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MONITORING AND PREDICTING THE LAND USE / LAND COVER TRANSFORMATIONS USING CELLULAR AUTOMATA (CA) MARKOV MODEL IN AGULU-NANKA-OKO AND EKWULOBIA GULLY EROSION COMPLEXES OF ANAMBRA STATE NIGERIA

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Abstract

The determination of land use and cover changes during long periods of time and predicting the future changes is highly important and useful for the land use managers. In this study, the land use maps in Agulu-Nanka-Oko and Ekwulobia gully erosion complexes of Anambra state south east Nigeria for four periods (1985, 1995, 2005 and 2020) were extracted and analyzed with Remote Sensing technique, using the Land-Sat Satellite Images. Then, the future land use changes are simulated for 2030 using Integrated CA-Markov Model according to the scenario of continuing current management process. Satellite Image analysis showed that between 1985 and 2020, eroded land, built up land and agricultural land increased, while vegetation and water body decreased. Vegetation and water bodies were converted to eroded land, built up land and Agricultural. The projection made by the application of CA-Markov showed that in the year 2030 the eroded land would increase significantly in the next 10 years (2030). The obtained Kappa values for the model accuracy assessment was higher than 0.8, this is an indication that the model has capacity to predict future Land use/cover changes in the study area. Thus, analyzing Land use and cover changes trends from past to near future using CA-Markov model can play a significant role in land use policy making, planning, and managing of the restricted plains especially in the proposed study area.

Keywords: CA-Markov, Land Cover, Land-Sat, Land Use, Remote Sensing

Introduction

Land is vulnerable to deterioration due to abuse and misuse by man and his activities. Similarly, land is subjected to degradation by forces of nature such as erosion, landslides, weathering, etc. It is perceived that the intense Land use land cover change can fundamentally affect the environment of a geographical region, water budget, river sedimentation, socio-economic practices, and biological diversity (Tadese, Soromessa and Bekele, 2021). Land use/land cover change is the most phenomenal change that is taking place globally on spatial and temporal scales.

Land use and cover changes (LUCCs) are among the most important changes on the land surface which have considerable influence on the environment and environmental processes (Azizi, Malakmohamadi, and Jafari, 2016). Thus, LUCCs are recognized as the main driving force of the global ecosystem change (Behera, Borate, Panda, Behera, and Roy, 2012; Zhang, Jin, Wang, Zhou, and Shu, 2015). Land use change is rooted in the spatiotemporal interaction between

biophysical and human aspects (Arsanjani, Helbich, Kainz, and Boloorani, 2013; Dubovyk, Sliuzas, and Flacke, 2011; Poelmans and Van Rompaey, 2010; Veldkamp and Verburg, 2004), which has increased in recent years due to the increasing human activities and the loss of balance between human activities and nature (Memarian, Balasundram, Talib, Teh Boon Sung, Mohd Sood, and Abbaspour, 2013; Halmy, Gessler, Hicke, and Salem, 2015).

Forest destruction, desertification, destruction of fertile agricultural lands and uncontrolled urban development are some of the phenomena that threaten the environmental balance directly and indirectly (Farsaei, 2012). These changes will consequently influence significantly some aspects such as human health, ecosystem quality and natural resources (Milà, Canals, and De Baan, 2015). Identifying LUCCs dynamics from the past to the future can be an important step towards recognizing potential effects (Azizi *et al.*, 2016).

A variety of land use modeling methods exist: Mathematical models (linear and static), systems models (stocks and flows), statistical models (regression), cellular models (cellular automata (CA), Markov chain, evolutionary models (neural networks) and modeling with an agent-based approach (Agarwal, Green, Grove, Evans and Schweik 2002; Parker, Manson, Janssen, Hoffmann, and Deadman, 2003; Subedi, Subedi, and Thapa, 2013; Al-sharif, and Pradhan, 2014). The Markov chain and cellular automata are widely used because of their bottom-up approach, simulation capability, and high flexibility (Amini Parsa, 2014; Nejadi, Jafari, Makhdoum, and Mahmoudi, 2012). Both Markov chain and cellular automata are models that are discrete in time and space. The changing Earth's surface can be monitored effectively by the application of

Remote Sensing technologies as they are equipped with Spatial, Spectral, and Temporal resolutions. Remote sensing technologies have many advantages with respect to time, cost and re-visit time. For the extraction of land use/land cover material, remote sensing has a huge data source, which at times freely available (Taati, Sarmadian, Mousavi, Pour, and Shahir, 2015). Remote Sensing techniques are distinctly used to identify land use/land cover transformations. Progress in the Science of Remote Sensing and human ability to evaluate sequential changes in the topography put to rest on the relevance of Remote Sensing (Civco, Hurd, Wilson, Song and Zhang, 2002).

According to Egboka (2004), the problems resulting from soil erosion in Agulu-Nanka-Oko and Ekwulobia gully erosion complexes are so many. Every year new erosion sites develop while the existing ones' increase. Hence, there is need to assess the current situation of the gully hazard in the study area for effective mitigation measures and to cushion the effect on the livelihoods of affected communities. The aim of this paper is to assess the current situation of land use land cover as well as to predict future scenarios using integrated CA-Markov model for effective mitigation measures of gully hazard and to cushion the effect on the livelihoods of affected communities. This study has been performed in Agulu-Nanka-Oko and Ekwulobia gully erosion complexes of Anambra state.

Materials and Methods

Study area

Agulu – Nanka – Oko and Ekwulobia gully complex is located in the Southeastern part of Anambra state Nigeria. It is situated between latitudes 6° 10′ and 6° 05′ North of the Equator and longitudes 7° 05′ and 7°10′ East of the Greenwich Meridian, covering an area of about 1709 km^2 within the Anambra Basin. (Figure 1).

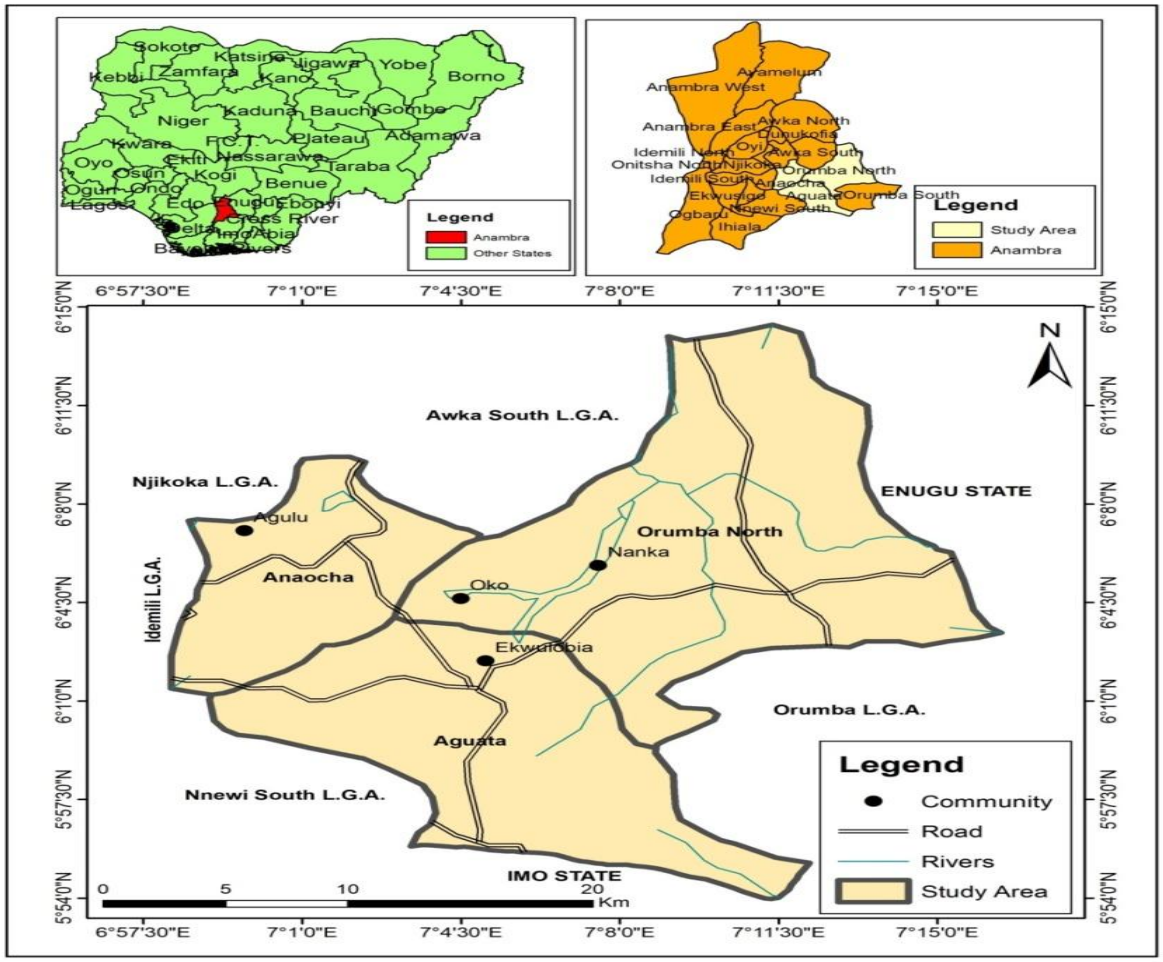


Figure 1: Anambra State showing Agulu, Nanka, Oko and Ekwulobia communities.

The study area is characterized by uniformly high temperature and a seasonal distribution of precipitation and high relative humidity. The average annual temperatures range from a minimum of about 24^0C to a maximum of about 30^0C. The area experiences distinct wet and dry seasons (eight months of rainfall and four months of dryness) in the year. The rainy season begins in March and ends in October while the dry season runs through the months of November to February of each year (Okoro, Egboka, and Onwuemesi, 2010). The study area forms a part of the Anambra sedimentary basin of the southeastern Nigeria. The geologic formation of the study area is the Eocene Nanka unconsolidated or poorly consolidated sands (Ezechi and Okagbue, 1989).

Anambra State falls into two main landform regions: a highland region of moderate elevation that covers much of the state south of the Anambra River, and low plains to the west, north, and east of the highlands. The highland region is a low asymmetrical ridge or cuesta in the northern portion of the Awka Orlu Uplands, which trend roughly southeast to North West, in line with the geological formations that underlie it (Okoro *et al.*, 2010). The Agulu Nanka, Oko and Ekwulobia soils are typified by the coastal plain sands characteristics and are highly susceptible to erosion. The vegetation in Anambra State consists mainly of deciduous forests, which are made up of tall trees with undergrowth. The African oil palm tree (*Elaeis guineensis*) is a common tree in Anambra State. This is influenced due to the high annual rainfall in Anambra State, which ranges from 1400mm in the north to 2500mm in the south (Okoro *et al.*, 2010).

Markov Model

Cellular Automata (CA) Markov Model

The CA-Markov model is extensively used in LULC modeling (Zhilong, Xue, Yili, and Jungang, 2017; Sang, Zhang, Yang, Zhu, and Yun, 2011; Brown, Pijanowski, and Duh, 2000). The model can predict effectively the future change in LULC in space and time. Markov chain predicts the future changes based on the previous state in each classes and probability of transition (Behera, Borate, Santosh, Panda, Behera, and Roy, 2012). Markov chain is formed from the distribution of LULC classes in the earlier and end of a discrete time period, and from transition matrix which demonstrates the changes that occurred in the intended period of time. Based on this assumption, LULC changes projects based on the transition matrix and the estimation of probabilities (Muller and Middleton 1994).

Cellular Automata

Many studies have used Cellular Automata (CA) model for modeling spatial dynamics (Agarwal *et al.,* 2002). This model is well-known as a simulation model because its models changes in time and space separately (Arsanjani, Helbich, Kainz and Boloorani, 2013). In cellular automata the predetermined transition matrix and the state of adjacent cells in time are used to update each cell in landscape. An integration of spatiotemporal dynamic and cellular automata technique used to simulate changes in two-dimensional space (Wolfram, 1983). Cellular automata have four elements: cell states, cell space, time stages and transition matrix (Azizi *et al.,* 2016). This method can simplify the dynamic of complex system and model spatial future of the system (Torrens and O'Sullivan, 2001).

CA –Markov

CA-Markov model is integrated with cellular automata to predict spatiotemporal changes in LULC. The two models are discrete in space and time. In Markov chain no knowledge is added about the random spatial distribution of LULC groups. This means that, no spatial components can be provided by the outputs of modeling (Nejadi *et al.,* 2012). This model adds both spatial contiguity and probable spatial transition that have occurred in specific area over time. Both Markov and CA-Markov models are utilized in IDRISI Selva to present transition probability and transition matrix for selected area of interest. This transition probability matrix can be provided through the cross tabulation of two different images in times. In other words, it provides the probability of changes in pixel from LULC class into different class during the same time. A transition matrix is the expected changes in the number of pixels into other classes during the period of time (Subedi, Subedi, and Thapa, 2013). There are some reasons which make this model interesting when predicting spatiotemporal LULC changes: a) it uses transition probability to control the dynamics of time between many LULC classes, b) transition probability and the state of neighborhood cell of each LULC with CA mechanism utilized to control space dynamics, c) its capability to use in remote sensing and geographical information system. Therefore, an integrative approach of Markov and CA Markov play a powerful role in effectively predicting LULC changes (Kamusoko, Aniya, Adi, and Manjoro 2009). Zhilong *et al.,* (2017) has briefly mentioned the process of this method as a) transition probability matrix will be calculated in Markov chain, b) utilize transition probability to generate LULC atlas, and c) the spatial distribution of LULC changes will be simulated.

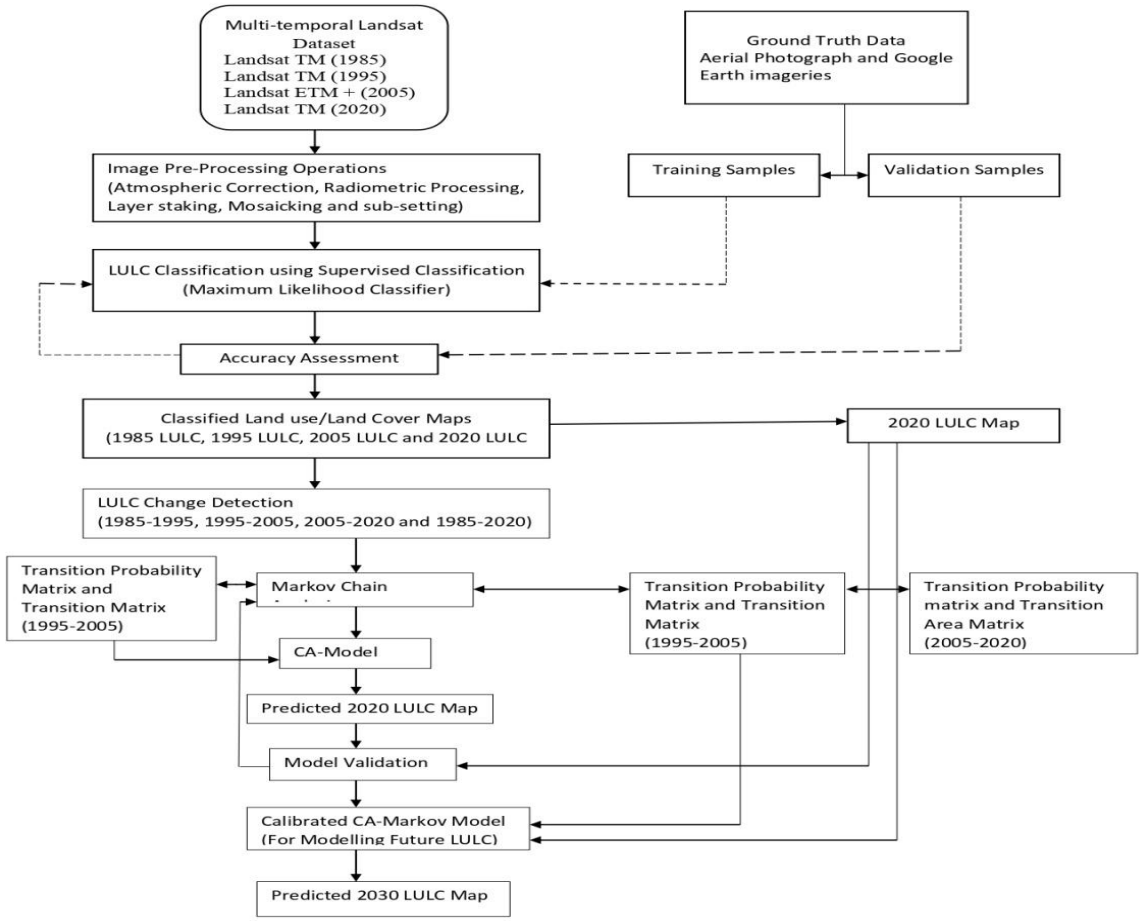


Figure 2: Flowchart of methodology used for CA-Markov model (Modified from Koko, Wu, Ghali, Roknisadeh, and Akram, 2020)

Table 1: Land sat data sources

Satellite	Sensor	Spatial resolution (m)	Total bound	Date
Landsat 5	TM	30	7	24-11-1985
Landsat 7	TM	30	7	19-01-1995
Landsat 7	ETM+	30	8	03-02-2005
Landsat 8	OLI	30	11	17-12-2020

Method

The research process is shown in Fig. 2. In this study, the images of the Landsat satellite are used to analyze the land use changes in Agulu-Nanka-Oko and Ekwulobia gully erosion complexes (Table 1). Criteria such as accessibility, cloud-freeness, same resolution and time period have been considered in selecting images. The images have been collected from the Landsat satellite in a time span of 35 years (1985, 1995, 2005 and 2020). In the preprocessing stage, atmospheric correction, geometric correction and enhancement were done. Then the unsupervised classification was conducted to have a general understanding of the land use classes.

In classifying the images into various classes, supervised classification technique was performed using maximum likelihood classification (MLC) algorithm. This technique enabled generation of training classes based on the actual land-use/land-cover themes present within the study area

and helped in curtailing ambiguity that is associated with the unsupervised technique of image classification. The attribute and statistics from the classification result were generated and used for post-classification comparison between the years.

An accuracy assessment was performed on the classified imagery. Random points as collected from the field was imported to Erdas Imagine software. The points represent the various sample points, and this was checked against the classified imageries to determine the degree of conformance. Table 5 shows the results of accuracy assessment from 1985 to 2020.

The Kappa Index of Agreement (KIA) compared the predicted data with reference data using the VALIDATE module. Using the CROSSTAB module in IDRISI, the predicted LULC of 2030 is compared with the 2020 observed results to obtain the Kappa index. When the Kappa index is acceptable, the land use and land cover in 2030 can be predicted.

Results and Discussion

Table 2: Land use / cover change in the study area (1985-2020)

Land cover classes	1985		1995		2005		2020		Relative change of area
	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	1985 to 2020
Vegetation	129.33	21.58	120.66	20.13	102.1	17.04	91.06	15.19	-29.59
Built-up land	290.2	48.43	294.08	49.08	300.14	50.09	317.53	52.99	+9.41
Eroded land	6.04	1.00	9.94	1.65	11.93	1.99	13.8	2.30	+128.47
Agricultural Land	170.04	28.37	171.43	28.61	181.96	30.36	173.8	29.00	+2.21
Water body	3.56	0.59	3.06	0.51	3.04	0.50	2.98	0.49	-16.29
Total	599.17	100	599.17	100	599.1	100	599.17	100	

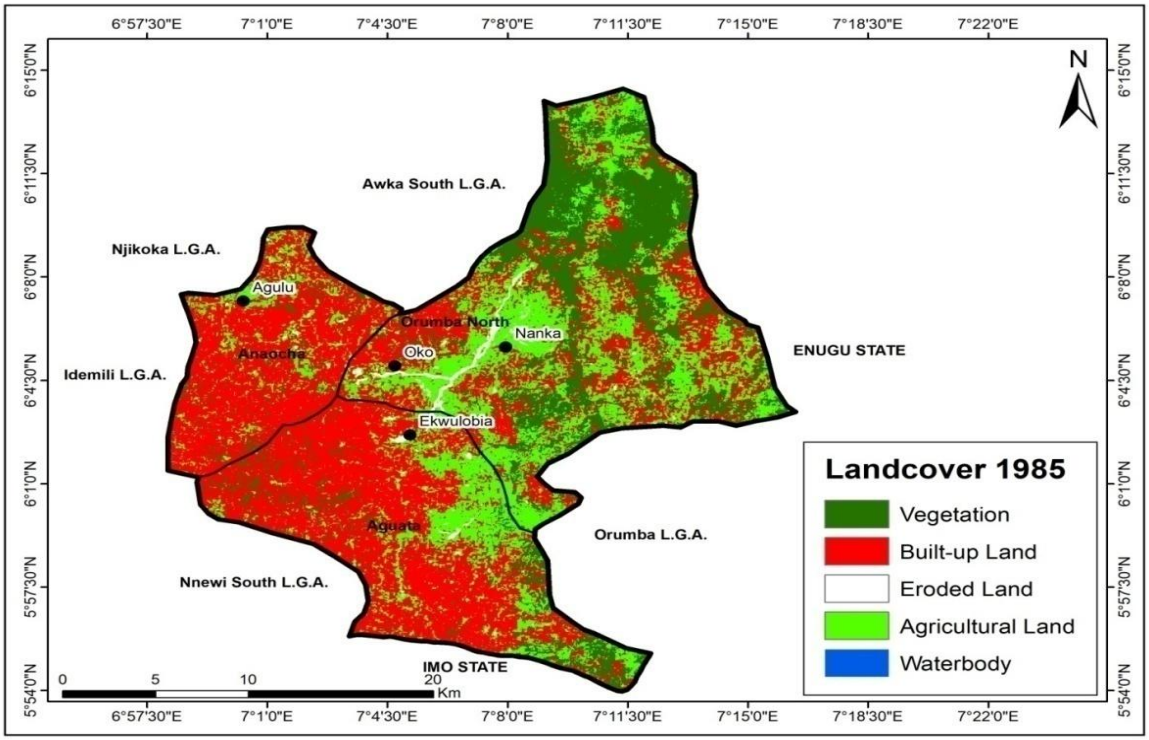


Figure 3: 1985 LULC classifications

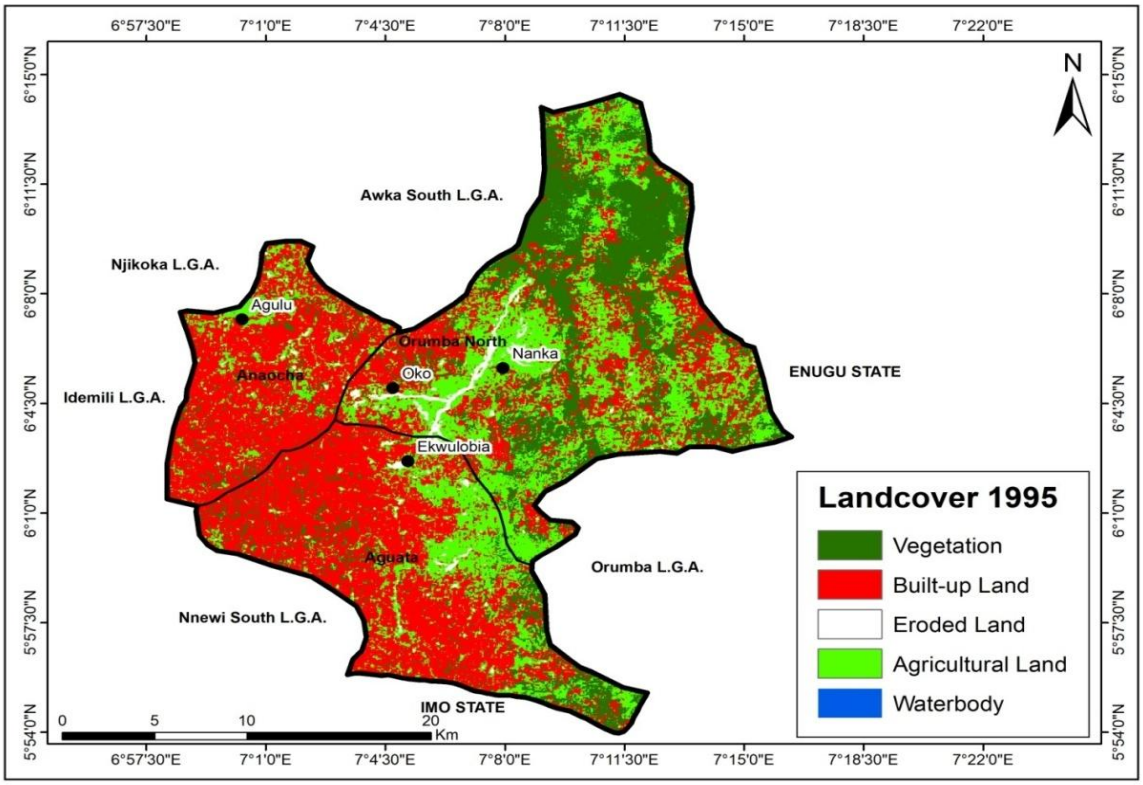


Figure 4: 1995 LULC classifications

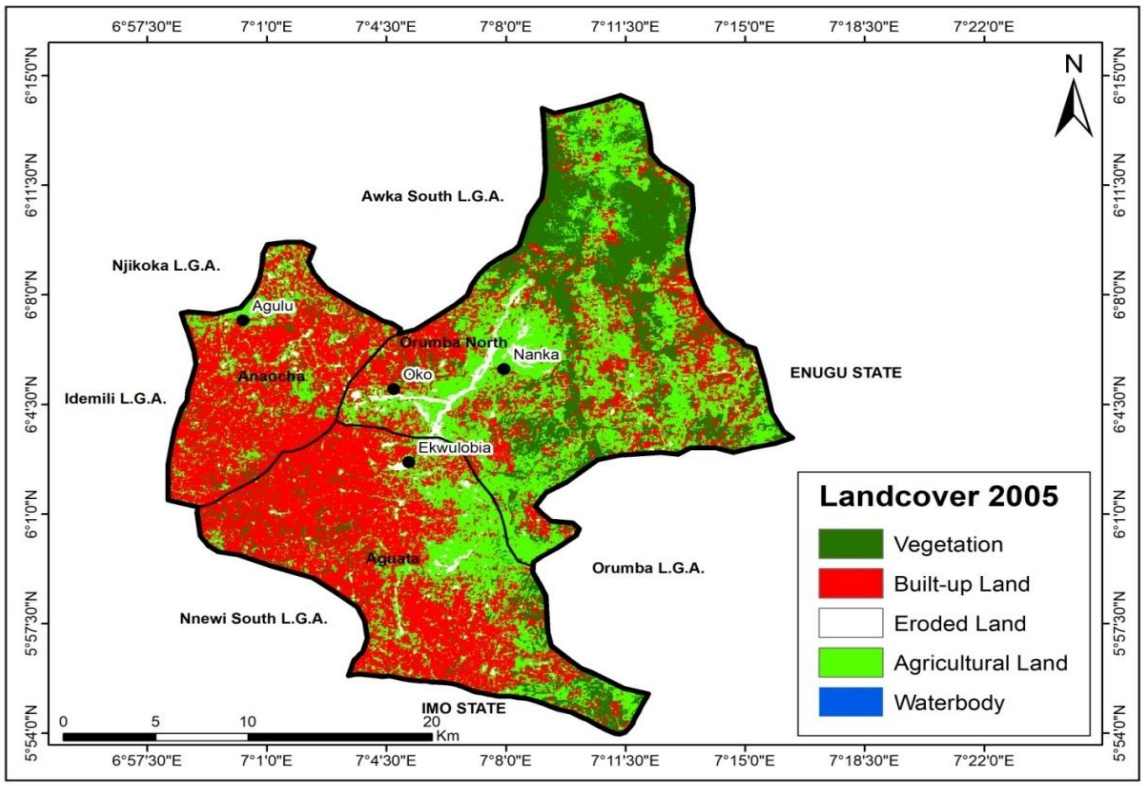


Figure 5: 2005 LULC classifications

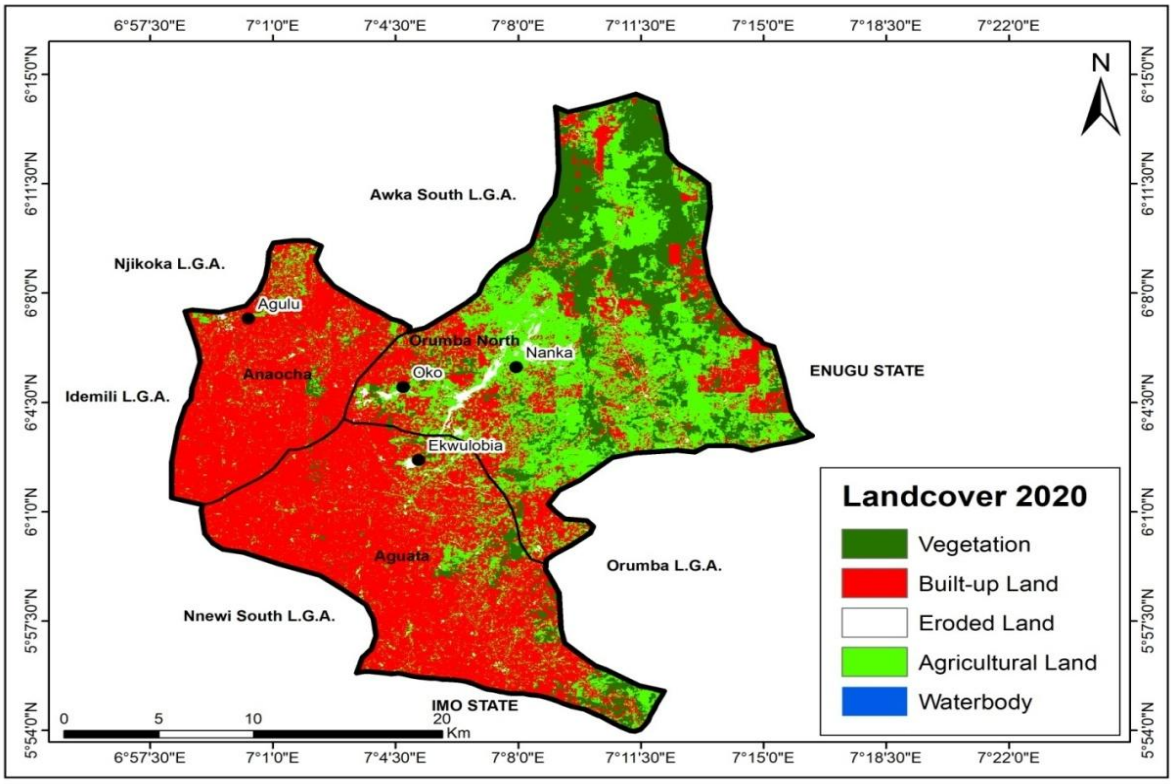


Figure 6: 2020 LULC classifications

Land use/ land cover changes between 1985 and 2020

Land use land cover types in the study area have changed from 1985 to 2020. Five major different land use classes were identified in the study area, these include: vegetation, built up area, eroded land, agricultural land and water body. Land cover classification map for 1985, 1995, 2005 and 2020 are presented in Figures 3 - 6.

The analysis in Table 2 reveals that in 1985 the predominant category of Land use/ cover is built-up land 290.2 Km^2 (48.43%) of the study area. Despite the presence of gullies and badlands, there was the presence of settlement in the study area. Vegetation area occupied only 129.33 Km^2 (21.58%), eroded land covered 6.04 Km^2 (1.00%), Agricultural 170.04 Km^2 (28.37%), and water body 3.56 Km^2 (0.59%).

In the 1995 land use category, there was slight increase in built-up land to 294.04 Km^2 (49.08 %) of the total land cover of the study area. Settlement increased due to the influx of people that led to increase in economic activities. Vegetation decreased to 120.66 Km^2 (20.13%). Deforestation and bush burning activities reduced vegetation cover. Eroded land increased to 9.94 Km^2 (1.65%) due to deforestation, concentrated run-off and bush burning. Agricultural land slightly increased to 171.43 Km^2 (28.61%). There was a decline in water body which decreases to 3.06 Km^2 (0.51%). The change could be attributed to pressure on land.

The land use distribution trend differed slightly from 1995 to 2005 as seen in table 2. The overall increase in built up land from 1985 to 2020 was (+9.41 Km^2). This is attributed to change in demography and other physical modifications in the study area. As a result of continuous deforestation, bush burning, there is a general decrease in vegetation from 1985 to 2020 to (-29.5Km^2). Total eroded land from 1985 to 2020 increased to (128.47 Km^2). More land is covered by Agricultural land because there was an overall increase to (2.21 Km^2) from 1985 to 2020. There was a general decrease in water body category to (-16.29 Km^2) from 1985 to 2020.

Satellite image analysis showed that land use and land cover changes have occurred in the area between 1985 and 2020. Between 1985 and 2020 (Table 2), eroded land, built up land and agricultural land continued to expand, while vegetation and water body decreased. Vegetation and water body were therefore converted to eroded land, built up land and Agricultural. Although eroded land, built up land, agricultural land, vegetation and water body did not change significantly for the period under investigation. An increase in built up land and agricultural land and a decrease in vegetation and water body are probable drivers of gully and badlands in the study area. An increase in built up land, eroded land and agricultural land result in a decrease in vegetation and water body.

Similar result to this study was observed by Gachene, Kathumo, Okello, and Ngigi, (2015) in Lower Tana river forest complex reveals that most of the area (80%) previously under forest was lost to cultivation. A study by Ayuyo, and Sweta, (2014) also showed that changes in land use and land cover had occurred in the Mau forest complex, resulting in the reduction of forest cover. This is because the local community depends on forest products for farming, building materials, wood fuel, and charcoal burning which could be the Scenarios in the study area. Another study by Njoka, Muriuki, Reid and Nyariki, (2003) in Lambwe Valley, south western Kenya reveals that human settlement caused land-use and cover changes, resulting in a scramble for the remaining high potential land, which could be the case in the study area. In the study area, vegetation decreased by -29.59Km^2 from 1985 to 2020.

With no interventions, gully erosion activity will continue resulting in a threat to livelihoods and environment. Scenarios of land-use and land cover change therefore help to explore possible futures and can generate indicators of ecological sustainability or of vulnerability of ecosystems and people.

The overall accuracy of LULC classification was (87.15%) in 1985, (88.50%) in 1995, (86.23%) in 2005 and (92.19%) in 2020 (Table 5). Anderson (1976) specifies that the minimum acceptable standard of overall accuracy assessment should exceed ≥85% specified by United States Geological Survey (USGS) classification scheme. In other words, results of accuracy assessment of classified images will not be reliable if overall accuracy is less than 85%. The overall accuracies for all the selected images in this study meet this standard criterion (Table 5).

Probability of change in land use land cover types by 2030

Table 3: Transition probability matrix for 2030 in percentage

Changing from:	Probability of Changing by 2030 to				
2020	Vegetation	Built-up	Eroded Land	Agricultural	Water body
Vegetation	59.242	24.029	1.836	3.540	0.000
Built-up	11.367	59.746	1.239	1.475	0.000
Eroded Land	16.502	6.956	46.497	23.875	0.018
Agricultural	12.889	9.269	9.717	71.110	0.000
Water body	0.000	0.000	40.711	0.000	99.982

Table 3 presents the probability matrix in percentage changing from 2020 to estimate the future changes in land use land cover types.

The result reveals that water body has the probability of changing into eroded land by 40%. Vegetation has the probability of 24% changes into built up land and 1% to eroded land. This change could be attributed to erosion at slope in the study area and it remains as vegetation by 59%. Water body will have the lowest percentage of changes among other classes which will change into vegetation by 0% and 0% to built-up, and 0% to agricultural land as well as to remain as

water by roughly 99%. This means that it will continue to increase in near future. Therefore, it can be clearly seen from probability matrix water body has the highest stability to remain unchanged with the probability of 99%. Likewise, built-up have the probability of 59% unchanged. Eroded land has probability of 46% to remain as eroded land. Abdulrahman, and Ameen, (2020) predicted land cover land use spatial temporal changes in Duhok district between 1999 and 2033 and found that soil and vegetation constitute the majority of changes among land use land cover classes. Mhangara, Kakembo and Lim. (2012) Investigated land use land cover trends and predicted future land use and land cover scenarios in Keiskamma catchment of Eastern Cape Province, South Africa with the use of Markov model. Markov cellular automata simulation predicted a decline in vegetation and an increase in bare and degraded soil in 2019.

Predicting the future LULC changes in 2030

In year 2030 a notable decline to about 2.91 km^2, (0.49%) (Table 2) was recorded for water body. The declines are likely to occur following the extended use for domestic and agricultural purpose coupled with the extended decrease following the impacts in hydrological cycle. On the other hand, substantial increase in built-up land was estimated to 323.62 km^2 (54%). The expected increase in built up land is resulting from expansion following the increase in human population which depends on agriculture as main economic activity. This is in line with the findings of (Abdulrahman *et al.*, 2020). Eroded land will reach 17.45 km^2 in the next 10 years. The increase in eroded land could be attributed to the nature of the terrain, environmental factors as well as human interaction with the land by their activities.

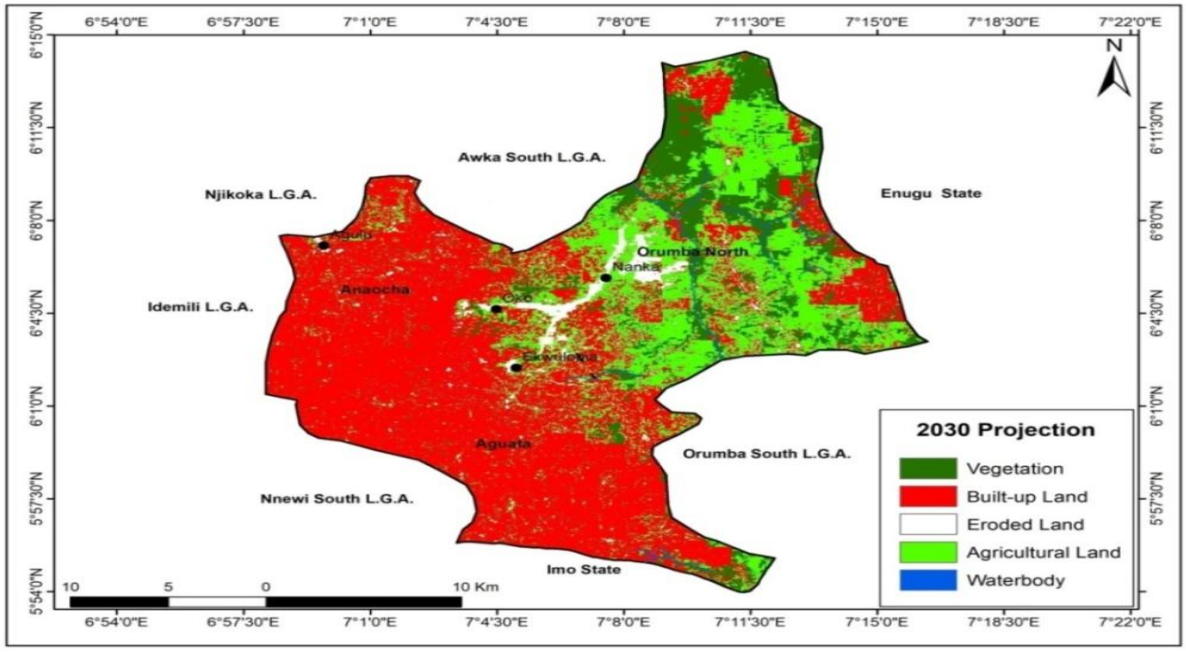


Figure 7: **Simulated LULC categories in year 2030**

Liping, Yujun, and Saeed, (2018) analyzed land use land cover in Jiangle County in Fujian, China and found that in 2025 and 2036, the woodland area decreased greatly, and the remaining land area increased by a certain amount especially in 2036 and the area of woodland decreased significantly. Similar result was obtained by Ikegwuoha, Weepener, and Dinka, (2021) who investigated future land use change for the Lepella river basin in South African using Markov model and found an array of losses and gains for certain land use land cover classes in the basin by 2040: vegetation (gain 8.5%), water bodies (loss 31.6%), cultivated

land (loss 29.3%), built up areas. (gain 10.6%). Yahaya, Terwase, Aliyu, Adamu and Christianah, (2020) monitored and forecast spatio-temporal LULC for Akure rainforest in Nigeria and found an upsurge in built area class. The upsurge in built area could be attributed to growth of population as well as migration of people into the area.

Table 4: Area of 2030 projection of gully erosion

Area in Km^2		
Land cover	**2030 Projection**	**%**
Vegetation	84.68	14.13
Built-up Land	323.62	54.01
Eroded Land	17.45	2.91
Agricultural Land	170.51	28.46
Water body	2.91	0.49
Total	599.17	100

Table 5: Result of classification accuracy assessment

Image	**The overall statistical Kappa**	**The overall classification accuracy (%)**
Landsat 1985	0.8370	87
Landsat 1995	0.8562	88
Landsat 2005	0.8206	86
Landsat 2020	0.8567	92

Conclusion

Satellite image analysis showed that between 1985 and 2020, eroded land, built up land and agricultural land increased while vegetation and water body decreased. Vegetation and water bodies were therefore converted to eroded land, built up land and Agricultural. Although eroded land, built up land, agricultural land, vegetation and water body did not change significantly for the period under investigation. By the year 2030 as projected, eroded land will increase significantly in the next 10 years (2030).

Looking into the future, the Markov Cellular Automata simulation results predicted that eroded land would reach 17.45 Km^2 by 2030 and agricultural land will decrease by 170.51 Km^2. The loss of soil in the area will lead to loss of agricultural productivity and disruption of socio-economic activity in the area of study. This provides a useful prediction that could serve as an early indicator of possible future scenarios. The developed model is beneficial for the rapid assessment of soil erosion and for planning appropriate conservation measures.

Recommendations

i. Looking into the future, the Markov Cellular Automata simulation results predicted that eroded land will reach 17.45 Km^2 by 2030. Extensive afforestation program can be very effective in the control of gully erosion. This helps to protect the soil from the direct impact of raindrops and runoff as well as maintain the moisture content of the soil at responsible level during the dry season.
ii. Environmental awareness campaigns should be done at grassroots level to ensure proper land use management.
iii. Bio-remediation using Vetiver grass and bamboo planting. These were found to be effective in similar environment
iv. Government should ensure that adequate data (rainfall and soil data) that will enhance the sustenance of the model are readily available. This will enhance the efficiency of soil erosion prediction

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