PREDICTING URBAN LANDUSE CHANGE IN PORT HARCOURT METROPOLIS, RIVER STATE, NIGERIA USING CA-MARKOV MODEL

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ABSTRACT

LandSat Images of 1986/87, 2002 and 2018 obtained from the Archives of the United States Geological Survey were used to analysed and predict urban landuse change in Port Harcourt metropolis. Images were supervised and classify into five classes, built- up area, agriculture/cleared land, bare-soil, forest and water using the maximum likelihood classification algorithm. The results revealed that built-up area increases from 7.93% in 1987 to 12.38% in 2002 and 22.47% in 2018, Agriculture/cleared land also increases from 20.92% in 1987, 25.60% in 2002, and 34.18% in 2018. Between 1986/87, 2002 and 2018, built-up area and agricultural/cleared land use increased and gained more persistence than other land use which showed a decline and loss in persistence due to rapid urban expansion and development in the study area. CA-Markov model was used to predict urban land use change for the next 16 years 2018-2034, the predicted result revealed that built-up area will increase from 22.47% in 2018 to 29.0% in 2034 and agriculture/cleared land will increases from 34.18% to 37.0% in 2034. More urban landuse with potential expansion in built-up area and agriculture/cleared land over forest, bare-soil and water in the cities. The study therefore recommended that suitable landuse control measure should be put in place and urban dwellers be involved in land use planning process and implementation of laws.

1 INTRODUCTION

Urban development is a universal socio –economics phenomenon taking place around the world this process has brought about the anthropogenic forces that changes the fundamental landscape pattern around the globe and affect the physical dimension of the environment (Lal, Kumar, & kumar, 2017). The rapid increase in population growth, especially in the developing countries of the world has brought about an increase in the rate of urbanization (Adeoye, 2012) and a consequent growth in the cities around the world this has led to drastic change in land use. Land use change is a key component of research in environmental management worldwide. (Essien & Cyrus , 2019). In Nigeria more especially the state capitals are struggling with rapid urban growth and development, and this has plays a major role in landuse change in the country. (Oluseyi, 2006).

According to the United Nations (UN, 2014), the world is experiencing urban growth at an unprecedented rate, nearly half of the world's population resides in cities, this number is expected to increase to 69.6 % in the next 30 years (Yuanbin, Zhang, Wenbin, Chen, & Wang 2012). Urban development is often correlated with economic growth and is considered a sign of economic liveliness (Yuanbin, Zhang, Wenbin, Chen, & Wang 2012). Ade and Alofabi (2013) noted that urban areas are monopolies of innovation, employment, and production attracting people to them. Consequently, large urban populations are putting a strain on the already fragile urban ecosystems resulting in environmental degradation, land fragmentation, and loss of ecosystems and ecosystem services. According to Adeyemo and Arokoyu, (2002) landuse planning aims at organizing various landuse to secure maximum economy and convenience for the inhabitants is becoming a huge challenge in the developing world. The study of urban landuse and urban development is very important to have proper planning and utilization of natural resources and their management. One of the critical concerns of the world today is on urban landuse change because of the consequences they have on weather and climate, surface run-off in relation to erosion and flooding, ecological biodiversity, socio-economic and health (Lambin , Geist, & Lepers ,2003). This is largely because landuse change has considerable effects on bio-physical, bio-geophysical, biogeochemical, hydro-meteorological processes (Ndabula , Averike, Jidauna, Abaja, Oyatayo, & Iguisi, 2013). Given the fact that the dynamic process of urban development with its temporal–spatial dimensions cannot be prevented, prediction of future urban land use change would be applicable as one of the planning tools and policies to overcome the problems arising from rapid growth and development of urban areas, and to reach land use stability, understanding about interactions between the natural and man-made environments and finally the goals of sustainable urban development. Land use and land cover is driven by a variety of socio-economic, economic, political, cultural, technological and bio-physical factors (De Sherbinin, 2002). The quest and strive toward industrialization, technological innovations and the drive to modernism have resulted to modification and change in landuse in a region.

In recent years, rapid and unprecedented growth of technologies such as remote sensing (RS) and geographic information systems (GIS) and their use in urban and environmental planning have resulted in both the formation and presentation of spatial modeling methods as a decision support tool, such as cellular automata, neural networks and statistical models (Behera, Borate, Panda, Behera,& Roy, 2012). These models are capable of presenting a quantitative tool to assist in making decisions for urban and environmental planning, capability management and for assessing the suitability of land for development (Nouri,Gharagozlou, Arjmandi, Faryadi, &Adl, 2012) . Numerous studies have revealed that the CA–Markov model, which efficiently matches with GIS and RS, is able to devise an appropriate approach in dynamic temporal and spatial prediction of land use changes (Guan, Li, Inohae, Su, Nagaie, & Hokao, 2011.) Among all the numerous developed model Cellular Automata and Markov chain Model is most accepted model for the predicting urban landuse patterns. The two techniques was used in this study to predict urban landuse change Markov Chain Analysis and Cellular Automata Analysis. Markov

Chain Analysis is a convenient tool for modelling land use change when changes and processes in the landscape are difficult to describe. A Markovian process is one in which the future state of a system can be modelled purely on the basis of the immediately preceding state. Markov Chain analysis describe land use change from one period to another and use this as the basis to project future changes (Falahatkar , Soffianian, Ziaee, & Nadoushan, 2011). This is accomplished by developing a transition probability matrix of land use change from time one (T1) to time two (T2), which will be the basis for projecting a later time period. A hybrid Markov-Cellular Automaton (M-CA) model is developed which models both spatial and temporal changes(a) the Markov process controls temporal dynamic among the cover types through the use of transition probabilities (Thomas Houet and Laurence2009), (b) spatial dynamics are controlled by local rules through a CA mechanism which considers several factors such as Cell State: State of cell out of the present classes, Contiguous neighbourhood: The cell adjacent to a particular cell, Transition rule: Define the dynamics of the area in the mentioned time period and the Temporal space: time steps considered in the mechanism (Sandeep et. al 2010).

Port Harcourt City is characterized by remarkable urban growth in, expansion and developmental activities which has resulted in increased land use consumption and alteration of the earth surface. The increasing concern for the management of natural resources in recent times has been necessitated by the increase in demographic pressure and its associated anthropogenic activities which have led to serious environmental stress and ecological instability. The outcome of the natural and socio-economic factors of landuse in the city of Port Harcourt calls for an accurate investigation in the causes, processes and rate of landuse change in the metropolis.

During the last quarter of the twentieth century, Port Harcourt experienced tremendous structural transformation due to population and economic growth and development of its transportation and communication systems and the impact of globalization (Obinna, Owei & Okwakpam, 2010). Like many cities in Nigeria, Port Harcourt has recorded rapid growth in population and aerial spread. From an estimated population of 500 in 1915 it grew to 30,200 in 1944. By 1963, its population was 179,563 and by 1973 it has reached 231, 532 persons. The Port Harcourt municipality's population was given as 440,399 by the 1991 national census (Derefaka, 2001). The 2006 national census show this population is more than a million (Obinna, Owei & Mark, 2010). In terms of its physical size, the city grew from 15.54 sq. km in 1914, to a metropolis covering an area of 360 sq. kilometers in the 1980s. Urban development is denser on the corridors determined by geographic thresholds and major transportation connections. Port Harcourt as a result of population increase and economic growth spreads to the periphery as in the other metropolitan cities. However, this decentralization is not realized with an integral and regional planning but with patchwork of partial plans. This causes negative effects on urban environment, forests, fertile agricultural land and cultural values are threatened. This kind of sprawling process creates a settlement pattern that increases the costs of infrastructure. Urban development dynamics of Port Harcourt has been very rapid (Wizor, 2012), physically spread has occurred in both a south – easterly direction and a northerly direction. To the south, growth was through marshland colonization in squatter settlements locally called "waterfronts". The Port Harcourt urban fringe currently stretches to Iriebe, Eleme, Elelewon Rukpoku, Woji, Choba, Rumokwurusi and Onne (Wizor, 2012). Much of this growth is unplanned and unregulated (Owei, Ede, Obinna & Akarolo, 2008). As part of its efforts to manage the city's growth, the Rivers State Government in 2009 established the Greater Port Harcourt City Development Authority with jurisdiction covering Port Harcourt city and Obio Akpor Local Government Areas (LGA) and parts of eight other local government areas.

It covers an area of approximately 1,900 square kilometers (40,000 hectares of land) with a projected population of about two (2) million people (GIBB, 2009). Rapid urban development and increasing land use changes due to increasing population and economic growth is being witnessed in Port Harcourt and cities in other developing countries. The measurement and monitoring of these land use changes are crucial to understand urban development dynamics over different spatial and temporal scales. Today, with rapid urbanization, there is increasing pressure on land particularly in the metropolitan cities. The pattern of land use in the area is dynamic and changes from rural land use to urban land use over short periods of time and distance. This paper attempts to predict urban landuse change of Port Harcourt metropolis using a CA–Markov model, and the analysis of temporal and spatial changes of its landuses from 1986 to 2018 was carried out using satellite imaging Geographic Information Systems (GIS) to ensure that the desire for efficient urban planning is achieved.

2 Materials and Methods

2.1 Study Area.

The Study Area Location Port Harcourt metropolis is located between Latitude 4°45'N and Latitude 4°55'N, and Longitude 6°55'E and Longitude 7°05'E in Rivers State. It is a city in the Niger Delta region of Nigeria. The city lies at the mouth of River Bonny in Rivers State. It is located at about 25 km from the Atlantic Ocean and is situated between the Dockyard creek/Bonny River and the Amadi creek. It lies at an average altitude of about 12 m above mean sea level. Port Harcourt metropolis spans over two local government areas (LGAs) viz Port Harcourt and Obio/Akpor (Figure 1). The study area lies within the Koppen Tropical Rainy climatic zone of the Koppen classification (Koppen, 1936). Here, the average temperature for every month is above 18°C, and there is adequate moisture in virtually all the months. Port Harcourt metropolis experiences two seasons, that is, dry and rainy seasons. Temperatures over Port Harcourt metropolis are constantly high with a mean maximum of about 34°C and a mean minimum of about 21°C. The highest temperatures are recorded between the months of April and October.

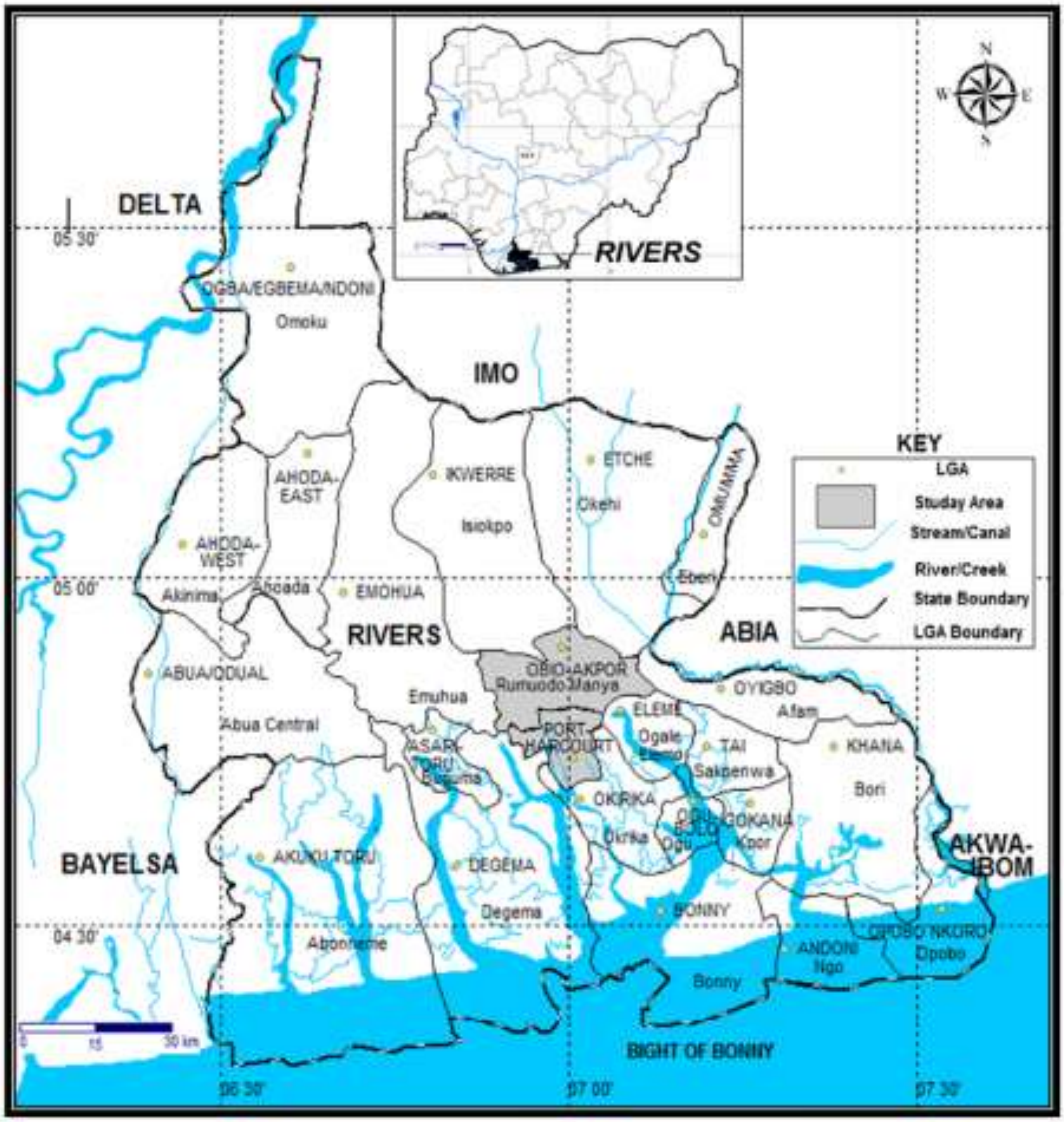


Figure 1. Study Area.

2.2 Data and Processing

To analysed urban development on land-use change in the study area, free Landsat images of 1986/1987, 2002, and 2018 15, 16 years intervals were obtained from the archives of the United States Geological Survey (USGS) for the study area. The satellite images were utilized with a spatial resolution of 30m, a major issue with remote sensing images of the study area is cloud cover, this is because many parts of the study area experience all-year-round rainfall this makes it difficult to obtain useful cloud-free image scenes (Kuenzer, Van baijma, Gessner, & Dech, 2014), in the spite of this difficulty dry season and cloud-free images were used to avoid the effect of seasonal variation (Belay, & Mengestu 2019) the dry season is mostly considered the best period for analysis, as the difference croplands and natural environment are the best marked. All the images acquired were within December, January, and February of 1986/1987, 2002, and 2018. This was to ensure that differences in the images were minimal.

The satellite image was processed and analysed using ENVI 5.1. (Environmental for Visualising Images) software. To relate data to the true biophysical environment several sub-processes were undertaken which include mosaicking, geometrical correction, atmospheric correction, and image enhancement. All acquired satellite images were corrected before analyses and improve image quality also the satellite datasets were projected to the Universal Transverse Mercator map projection system and Datum of the world Geodetic system 84(WGS84) ensuring consistency between datasets during analysis.

A supervised image classification method was employed using the Maximum Likelihood method in classifying the images. The pixel-based supervised image classification algorithm was used to produce land use maps of the study area supervised image classification was recommended to yield good results.

Five land use categories were considered in the image classification, the land use categories are water body, bare soil, forest, agricultural, and built-up/ residential land use. A subset of data collected from the field survey was combined with existing maps and goggle earth image data to assess the accuracy of maps derived from analysis. Overall accuracy was performed to validate the classification using transition matrices.

Change detection analysis is an important application in remote sensing techniques because of its capability to acquire an image on a global scale. Change detection is the process of identifying the difference in land use and land cover at a different time interval (Singh, 1989)

The general goal of change detection in remote sensing includes identifying the geographical location, recognising, quantifying the type of change, and finally assessing the accuracy results. There are so many approaches for analyses of changes in the landscape for this work post-classification comparison method, (PPC) was applied in this study, it is the most efficient method of change detection that identifies changes between pre-determined classes, PCC has been found to offer precise indications of land-use change and frequently rated among numerous another method (Mishra, Shrivastava, & Dhurvey, 2017).

The Cellular Automata -Markov Model

Cellular Automata and Markov Chain Model is accepted for modeling and predicting urban land-use change. In this research work, the two methods were used to predict the land-use change in the study area.

The Markov Chain analysis is a tool for modeling land-use change when changes and processes in the landscape are difficult to describe, a Markovian process is a simple stochastic process in which the distribution of future states depends only on the present state and not the how it arrived in the present state, (Jain, Siddiqui, Trwari, & Shashi 2016). This can be done by developing a transitional probability matrix of the land-use change from one point in time T_1 to T_2 which form the basis for the projection for another point in time T_3, however, the Markov Model does consider the spatial characteristic of the distribution of transition probabilities of landscape state (Wu&Silva 2010) for this case a combination of Markov-Cellular Automaton (M-CA) model was developed to help add and solve problems of spatial and temporal land-use changes.

This research work utilizes the Markov chain model and a CA filter, jointly called CA–Markov, to predict and simulate the directions of future urban development in the study area. This model was based on using and evaluating land use layers of previous years and predicting the spatial distribution of land uses in the future using GIS (Wu & Silva, 2010). The simulated model of land-use changes developed in IDRISI Software. This model comprises two main stages:

(1) Calculating conversion probability, including the conversion probability matrix, Conversion area matrix, and layers of conditional probability, using Markov chain analysis, and

(2) Spatial specification of land use coverage simulated based on CA spatial operator

In the CA model, the land use map in 1986/87 and probability matrix from 1986/1987 to 2018 from the basic map.

In the first step, land use maps of 1986/1987, 2002, and 2018 was extracted from the satellite images of TM, ETM+, and OLI TIRS Likewise, the layers related to the years 1986/87 and 2018 was selected to be input into the model, to calculate matrices of conversion areas and conversion probabilities using Markov Chain Analysis. In the second step, the conversion matrix was applied to provide a set of conditional probability data for the five determined main uses, i.e., built-up, agricultural, bare soil, forest, and water bodies, from 1986 - 2018. The probability data set was derived from the result calculated from the prediction of the two old and new (1986/87 and 2018) land use layers.

In the final step, to Model the urban land use map for 2034, the land use map of 2018 was set as a base map, the matrix conversion probabilities of 1986/1967–2018 and conditional probability data were integrated using the CA spatial operator in IDRISI based on Markov Chain Analysis and Multi-Criteria Evaluation (MCE).

3 RESULTS AND DISUSION

3.1 Spatial Pattern of Land use change

In examining the spatial pattern of land use change, this was done by computing the total area gain and loss persistence , the total change, swap change and absolute value of net change for each time interval. (1986/1987, 2002, and 2002, 2018) using the cross-tabulation of the land use map of the study area following the method describe by *Pontius et al*. (2014, 2012).

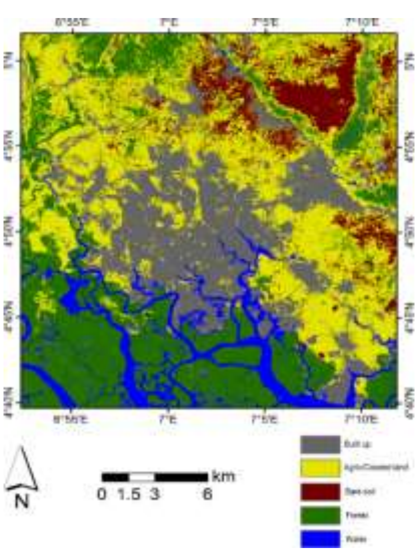


Fig 1. Land use pattern of Port Harcourt 1986.

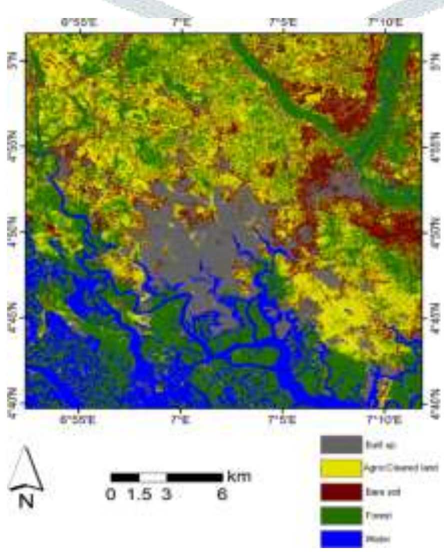


Fig 2. Land use pattern of Port Harcourt 2002

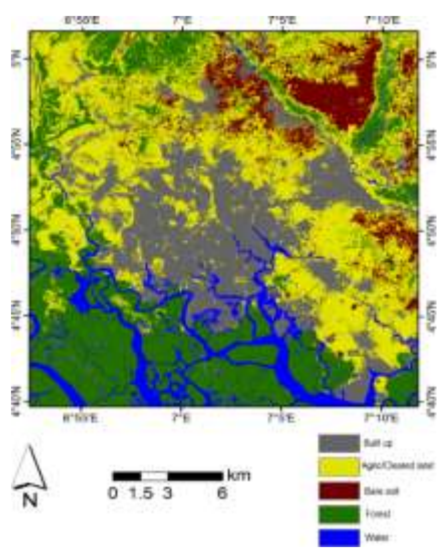
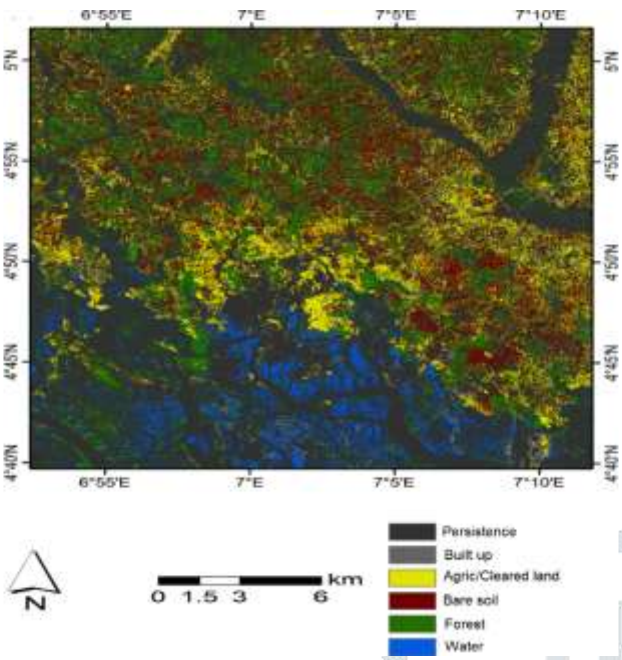


Fig 3. Land use pattern of Port Harcourt 2018.



. **Fig 4. Port Harcourt loss - persistence 1987 and 2002**

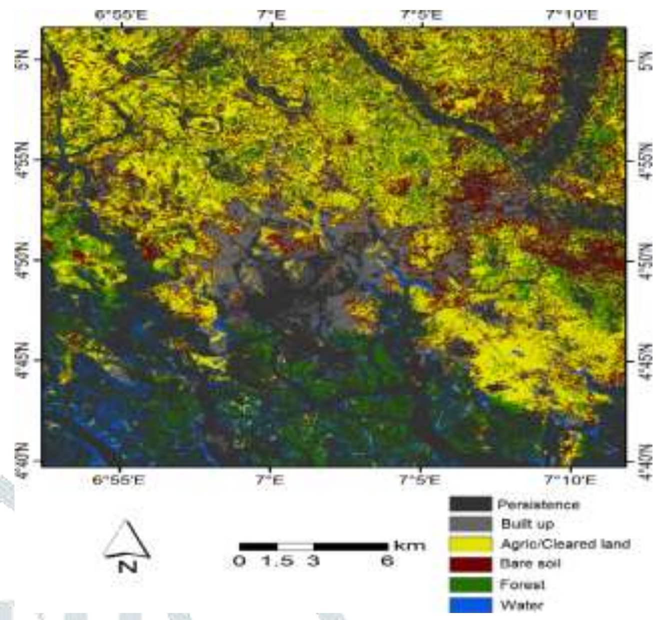


Fig 5.Port Harcourt Gain - persistence 1687 and 2002

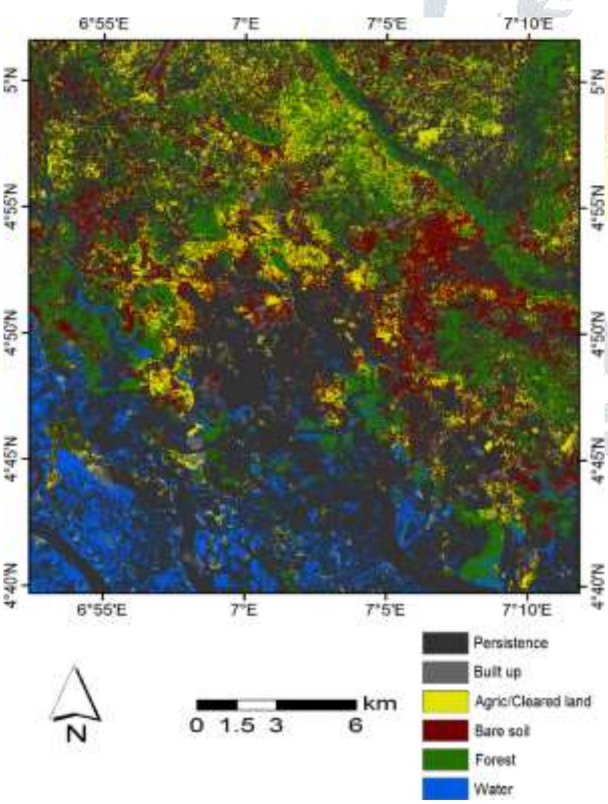


Fig 6. Port Harcourt loss- persistence of 2002 and 2018

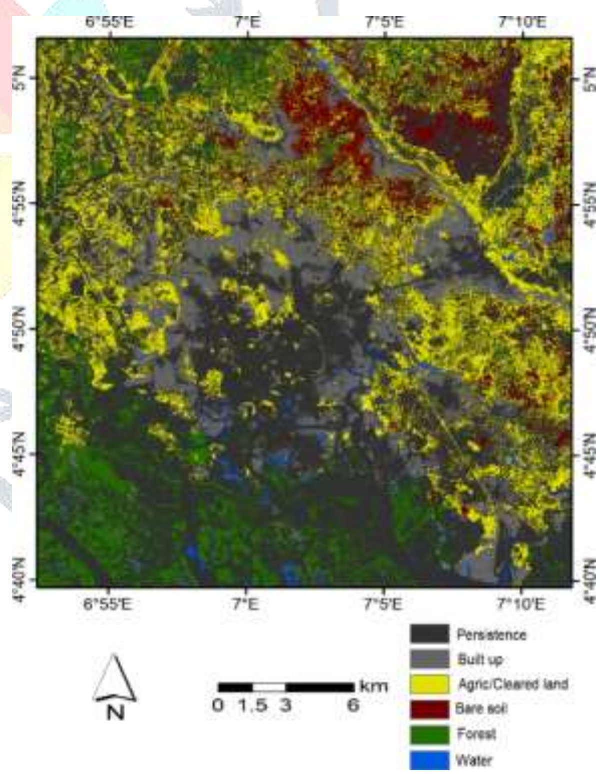


Fig 7. Port Harcourt Gain - persistence 2002 and 2018

Table 1. Land use pattern of Port Harcourt 1987 and 2002

Land Use categories	Total area covered in 1987 km^2	Percentage of total area covered in 1987	Total area covered in 2002 km^2	Percentage of total area covered in 2002	Percentage of total area Gain	Percentage of total area Loss	Total change of the area (Gain + Loss) (%)	Absolute value of net change (Gain – Lose) (%)	Swap (total change – absolute valve of net change) (%)
Built up	131.8248	7.93	205.4034	12.38	7.02	2.57	9.59	4.45	5.14
Agriculture/cleared land	347.1417	20.92	424.7073	25.60	17.30	12.62	29.92	4.68	25.24
Bare soil	315.6939	19.03	267.3369	16.10	9.67	12.59	22.26	2.92	19.34
Forest	612.6003	36.92	528.6132	31.85	10.00	15.07	25.07	5.07	20.00
Water	252.378	15.21	233.2779	14.07	2.70	3.84	6.54	1.14	5.40
Total	1659.6387	100.0	1659.6387	100.0	46.69	46.69	46.69	18.26	75.12

Table 2: Land use pattern of Port Harcourt 2002 and 2018

Land Use categories	Total area covered in 2002 km^2	Percentage of total area covered in 2002	Total area covered in 2018 km^2	Percentage of total area covered in 2018	Percentage of total area Gain	Percentage of total area Loss	Total change of the area (Gain + Loss) (%)	Absolute value of net change (Gain – Lose) (%)	Swap (total change – absolute valve of net change) (%)
Built up	205.4034	12.38	373.0446	22.47	12.50	2.40	14.90	10.10	4.80
Agriculture/Cleared land	424.7073	25.60	567.2115	34.18	19.11	10.53	29.64	8.58	21.06
Bare soil	267.3369	16.10	150.0966	9.05	4.80	11.85	16.65	7.05	9.60
Forest	528.6132	31.85	446.1534	26.89	9.75	14.72	24.47	4.97	19.50
Water	233.5779	14.07	123.1326	7.41	0.69	7.35	8.04	6.66	1.38
Total	1659.6387	100.0	1659.6387	100.0	46.85	46.85	46.85	37.36	56.34

Table 1 and 2 shows the land use distribution pattern of Port Harcourt, the total percentage of built up area covered in 1987, 2002 and 2018 are 7.93%, 12.38% and 22.47% respectively. From 1987 to 2002 Built up land use gained 7.02% persistence and lost 2.57%, with a total change of 9.59%. An absolute net change of 4.45% and a swap change of 5.14%. Between 2002 and 2018, built up gained 12.50% persistence and lost 2.40% with a total change of 14.90%, absolute net change 10.10% while swap change of 4.80% was recorded.

Agriculture/cleared land use covered a total area in percentage of 20.92%, 25.60%, and 34.18% in 1987, 2002and 2018. From 1987 to 2002, agriculture/cleared land use gained 17.30% persistence and lost 12.62%, with a total change of 29.92%, an absolute net change of 4.68% and a swap change 25.24%. Between 2002 and 2018, agriculture/cleared land use gained 19.11% persistence and lost 10.53%, with a total change of 29.64%, absolute net change of 8.58% while 21.06% of swap change was recorded.

Bare soil covered a total area percentage of 19.03%, 16.10% and 9.05% in 1987, 2002 and 2018. From 1987 to 2002, bare soil gained 9.67% persistence and lost 12.59%, with a total change of 22.26%, absolute net change 2.92% and a swap change 19.34%. Between 2002 and 2018, bare soil gained 4.80% persistence and lost 11.85%, with a total change 16.65%, an absolute net change 7.05% and a swap change of 9.60%.

Forest land use covered a total area in percentage of 36.92%, 31.85% and 26.89% in 1987, 2002 and 2018 respectively. Forest gained 10.00% persistence and lost 15.07%, with a total change of 25.07%. The absolute net change 5.07% and a swap change 20.00% was recorded. Between 2002 and 2018, forest gained persistence of 0.69% and lost 7.35%, with a total change of 8.04%, absolute net change of 6.66% and a swap change of 1.38%.

Water bodies covered a total area in percentage of 15.21%, 14.07% and 7.41% in 1987, 2002 and 2018. From 1987 to 2002, water bodies gained 2.70% persistence and lost 3.84%, with a total change of 6.54%, an absolute net change of 1.14% and a swap change 5.40%. Between 2002 and 2018, water bodies gained 0.69% persistence and lost 7.35% with a total change 8.04%, absolute net change 37.36% and a swap change of 56.34%.

The result indicate that built up and agricultural/cleared land use experienced steady increase and constant gained between 1987 and 2018. Bare soil, forest and water body recorded decreased and loss during this period. The increase in buildup and agriculture /cleared land use is due to urban expansion, construction, development and opening of new lands for urban development

3.2 Predicting Land Use change in 2034

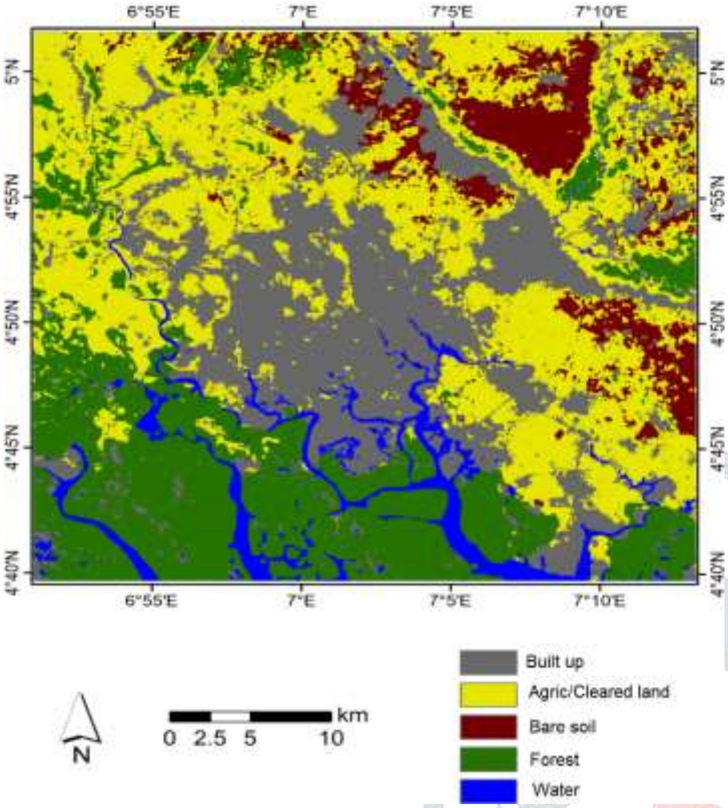


Fig 8. Predicted Land Use Map of Port Harcourt 2034.

Table 3. Predicted Land use change of Port Harcourt.

Land use class	Total area covered in 2018 (km^2)	Total area covered in %	Total area covered in 2034(km^2)	Total area covered in %
Built up	373.0446	22.47	475.51	29.0
Agriculture/Cleared land	567.2115	34.18	607.07	37.0
Bare soil	150.0966	9.05	128.01	7.7
Forest	446.1534	26.89	379.47	23
Water	123.1326	7.41	69.58	4.2
Total	1659.64	100.00	1659.64	100.00

Figure 6 showed that the projected land use/cover of Port Harcourt will gain prominent in the N/S/E/W part of the city. The proportional analysis (table 3.) showed that by 2034, built up and agriculture/cleared land will remain the most dominant land use/cover in the city of Port Harcourt while water will be the least dominant by proportion. The changes for built up area and agriculture/cleared land are represented by 6.53% for built up and 2.82% for agriculture/cleared land increase from 2018 to 2034. From table 2 it is an evident that built up and agriculture showed an increase. This indicates that there is a high probability that increasing dominant of built up area and agriculture/cleared land will continue into the future

4 Conclusions

Urban land use change is an unavoidable natural process. However rapid urban land use change caused by anthropogenic activities has led to several negative consequences. Monitoring the annual change and spatial, temporal land use change in the Port Harcourt city is an important component of urban planning and management. The city of Port Harcourt has undergone major landuse alteration between 1986-2018, the study area has experience a decline in forest, bare soil, water bodies during this period and also gain substantial increase in gain and persistence in built up area and agriculture/cleared land use, forest land, bare soil and water land use will likely continue to decrease due to population growth, and human settlement in the study area. This result has shown that the decline forest land and increase in agriculture land will lead to forest degradation and deforestation with implications on people livelihoods biodiversity and ecosystem services.

The increase of surface area covered by built up area and agriculture land use as well as decrease in the area covered by forest bare soil, water could increase the likeliness or probability of different types of natural hazards especially urban flooding which is predominant in the region. These changes in landuse is a reflection of the influence of local and national polices and human impacts on the study area which has resulted in the increased in built up and agricultural land use. Majority of the land are being converted to build up area to increase infrastructure development the major changes observed in this study requires urgent intervention from forest managers, environmentalist, decision makers and stakeholder to address.

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