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Assessment of Past and Future Land Use/Land Cover Dynamics of the Old Kumasi Metropolitan Assembly and Atwima Nwabiagya Municipal Area, Ghana

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Abstract

Ghana like all countries in Sub-Saharan region of Africa have long been undergoing intense land use land cover changes (LULCC) which have given rise to extensive forest loss (deforestation and degradation), loss of arable land and land degradation. This study assessed the past LULCC in the Atwima Nwabiagya which contains the Barekese and Owabi Headworks) and the old Kumasi Local Assemblies' areas in Ghana and projected the scenario in 2040 for business-as-usual (BAU). The synergies of satellite imagery of 1990, 2000, 2010 and 2020 were classified with an overall accuracy of 90%. Markov Cellular-Automata method was used to forecast the future LULC pattern after detecting main driving forces of LULCC. The findings showed an extensive increase in built up areas from 11% in 1990 to 39% in 2020 owing largely to 23% decrease in forest cover and 6% decrease in agricultural lands within the past 30 years (1990-2020). The projected LULC under the BAU scenario for 2040 showed built-up surge from 39% to 45% indicating additional forest loss from 43% in 2020 to 40% and decreasing agricultural land from 17% to 14%. The main driver for the LULCC is clearly anthropogenic driven as the human population in the study area keeps rising every censual year. This study exemplifies the fast-tracked forest loss, loss of arable land and challenges on ecosystem sustainability of the Barekese-Owabi-Kumasi landscape. The current and projected maps necessitate the apt implementation of suitable interventions such as reforestation, protection measures and policy decision in deliberate land use planning to mitigate further loss of forest cover and safeguard the Barekese and Owabi headworks.

Keywords

Forest Loss, Random Forest Classifier, Change Detection, Urbanization, Markov-Cellular Automata

1. Introduction

Rapid ecological changes and the consequent effects have engaged the attention and debate among academics and politicians globally (Shrivastava et al., 2020). Experimental analyses posit that human caused actions are the principal sources of environmental transformation because of increasing human population and developmental needs (Ahmed et al., 2019; Ahmad et al., 2020). Land use and land cover change (LULCC) is reckoned to be the key driver in the worsening destruction of the natural environment worldwide (Muhati et al., 2018; Koranteng et al., 2020). The changing aspects of anthropogenic land use and land cover (LULC) variations have consequences for land use, management of the environment and development in peri-urban areas which are characterized by increasing human population (Alipbeki et al., 2020; Clerici et al., 2019). Sustainable development globally is heavily impacted by LULCC occurring at different areas of the earth (Tonini et al., 2018; Liu et al., 2022; Roy et al., 2022). Lambin & Meyfroidt (2010), Swette & Lambin (2021) advance that, there exist complex drivers of LULCC which emanate from the interaction between established program, socio-economic systems and the human environment.

Urbanization plays a vital role in economic development, improvement in social welfare and provides a measure of human development, however it has also been a key focus of intellectual and political considerations because of the adverse influences on the natural environment locally and globally (Estoque et al., 2021; Liang & Yang, 2019). Urbanization rate in Africa has exceeded all forecasts (Ritchie & Roser, 2018). Previously the African continent was deemed a rural one, but this narrative is fast changing (Förster & Ammann, 2018; Yatta, 2018). Urbanization in developing regions of the world especially for countries in Africa is typified by disorganized growth and amplified immigration (Magidi & Ahmed, 2019; Smit, 2021). This situation is exacerbated by the discovery of mineral deposits at such places. The quest to live in developed cities has the propensity to drive an influx of people to neighbouring towns and cities triggering urban sprawl (Gougha & Yankson, 2000; Cooper, 2019; Korah et al., 2019). In Ghana for example, the expansion of cities sprawling into out-of-town-peri urban zones has had detrimental effects on the natural environment by obstructing and altering local ecosystem activities, biogeochemical cycles and climate. Arable lands have been lost due to the relocation of businesses and residential activities into countryside areas that are at the edge of metropolitan areas in many countries (Acheampong et al., 2018; Doe et al., 2022).

The determination of spatio-temporal alterations and its plausible effect on the environment at the local, national and global scale are deliberated as remote sensing (RS) provides the means for quick data procurement of LULC data at comparatively lesser cost than ground survey techniques and gives time sequence data of LULC (Wulder et al., 2018; Koranteng et al., 2016). RS and geographic information systems (GIS) technologies offer cost-effective means for studying the LULCC dynamics and are nuseful for mapping, monitoring, and management of natural resources (Forkuor & Cofie, 2011; Giri, 2012; Halefom et al., 2018). RS and GIS methodology have been used for LULCC mapping and have showed fascinating outcomes and recommended some important policy proposals for ecological land management (Motlagh et al., 2020; Wang et al., 2021).

Data on LULCC dynamics thus is pivotal for sound environmental strategies and administration and provides a base line information necessary for accurate interpretation of historical LULC and the nature of variations to be envisaged in the future. This study investigates historical patterns of LULCC and assesses its causes that occurred from 1990-2020 and to forecast for 2040.

2. Methodology

2.1. Study Area

The study area (**Figure 1**) falls in the Moist Semi-deciduous Northwest Forest type zone and includes the old Kumasi Metropolitan area and Atwima Nwabiagya District in the Ashanti Region. It has the Owabi-Barekese headworks. The Owabi-Barekese watershed is the main source of treated water for the Kumasi Metropolis and its surrounding communities. The Owabi (wildlife sanctuary

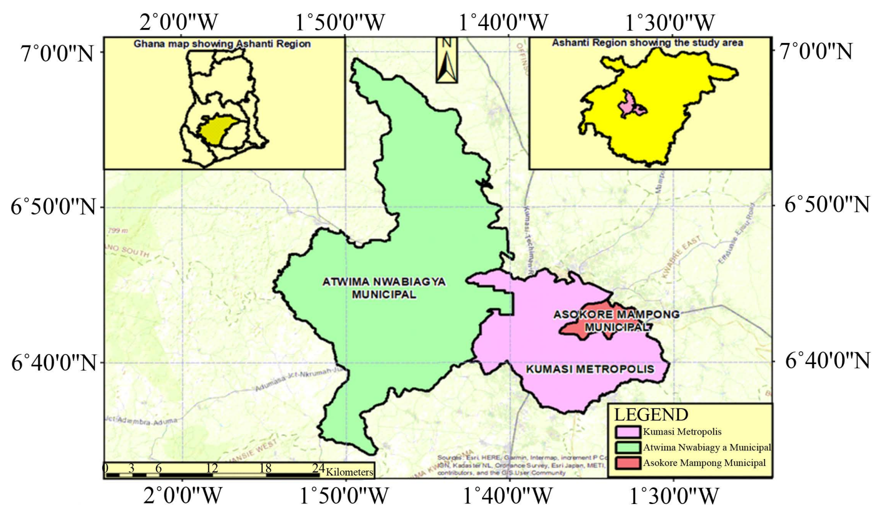

Figure 1. Study area comprising the Kumasi Metropolitan Assembly, Asokore Mampong Municipal and Atwima Nwabiagya Municipal.

and a Ramsar Site) and Barekese catchment were designated in 1920 and 1972 correspondingly through an Executive Instrument (Forestry Commission, 2014; Akoto et al., 2021). A forest cover within the catchment area was created to safeguard recharge areas, prevent siltation and rapid evaporation of water in the reservoir as well as improve rainfall. The catchment area has rich diversity of vegetation and wildlife and supports critical ecosystem services (Forestry Commission, 2014; Amuquandoh et al., 2011; Koranteng, 2017).

2.2. Data and Software

The major software employed in this study includes (Environmental Systems Research Institute (ESRI) ArcGIS 10.0, ERDAS Imagine and IDRISSI Selva. This study is based on the data sources listed in **Table 1**.

2.3. Image Processing and Classification

Preprocessing of satellite images is vital and seeks to harmonize data and the biophysical phenomena it signifies (Parsa et al., 2016). Pre-processing was done utilizing ArcGIS 10.0. All the images were re-sampled to 30 × 30 meter pixel resolution to make accurate analysis of the datasets and comparability possible.

Five LULC categories—Close_forest, Open_forest, Agriculture, Built_up and Water (**Table 2**) were chosen and used in the image classification (supervised classification) based on the authors' local knowledge of the study area and literature (Koranteng et al., 2020; Frimpong & Molkenthin, 2021). Random Forest Algorithm was employed to allocate pixels to their classes since the random forests are not limited by statistical assumptions.

Table 1. Satellite data used for LULC classification and reference data.

EO Data	Acquisition date	Resolution	Source
Landsat TM	December, 1990	30 m	USGS EROS Centre
Landsat ETM+	March, 2000	30 m	USGS EROS Centre
DMC (Disaster Management Constellation)	January, 2010	22 m	Forestry Commission, Ghana
Sentinel Image	January, 2020	10 m	USGS EROS Centre
Reference Data			
Topographical Map	2012	1:50,000	Survey & Mapping Division, Ghana
Aerial Photographs	2010	1:10,000	Survey & Mapping Division, Ghana
Land Cover Map	1990 & 2000	1:10,000	CERGIS, University of Ghana

Table 2. Classification scheme of LULC used in this study.

Land use Class	Feature
Close Forest	Land with dense woody tree cover with close canopy and forest patches.
Open Forest	Land with dense woody tree cover without close canopy. Forest Land in the national greenhouse gas inventory that is degraded Close forest.
Agriculture	Cultivated land and harvested croplands and pastures.
Built Up	Land with non-natural surface such as roads and highways, built up areas, bare grounds and human settlements.
Water	Rivers, streams, reservoirs, ponds, and lakes.

2.4. Random Forest Classifier

The Random Forest technique uses the construction of trees to classify satellite image data (Breiman, 2001). The algorithm has a lower computational time and a higher classification accuracy (Rodriguez-Galiano et al., 2012; Inglada et al., 2015). The spectral bands were the input data, and the LULC class with the most segments was the output. Due to the independence of each tree, training and testing were carried out simultaneously (**Figure 2**) (Breiman, 2001). Given a collection of multispectral images (spectral bands), denoted as X1, X2, …, Xn, where n denoted the sample count and L denoted the number of features, While "z" was the link between sample "I" and sample "xj," where "z" Z = "1, −1," "Xi" indicated the position of sample I in the space "RL × n." Z = 1 if xi and xj belonged to the same class.

Tree-structured predictors are present in the random forest. The collaboration formula for the kth tree was $f_k(x) = f(x, k)$, where $f(x, k)$ was a tree that grew in size as the training set and random vector k did, capturing the tree's many stochastic building blocks. Each tree cast a vote for the most popular LULC class, and the k was independent and evenly distributed (Breiman, 2001).

For a sample, the probability of correctly predicting class "z" was

$$P(z \mid x) = \frac{1}{K} \sum_{k=1}^{K} P_k(z \mid x) \tag{1}$$

where $P_k(z|x)$ was the projected density of class labels of the kth tree and K was the number of trees in the forest. As illustrated the decision function of the forest is given as

$$C(x) = \underset{j \in Z}{\text{arguments of the maxima}}\, P(j \mid x)$$

The margin function for the RF was

$$ml(x, z) = P(z \mid x) - \max_{\substack{j \in Z \\ j \neq z}} P(j \mid x) \tag{2}$$

If $ml(x, z) > 0$, might result the correct classification. The value of generalization error is limited as Random Forest can regulate without increasing the trees

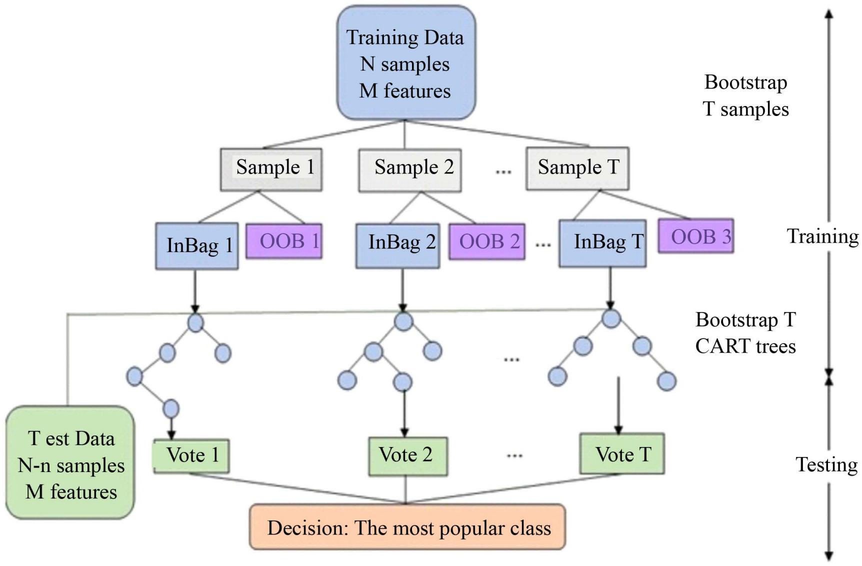

Figure 2. Random forest classifier.

(Amit & Geman, 1997; Ye et al., 2013). The convergence function at this point can be explained as;

$$ml(x,z) = P(z \mid x) - \max_{\substack{j \in Z \\ j \neq z}} P(j \mid x) < 0 \tag{3}$$

indicating that the generalization error decreases as the number of trees grows. The generalization error was given an upper bound by

$$PE \leq \bar{\rho}\left(1 - s^2\right) / s^2 \tag{4}$$

where s is the strength of the set of $f(x, k)$, PE is the generalization error, and is the average value ($\bar{\rho}$) of the tree correlation.

The generalization error of the RF converged to a fixed value once there were enough trees in the forest. Each tree produced a "yes" or "no" vote from the RF (**Figure 2**).

2.5. Accuracy Assessment

Accuracy assessment was performed on the 2020 satellite image, an assessment report was produced as Confusion Matrix (**Table 3**). For 1990, 2000 and 2010, these classified images were validated using ancillary data (**Table 1**).

2.6. LULC Change Detection Analysis

LULCC post-classification detection method adopted using the ERDAS Imagine, which entailed using two classified images to make a comparison to produce change information. Consequently, the differences between two images represent the change. The extent of change and percentage of changes can be stated in a straightforward formulation as used by Mahmud & Achide (2012) and Hua (2017):

$$K = F - I \tag{5}$$

Table 3. Confusion matrix.

OID	Class Value	Close forest	Open forest	Agriculture	Built up	Water	Total	User Accuracy	Kappa
0	Close forest	48	2	0	0	0	50	0.96	0
1	Open forest	2	47	1	0	0	50	0.94	0
2	Agriculture	1	0	49	0	0	50	0.98	0
3	Built-up	0	0	0	50	0	50	1	0
4	Water	0	0	0	0	50	50	1	0
5	Total	51	49	50	50	50	250	0	0
6	Producer Accuracy	0.94	0.96	0.98	1	1	0	0.98	0
7	Kappa	0	0	0	0	0	0	0	0.97

$$A = \frac{(F - I)x^2}{2!I} \times 100 \tag{6}$$

where K is extent of changes, A represent the percentage of changes, F is first data, and I is reference data.

Prognostication of LULC changes for 2040 used IDRISI Selva. This research utilized LULC methods in RS to ascertain differences and explain the percentage of LULC changes in that time, along with the approximation for the subsequent 30 years.

2.7. Markov Chain Model Analysis

Markov chains are stochastic processes (Caraka et al., 2019; Nemeth & Fearnhead, 2021; Shepero & Munkhammar, 2018) and the matrices indicate variations between land use types (premised on the assumption of perpetuation of past development) (Ghalehteimouri et al., 2022; Rahnama, 2021) and are often employed in simulation variations and developments of LULC (Chang et al., 2021; Sobhani et al., 2021). The consistency of Markov model for projection of LULC alterations can be accurately described in this mathematical way (Subedi et al., 2013; Okwuashi & Ndehedehe, 2021; Das & Sarkar, 2019):

$$L_{(t+1)} = P_{ij} \times L_{(t)} \tag{7}$$

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & P_{1m} \\ P_{21} & P_{22} & P_{2m} \\ P_{m1} & P_{m2} & P_{mm} \end{bmatrix} \tag{8}$$

where $L_{(t)}$ and $L_{(t+1)}$ represent land use status at time t and $t + 1$ respectively. Including $\sum_{j=1}^{m} P_{ij} = 1$ (i, j = 1, 1, 2, m) is the transition probability matric in a given state.

In this paper, 2010 and 2020 maps were used in Markov chain model to create the transition matrix changes between the existing 10 years, and the process is repeated onto map 2040 for upcoming land use to obtain the transition matrix changes in IDRISI Selva v.17 environment.

2.8. Cellular Automata (CA)

Ulam and Von Neumann in the 1940s originally proposed Cellular Automata (CA) for usage in land use changes theoretical study (Nugraheni & Natali, 2018; Xing et al., 2020). CA fundamental theory is summarized as the land use modifications for any place (cells) can be clarified by the present state and variations in neighboring cells (Mansour et al., 2020; Noszczyk, 2019).

2.9. Markov-CA Chain Model

Markov Chain and CA models are reckoned as valuable for predicting land use changes (de Oliveira Barros et al., 2018; Munthali et al., 2020). The Markov-CA model employs Markov Chain outputs to utilize a contiguity filter to facilitate the advancement of other land use types from one time to another (Parsa et al., 2016). CA then advances a not random spatial weighting on the places which have approximately the same features to the existing land use category based on classes (Subedi et al., 2013). Consequently, Markov-CA model is deemed a vigorous tool as it provides temporal, spatial and quantitative estimation and LULC dynamics in modeling for the future (Mishra & Rai, 2016; Subedi et al., 2013).

Figure 3 summaries the flowchart of the study.

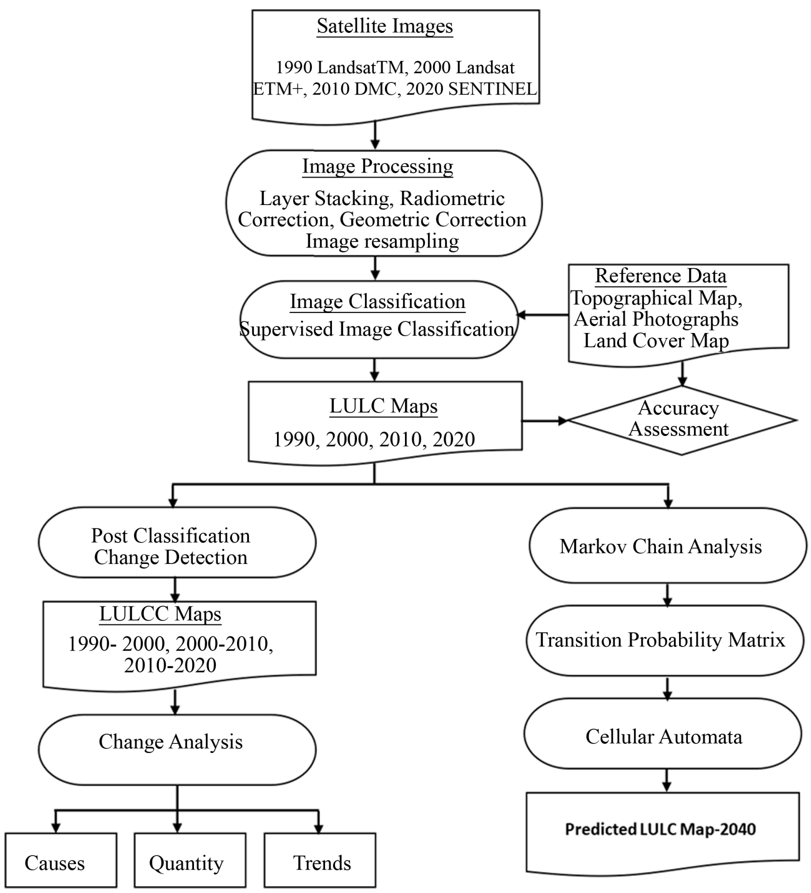

Figure 3. Methodology flowchart implemented in the study.

3. Results

3.1. Image Classification and Accuracy Assessment

LULC maps generated for the years1990, 2000, 2010 and 2020 from supervised classification which used the categories Closed Forest, Open Forest, Agriculture, Built-up and Water are shown in **Figure 4**. Foody (2002); Behera et al. (2012) theorize that accuracy assessment is vital when post classification change detection method is employed. The accuracy assessment conducted on the LULC Map 2020 is shown in **Table 3**. 98% represented the total classification accuracy and 0.97 achieved as the overall Kappa statistics. For the epoch years 1990, 2000, 2010, topographical map, aerial photograph, land cover map, digitized topographical data photographs, data and reference points from statutory bodies such as the Forestry Commission and Survey Department of the Republic of Ghana were used to check for accuracy assessment averaging 90%.

3.2. LULC Maps

In 1990 map, the entire area was covered by forest predominantly, open forest (58.31%) with close forest (7.85%). Aside from forest cover, agricultural lands

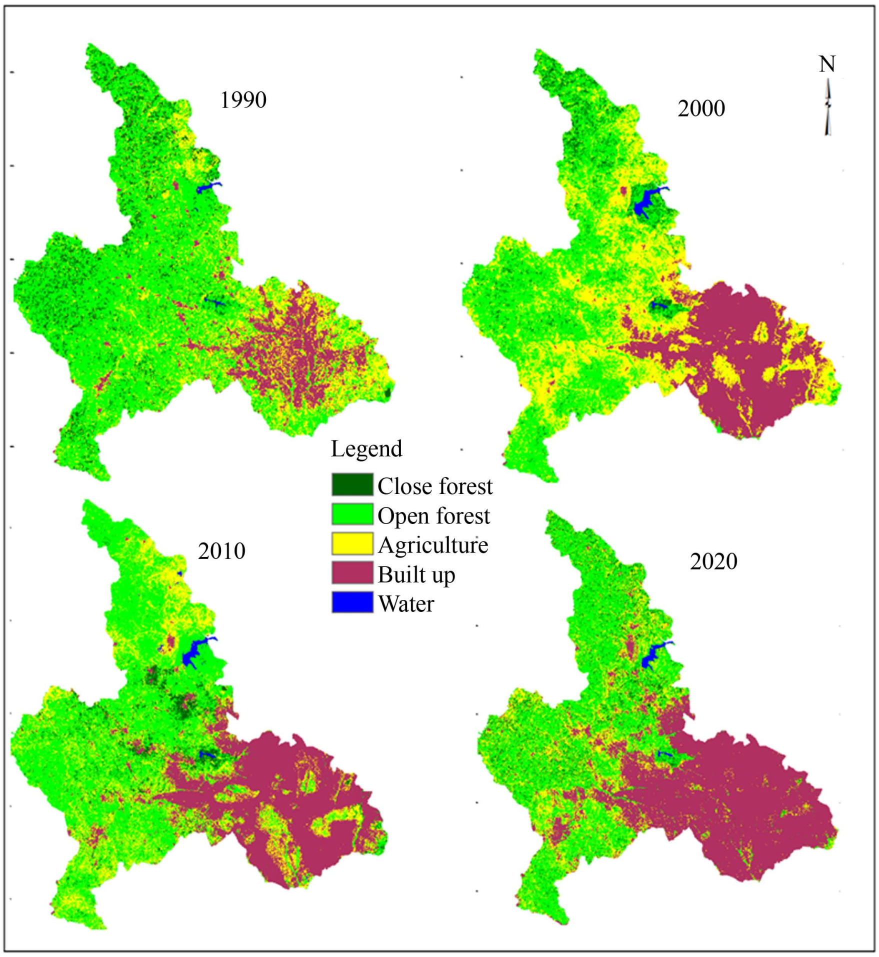

Figure 4. LULC maps for the Epoch years.

occupied 22.52% with the urban/built-up areas covering 11.15% whilst the waterbodies occupied a marginal 0.17% of the total area of 81838.9 ha. In the year 2000, both the close and open forest experienced reductions whilst agricultural lands increased. However, a substantial increase in built-up areas was observed. Waterbodies category experienced increases from 0.17% (1990) to 0.49% (2000). There was a rise in both the close and open forests in 2010. Conversely, agricultural lands decreased significantly but built-up areas also increased. The waterbodies again increased marginally in 2010. In the last year of study (2020), there was an increase in the close forest contrary to open forests that decreased. However, the dwindling of agricultural lands continued. Nonetheless, there was a substantial rise in the built-up areas (**Table 4** and **Figure 4**).

3.3. Change Detection Analysis

The close forest decreased from 1990 to 2000 but increased from 2000 to 2020. Averagely within the study period, the close forest decreased by 1.95%. The open forest decreased from 1990 to 2000 but there was an increase from 2000 to 2010. There was once again a decrease from 2010 to 2020. Generally, there was a decrease of −20.82% from 1990 to 2020. There was an increase from 1990 to 2000 agriculture class. On the other hand, a reduction in agricultural lands was observed from 2000 to 2020. Largely there was a decrease from 1990 to 2020 (−5.14%). The built-up areas intensified throughout the study period. In the case of the waterbodies, there was an increase from 1990 to 2010. It decreased from 2010 to 2020. Furthermore, there was an overall increase of 0.27% in the waterbodies (**Table 5** and **Figure 5** and **Figure 6**).

3.4. LULC Prediction Model and 2040 LULC Simulated Map

The simulated 2020 LULC map showed slight variation in the distribution and values compared to the actual 2020 LULC map (**Table 6**). This result indicated a very robust method for LULC map stimulation as there were marginal differences. The Statistical evaluation based on the Kappa coefficient was used to

Table 4. Quantification of land use land cover classes.

LULC CLASS	1990		2000		2010		2020	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Close_forest	6422.98	7.85	3314.02	4.05	3665.66	4.48	4825.12	5.90
Open_forest	47721.4	58.31	32395	39.58	37513	45.84	30682	37.49
Agriculture	18433.5	22.52	27248.4	33.30	17824.2	21.78	14230.9	17.39
Built_up	9122.12	11.15	18477.5	22.58	22353.2	27.31	31740.4	38.78
Water	138.9	0.17	403.98	0.49	482.84	0.59	360.48	0.44
Total	81838.9	100.00	81838.9	100.00	81838.9	100.00	81838.9	100.00

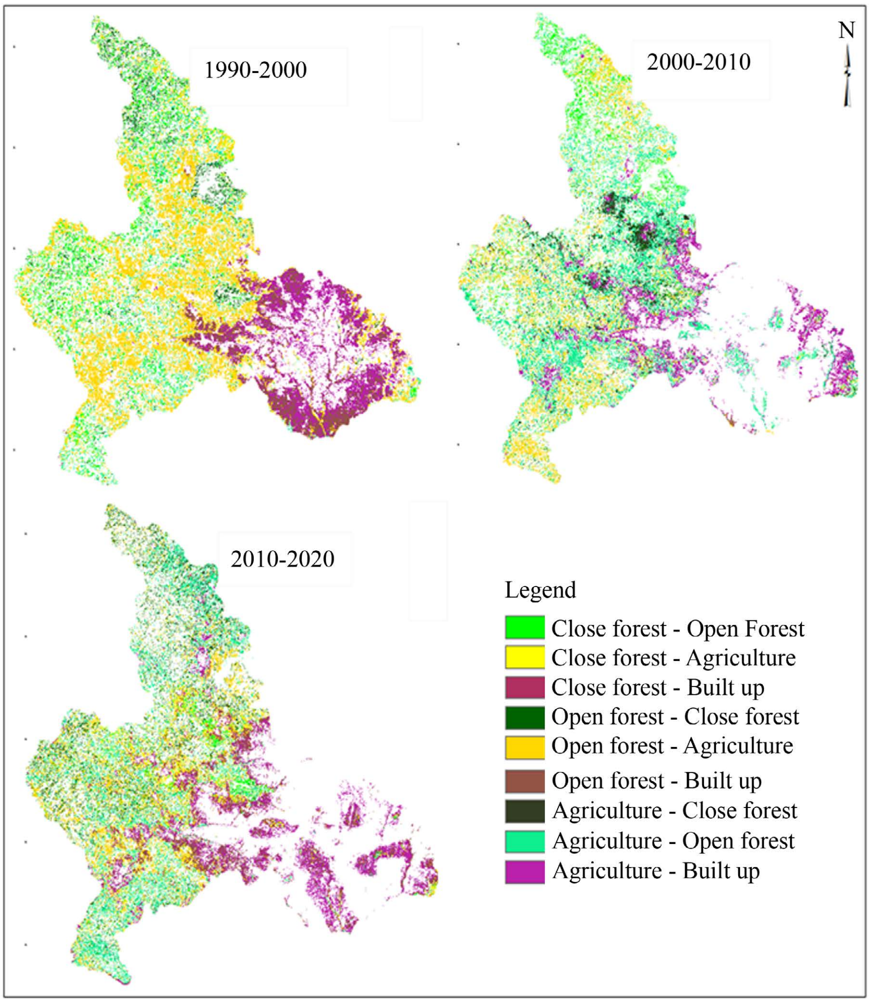

Figure 5. LULCC maps for 1990-2000, 2000-2010 & 2000-2020.

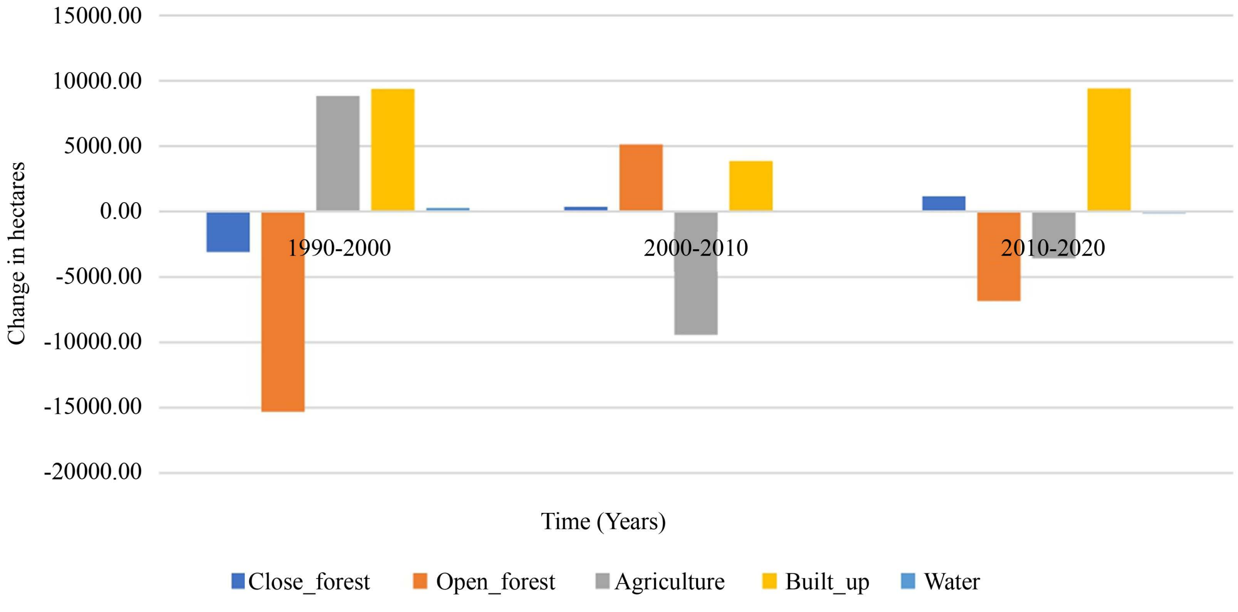

Figure 6. LULC change in Hectares.

Table 5. Change detection 1990-2000, 2000-2010 and 2010-2020 for Greater Kumasi.

LULCC Area	1990-2000		2000-2010		2010-2020		1990-2020	
	(ha)	(%)	(ha)	(%)	(ha)	(%)	(ha)	(%)
Close_forest	−3108.96	−3.80	351.64	0.43	1159.46	1.42	−1597.86	−1.95
Open_forest	−15326.40	−18.73	5118	6.25	−6831	−8.35	−17039.40	−20.82
Agriculture	8814.90	10.77	−9424.2	−11.52	−3593.3	−4.39	−4202.60	−5.14
Built_up	9355.38	11.43	3875.7	4.74	9387.2	11.47	22618.28	27.64
Water	265.08	0.32	78.86	0.10	−122.36	−0.15	221.58	0.27
Total Area of Changes	**36870.72**	**45.05**	**18848.4**	**23.03**	**21093.32**	**25.77**	**45679.72**	**55.82**

Table 6. Comparison of actual and projected LULC types in 2020.

LULC CLASS	Actual		Stimulated	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Closed Forest	4825.12	5.90	4775.45	5.84
Open Forest	30682.00	37.49	30654.33	37.46
Agriculture	14230.90	17.39	14125.34	17.26
Built_up	31740.40	38.78	31912.30	38.99
Water	360.48	0.44	371.48	0.45
Total	81838.90	100.00	81838.90	100.00

measure the overall agreement of the matrix, the ratio diagonal values' summation versus the total number of pixel counts within the matrix and the non-diagonal elements would be the best approach to assess the model accuracy (Arsanjani et al., 2013). The accuracy assessment obtained K values (Kstandard = 0.7595; K no = 0.8913; K location = 0.8841; KlocationStrata = 0.8241). These values agree with Monserud & Leamans (1992) standard values stipulate that a kappa value of 75% or greater indicates excellent classifier performance, as 40% value or less than is poor.

The simulated LULC map for 2040 is shown in **Table 7** and **Figure 7**. The cumulative forest category (Close and Open forests) had dwindled as the area has largely been transformed into built-up. Agriculture class decreased as transformed into built-up. Built-up areas and water increased to 45.15% and 0.61% respectively. Built-up category assumed the highest LULC class of the total area in 2040.

Table 7. 2040 Quantification of land use land cover classes.

LULC CLASS	2040 Area (ha)	2040 Area (%)
Closed Forest	3002.46	3.67
Open Forest	29461.60	36.00
Agriculture	11921.8	14.57
Built_up	36952.9	45.15
Water	500.14	0.61
Total	**81838.9**	**100.00**

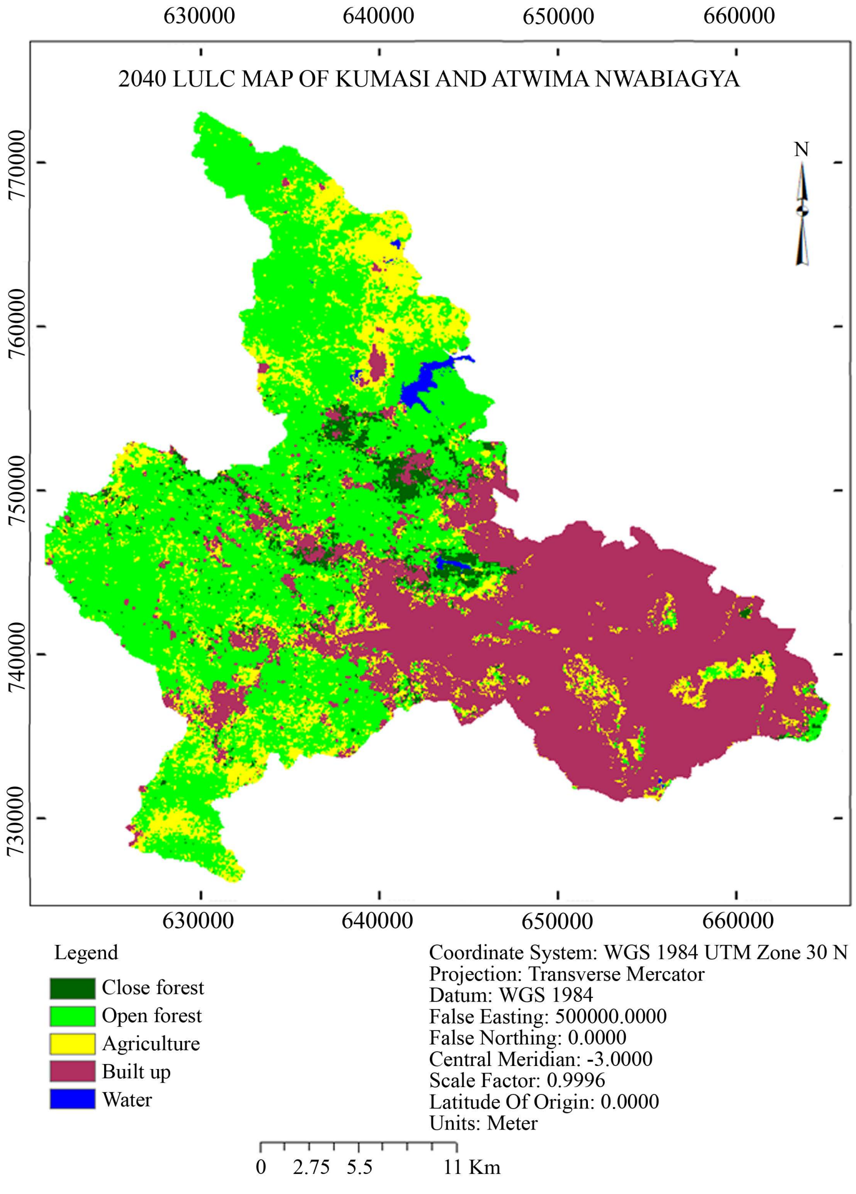

Figure 7. 2040 predicted LULC map.

4. Discussion

4.1. Satellite Image Classification and Accuracy Assessment

The RFC utilized for the classification of satellite images and the efficiency of this algorithm as used in the works of (Frimpong & Molkenthin, 2021; Nyamekye et al., 2021) was superior, when contrasted with the traditional classifiers used in the classification satellite images. The kappa, producer and user accuracies yielded satisfactory results and agreed with works by Abass et al. (2018); Buo et al. (2021).

4.2. LULCC Trajectory

The LULC maps showed that most built-up areas were in the south-eastern parts of the study areas in the Kumasi metropolis, which is almost completely denuded of natural vegetation. The diminishing agricultural lands could be ascribed to the heightened demand for lands for commercial centres and residential areas. The analysis of LULC revealed that forestlands have been subjected to intense pressure due to anthropogenic activities (Frimpong, 2015). The conversion of forestlands and agricultural lands into urban/built-up areas is considered rewarding in the Ghanaian setting (Abass et al., 2018; Buo et al., 2021; Wemegah et al., 2020). The rapid rise in the population is a perculiar reason that could have caused the growth in the built-up areas, and it endorsed by the outcome of the study of (Ghana Statistical Service (GSS), 2013; Addae & Oppelt, 2019). The results support the findings in previous literature that the research utilized the same LULC classes in earlier works (Frimpong & Molkenthin, 2021; Koranteng et al., 2015). The populace living in the peri-urban areas tends to rely on forest resources for sustenance (Cobbinah et al., 2020). It was found out that forestlands are the foremost to be transformed to built-up areas. This outcome is supported by the work of (Frimpong, 2015). Consequently, urban spatial growth is largely attributed to the comparatively lower prices of land at the urban fringes for residential purposes (Wellington, 2009). This could be the reason for the urban/built-up areas growing outwards from the already existing urban/built-up centers.

4.3. Forest Loss and Other of the LULC Changes

The forest cover (especially the Open Forest category) was the most depleted LULC category under the study period. Forest loss has always been a crucial problem in Ghana even before independence due of the different forces behind it (Benneh & Agyepong, 1990). Forest lands forcefully appropriated from indigenous landowners and families for various reasons by the colonial master's forest policies led to the wanton exploiting the forest cover haphazardly (Agbosu, 1983). After independence (1960-1970), deforestation was intensified due to the cultivation of cocoa as an export product (Dei, 1992). From 1981 to 1985 timber had become the primary driver of deforestation as it was the third largest export article of trade providing 5% - 7% of Gross Domestic Product (GDP), (International Institute for Environment and Development (IIED), 1987; Owusu, 2010). The period 2003-2013 has been characterized by plantation establishments which resulted in incremental surge in the annual rate of forestlands loss (Davis & Philips, 2005; Afele et al., 2022). The period 2013-2022 has experience intensification of forest loss due to unbridled urbanization (Kyere-Boateng & Marek, 2021; Ofori et al., 2022).

Anthropogenic activities and actions are the immediate causes of loss (deforestation and forest degradation). The underlying forces and causes of forest loss are multi-faceted, complex and differ from place to place. The drivers of the rapid LULC in the study are largely attributed to unbridled urbanization, Population growth and Settlement, Infrastructural Development, Mining and Unsustainable Agricultural Practices.

4.3.1. Unbridled Urbanization

Unbridled urbanization is witnessed in the study area as depicted by the LULC maps for the epoch years. Clearly the Kumasi metropolis has expended in all direction and small towns in the study area keep increasing in all direction (Cobbinah et al., 2020; Akubia & Bruns, 2019; Agyemang et al., 2019). This development has serious ramification on other critical LULC such forests arable land and water resources (Bawa et al., 2022; Appiah et al., 2019; Obeng-Gyasi, 2022). The continues and uncontrolled urbanization have serious effects water supply systems as forests which protect rivers and streams (source of water to the Barekesses and Owabi Dams) are polluted or dried up. There are several studies that supports this assertion in the study area (Antwi-Agyei et al., 2019; Ayesu et al., 2021; Forkuo et al., 2021).

Unrestrained urbanization in the study area traces its origin to the connection between the inherited colonial official land administration and post-colonial policies. The supplanting of native land tenure system with variations of European ones led in the commodification of land and establishment of uncontrolled land use actions. The planning ramifications have been huge, leading to the disconnect amid post-colonial land reorganization rules and local land use decisions. Other challenges involve the intra and inter-community land use changes as indigenous players fight with government officials over land decisions. Consequently, there is a diminished national capability to enforce land use activities within Africa's liberalized land markets (Onodugo & Ezeadichie, 2019; Adeyanju et al., 2021; Boateng, 2020).

4.3.2. Population Growth and Settlement and Infrastructural Development

Ghana's population over every censual year is always on the rise (**Table 8**). Ashanti region has the highest population in all censual years and Kumasi being the regional capital and its adjourning districts contains most of the population. The rapid increase in population of the study area has serious ramifications for the provision of urban land for housing, infrastructural and other social amenities provision (Ghana Statistical Service (GSS), 2022). The loss of forest lands in

Table 8. Ghana's population and Ashanti region shares, 1960-2021 (Ghana Statistical Service (GSS), 2022).

Year	Total (Ghana)		Ashanti	
	Size	%	Size	%
1960	6,726,815	100.00	1,109,133	16.3
1970	8,559,313	100.00	1,481,698	17.3
1984	12,296,081	100.00	2,090,100	17.0
2000	18,912,079	100.00	3,612,950	19.1
2010	24,658,823	100.00	4,780,380	19.4
2021	30,832,019	100.00	5,440,463	17.6

Source: Ghana statistical service.

the study area is largely attributed to the enlargement of urban, into the rural areas for the construction of roads and other infrastructural development. Theses remove land vegetation as parcels of lands are cleared to make way for the increasing population. The surging population growth acting in sync with domestic migration is responsible for the surging rates of forest loss and degradation. The cost of acquiring pieces of plots of land has increased astronomically, and peasant farmers are being forced out due to economic pressures. When population upsurges, there is the corresponding demand for land, to expand settlement infrastructure and other utilities (Abass et al., 2020; Takyi et al., 2021; Ayambire et al., 2019).

4.3.3. Mining

Active gold mining sites were detected in the area of study (especially in the Atwima Nwabiagya district). Land degradation and environmental problem from the extraction of natural resources and associated activities have been significant in Ghana in recent decades (Nti, 2020; Asabere, 2020). The negative impact of mining activities on the environment and health is well documented (Nti, 2020; Antwi-Agyei et al., 2019; Frimpong Addo, 2019). Mining is a great factor of deforestation and land degradation, especially, gold prospecting and mining present one of the greatest national threats to forests reserves and indigenes in surrounding communities (Siqueira-Gay et al., 2020; Timsina et al., 2022). Surface mining operations are predominantly practiced, and their operations extensively promote the destruction of natural vegetation, economic trees and cash crops. Water resources and watershed from the forest environment are heavily polluted, posing danger to the drinking water sources for the rural communities (Worlanyo & Li, 2021; Ogidi & Akpan, 2022; Koranteng et al., 2018).

4.3.4. Unsustainable Agricultural Practices

Although there was a decreasing trend in agricultural activities in the study area, some forest loss could be attributed to the farming activities. Unsustainable agricultural practices were widespread in the study area. The slash and burn of forest cover for farming rises every year in Ghana and the extended fallows necessary for the forest to regenerate fully are impractical owing to the ever-increasing population (**Table 8**). World market demand for cash crops like cocoa, tobacco, coffee, oil-palm and cashew exacerbate the (Ministry of Lands Forestry and Mines, 2012).

4.4. LULC Projection for the 2040

The Markov-CA model employed in this research was observed to be satisfactory and agrees with other studies (Hasan et al., 2020; Fitawok et al., 2020; Kushwaha et al., 2021). The Kappa value of 85% was achieved in accuracy assessment. The result is supported by several papers and is indicative of a robust model (Rwanga & Ndambuki, 2017; Mondal et al., 2016; Kaul & Sopan, 2012). However, the prognosis for 2040 is not encouraging for forest cover protection. This result is indicative of an unbridled urbanization and agrees with earlier study by Koranteng & Zawila-Niedzwiecki (2015) in the Ashanti Region of Ghana where Built-up class surge was very intense and buttressed by studies from Cobbinah et al. (2015) and Obeng-Odoom (2014) which states that Ghana's population tend to amass in urban areas.

5. Conclusion

This study exemplified the effectiveness of satellite images for insights into the observation and appraising of LULC at the Owabi-Barekese headworks catchment area and the Kumasi Metropolis in Ghana from 1990 to 2020 using remote sensing and GIS techniques. The image classification was achieved using the RF algorithm. The research showed that the RF algorithm is a good classifier.

The study exposed an increasing trend in unbridled urbanization in the study period from1990 to 2020. The conversion from forest and agriculture to built-up land was the predominant LULC patterns. Forest cover surrounding the Barekese and Owabi Headworks are relatively intact. But forest beyond these protected zones have been significantly depleted and transformed into other land uses. 2040 LULC projected map showed a decreased forest land indication both deforestation and degradation. The study buttresses Markov-CA model is an expedient technique for LULC future estimation.

The analysis of both the historical and future stimulated of LULC maps indicates a very disturbing trend. This suggests that land use policies should be obligatory to curb the widespread obliteration of the greenery in the study area and to protect the source of portable drinking water.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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