tiantian M. Xiaowen, L., Junhong. B., Shiyuan, D. Fangwen Z. Baoshan C., 2019. Four decades' dynamics of coastal blue carbon storage driven by land use/land cover transformation under natural and anthropogenic processes in the Yellow River Delta, China. Science of the Total Environment 655,741–750.

Twumasi, Y.A., Merem, E.C., 2005. GIS applications in land management: The loss of high quality land to development in Central Mississippi from 1987–2002. Int. J. Environ. Res. Public Health, 2, 234–244.

Xindong, D., Xiaobin, J., Xilian, Y., Xuhong, Y., and Yinkang Z., 2014. Spatial Pattern of Land Use Change and Its Driving Force in Jiangsu Province. Int. J. Environ. Res. Public Health. 11, 3215-3232.

Sérgio, G., Milheiras, Georgina M., Mace., 2019. Assessing ecosystem service provision in a tropical region with high forest cover: Spatial overlap and the impact of land use change in Amapá, Brazil. Ecological Indicators 99. 12–18.

Singh, A., 1989. Review article digital change detection techniques using remotely-sensed data. Int. J. Remote Sens. 1989, 10, 989–1003.

Zhao, H. M., Chen, X. L., 2005. Use of normalized difference bareness index in quickly mapping bare areas from TM/ETM+. Geoscience and Remote Sensing Symposium, 3(25–29), 1666–1668.