

# Multi-Temporal Study of Land Use Land Cover Changes



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## Abstract

Anthropogenic activities have profound impact on Land use and land cover (LULC) the world over affecting all abiotic and biotic components in all environments. Studying the effects of past, present and future LULC on forest cover and other dynamic land uses provide valuable information for environmental, land planning and climate change mitigation measures. This study uses a combined methodology of Remote Sensing and Geographical Information System to map historical, current and future LULC through Satellite imagery (Landsat TM, Landsat ETM+, ALOS, Disaster Monitoring Constellation-DMC and SENTINEL) covering Greater Kumasi in a 40-year period. LULC classes such as Agriculture, Built-up, Close Forest, Open Forest, and water were considered based on the predominant geographical sceneries, remote sensing data and field study. Markov Cellular Automata modelling was employed for the estimation of likely LULC changes for the year 2040. The study discovered a perturbing development of forest loss (forest degradation and deforestation), decreasing agricultural activities while the Built-up share ballooned. Increasing urbanization at the expense of forest cover and transformation of agricultural lands into human settlements were observed. The forecasted LULC map for 2040 indicated an upward growth in Built up areas at the detriment of the other LULC categories. The outcomes validate the urgent necessity for critical review of regulations in LULC policy strategy, design, and development for the protection of forests and other critical ecosystem services to be preserved. This trend encompassing historical, current and future LULC necessitates that prudent resolutions have to be made to guarantee forest cover, make available land for agriculture and to mitigate the effects of the climate change

**Keywords:** Remote sensing; Cellular-automata-markov; Forest loss; Urbanization

## Introduction

The Climate Change phenomenon is reckoned to be linked to Land use land cover (LULC) changes and the activities of humans [1-3]. Consequently, Land use land cover change (LULCC) information at varying spatial and time-scales is vital in appraising abiotic and biotic components in all environments trends [4,5]. For optimum planning, management, regulation and utilization of the of the earth's resources it is vital for resource managers and users to understand the nature of change and the rate of LULCC [6,7]. Kagombe et al. [8] reasoned that, information on LULCC is also essential in resource economics as it impacts the dynamics of proximal livelihood opportunities as well as distal interrelated economic activities and resources.

Gatsi & Appiah [9] project Ghana's urban population to hit 65% by 2030 from the current 52% of the total population to

about 65% by 2030. This surging rate undoubtedly has serious ramifications for natural environments in urban hubs as economic forces escalate [10]. For a long time, Ghana's second largest city (Kumasi) was fondly referred to as West Africa Garden city, unfortunately this is not the case anymore. This prestige has been lost due to urban development [11]. An economic analysis study by Quartey [12] in Kumasi via a Hedonic Price Model contrasted the overall economic usage value of forests with the user value of the forest. The assessment revealed that Kumasi (Ghana) loses a net minimum of US\$ 35 million each year in carbon credits because of deforestation.

Remote sensing and Geographic information system (GIS) provide a cost-effective technology which have unique environmental capabilities to monitor vast region of the earth

for extracting information related to the earth's land, ocean, and atmosphere [13,14]. Remote sensing offers a cost-effective alternative of mapping landscape resources and analyzing changes over the traditional ground-based surveying methods. While the latter methods will continue to be important in ground-truthing exercises for validation and calibration of remotely sensed data, it is generally agreed that application of remote sensing technologies for mapping of resources over large areas and with need for temporal replication is far much economical in comparison to traditional methods. They provide effective tool for analyzing the land use dynamics of a region, as well as for monitoring, mapping and management of natural resources, [15,16]. Indeed, remote sensing approach employing the moderate resolution satellite imageries like Landsat Thematic Mapper, Landsat Enhanced Thematic Mapper Plus, SPOT Vegetation among others has widely been accepted [17,18]. It has gained prominence in wide range of application such as landscape resource assessment, resource monitoring, land cover change analysis, drought monitoring, and biomass estimation among others.

This study intends to produce past, current and future LULC map of Greater Kumasi. The study seeks to assess the LULCC for the period 1990 – 2020 in a ten-year interval. This is envisaged to offer an insight into the extent, and pattern of LULCC. The study also purposes to offer a synopsis of the key pressures causing the unbridled urban growth and to forecast the LULCC extent of the region by 2040.

## Methodology

### Study area

Greater Kumasi is centrally located in the middle belt of Ghana and its lies within longitude 1058'W and 1011'W and latitude 6022'N and 7011'N. The study area in the Ashanti Region includes the Afigya Kwabre, Asokore Mampong Municipal, Atwima Kwanwoma, Atwima Nwabiagya, Bosomtwe, Ejisu Juaben Kwabre, and Kumasi Metropolis. These administrative divisions are within the semi-deciduous forest zone and inundated with deforestation and degradation as a result of anthropogenic activities. The Ashanti Region remains the most populous region in all census years 1960-2010 [19]. The population of the region is anticipated at 5,792,200 as at 2019 from 1,109,133 in 1960 [19]. The climate conditions in study area features both wet and dry conditions with stable temperature throughout the course of the year, an average of 1400mm of rain per year. The topography of the study area is undulating with a number of rivers running through the study area and has an average elevation of 250m above Mean Sea Level (MSL). The Owabi and Berekese head works located in the study area are the main source of portable drinking water. Lake Bosomtwi is natural lake (formed from antique meteorite impact crater) is located within the study area. This lake offers means of livelihood such as a fishing industry to the neighboring towns and villages. It is also a hot hub tourism attracting foreign and local and tourist [20].

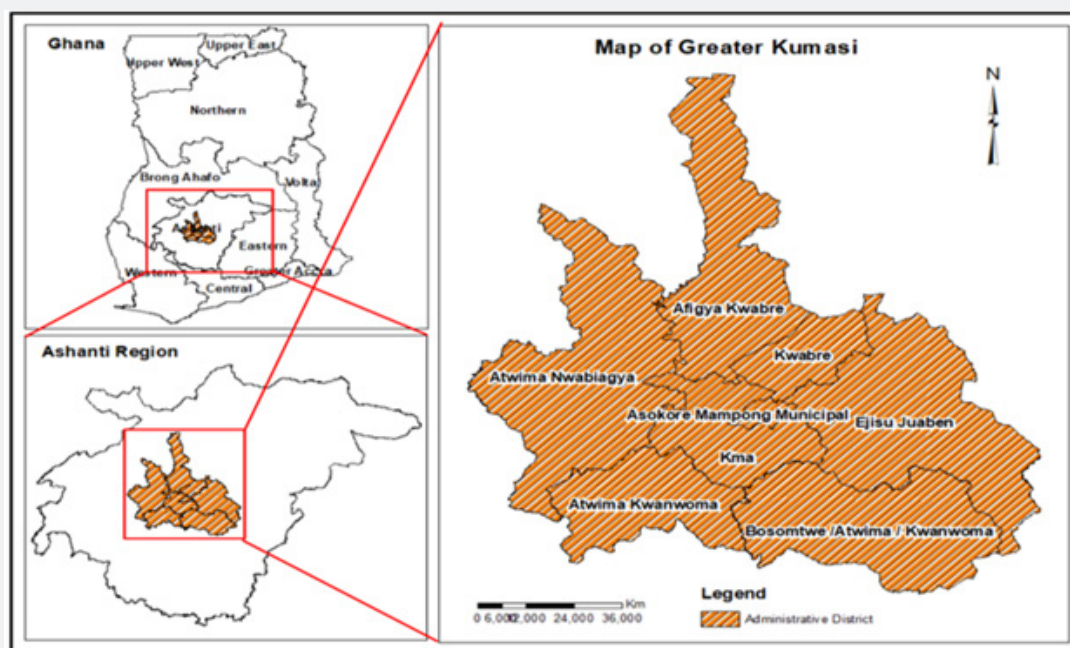


Figure 1: Study Area (Greater Kumasi, Ashanti - Ghana).

### Data acquisition

Inventory of Satellite data used for LULC classification and Reference Data are itemized in Table 1 & Figure 1.

**Table 1:** Inventory of Satellite data used for LULC classification and Reference Data.

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

### Image preprocessing

Parsa et al. [21] posit that image pre-processing is essential in to examining LULCC as errors emanating from imaging sensors, atmospheric effects and curvature of the Earth, when overlooked produce false results. Images procured from different months of the year based on obtainability of cloud free data, are mostly influenced by seasonal disturbances and atmospheric effects like aerosols, dust particles, cloud, varying sun angle etc. Also, noises in data emanating from limitations in sensing by the sensor, signal digitization, or data recording process significantly degrade the radiometric information of the image [22]. These images were subjected to a rigorous atmospheric and radiometric correction to minimize the influences of clouds, atmosphere and sun elevation

angle.

The individual bands of the downloaded satellite images (1990 LandSat TM & 2000 LandSat ETM+ and 2020 Sentinel) were merged into three different composite images. The 2010 DMC, the individual scenes of Landsat images were subsequently resampled to 10m resolution for better change detection analysis. The images were subsequently enhanced using Histogram Equalization. The 1990 and 2000 Landsat images were found to be hazy and were corrected.

### Land use classes

The following broad LULC classes were chosen based on satellite image availability and study of literature (Table 2).

**Table 2:** LULC Classification scheme.

Land use Class	Feature
Close Forest	All land occupied by woody vegetation consistent with thresholds used to define Forest Land in the national greenhouse gas inventory and a vegetation structure that currently fall below, but in situ could potentially reach the national threshold values used by to define the Forest Land category in Ghana
Open Forest	All land with woody vegetation consistent with thresholds used to define Forest Land in the national greenhouse gas inventory that are degraded Close forest.
Agriculture	All cropped land, including rice fields, and plantation where the vegetation structure falls below the thresholds used for the Forest Land category and land where over 50 of any defined area is used for agriculture, this may be currently cropped or in fallow and may include areas for grazing of livestock.
Built Up	All developed land, including social utilities such as transportation infrastructure (roads and highways), built up areas, bare grounds and human settlements of any size.
Water	These include lands that are covered or saturated by water for all or part of the year (for example peatlands). It also includes reservoirs and natural rivers and lakes.

### Image classification

The modified Anderson Level I classification Scheme [23] which is the worldwide accepted and widely used LULC

classification scheme was used in this study to achieve desired LULC categories from satellite imagery. A total of 160 ground truth data were taken randomly evenly distributed on site by a stratified random sampling. Using a total of 60 training points coupled with

local knowledge and google earth images, the 2020 image were classified and the remaining 100 points were used to assess the accuracy of the image classification. A supervised classification based on maximum likelihood was employed to classify the study area into five (5) land use categories: (1) Close Forest; (2) Open Forest; (3) Agriculture Lands; (4) Built Up and (5) Water. The 2010 ALOS images were classified using the 2010 aerial photographs covering the study area while the 2000 and 1990 Landsat images were conducted based on the land cover Map of Ghana obtained from CERGIS and prior "local knowledge" of the area. The various classified scenes of ALOS, DMC and Landsat images were then mosaicked into the individual classified maps (1990, 2000 & 2010 maps). All the individual classified LULC maps were later subset to our area of interest (study area) Confusion matrix and kappa statistics were used to assess the accuracy classified images.

### Accuracy assessment of LU/LC classification

Accuracy assessment vitally is an approach to validate the classification undertaken as meeting acceptable standards. The accuracy assessment tool in Erdas Imagine 2014 was applied so as to produce the accuracy for each LULC map. Image Accuracy assessment was measured in percentage (%) and that was in 80.45 % for 1990, 81.24% for 2000, 83.65% for 2010 and 90.89% for 2020.

### Change detection analysis

The study employed a Post-Classification Change Detection in assessing the LULCC that had occurred over the thirty year' period (1990-2020). The LULC categorized images converted into maps were in ArcGIS and Microsoft Excel used to produce tables of area and percentages. All the three LULC classified images in Erdas format (.img) were exported. Using ERDAS of the two thematic maps of the same dimensions at a time could be analyzed. By the 1990, 2000, 2010 and 2020 thematic maps as input, the following results were generated for the three-time epochs (1990 - 2000, 2000 - 2010, 2010 - 2020).

### Modelling and predicting LULC change

CA is a very efficient tool for forecasting spatial dynamic urban growth [24]. Verburg et al. [25] and Feng et al. [26] posit that apart from the optimum determination of CA transition rules based on the cell status and those of its neighbors in CA urban growth modeling, there are other factors called constraints (environmentally sensitive areas, restricted areas and development policies) and development potentials. This is given in equation (1)

$$S_{ij}^{t+1} = f(S_{ij}^t, \Omega_{ij}^t, Con, N) \quad (1)$$

Where:

$S_{ij}^t$  and  $S_{ij}^{t+1}$  - states of a cell at location  $ij$  at time  $t$  and  $t + 1$ ,

$f$  - is the transition function;  $\Omega_{ij}^t$  - neighborhood evaluation function,

$Con$  - constraints of influencing factors;  $N$  - is the number of cells.

Yang et al. [27] and Feng et al. [26] consequently add that, the development potential value of the cell at location  $ij$  at time  $t$  is expressed in equation (2)

$$(PC)_{ij}^t = (Pg)_{ij} \times \Omega_{ij}^t \times Con \times (1 + (-\ln' \gamma)^\alpha) \quad (2)$$

Where

$(Pc)$  - development potential value of the cell;  $ij$  - location

$t$  - time ;  $(Pg)$  - potential value of cell at location

$\gamma$  - stochastic factor ranging from 0 to 1,

$\alpha$  - parameter to control the degree of stochasticity.

Veldkamp & Lambin [28], Turner et al. [29] and Feng et al. [26] continue that LR is a multi-variant discovery method that is often combined with CA. LR has the ability to reduce spatial dependency among variables and remove spatial autocorrelation. Employing LR, the development potential of cell at location  $ij$ ,  $(Pg)_{ij}$  based on spatial factors is given in equation (3)

$$(Pg)_{ij} = \frac{1}{1 + \exp(-(a_1 x_1 + \dots + a_k x_k))} \quad (3)$$

where  $x_1, x_2, \dots, x_k$  are various spatial development variables impacting urban growth,  $a_1, a_2, \dots, a_k$  are different weights for the variables.

Furthermore, Wu [30] states that urban growth is impacted by dynamic factors such as the local interaction between a cell at location  $ij$  and its neighborhood cells. The potential of neighborhood effects ( $\Omega_{ij}^t$ ) within an  $n \times n$  Moore's neighborhood of the cell at location  $ij$  is denoted in equation (4)

$$\Omega_{ij}^t = \frac{\sum_{ij} Con(S_{ij}^t = urban)}{n \times n - 1} \quad (4)$$

where  $Con(S_{ij}^t = urban)$  displays the amount of urban cells in Moore's neighborhood.  $Stij$  is situation of cell at location  $ij$ . The value of the estimated development potential  $(Pc)_{ij}$  is constrained

with a threshold value ( $Q$ ) to choose either its a non- urban cell can be transformed to an urban cell at time  $t + 1$ .  $Q$  is a uniform random distribution grid in range of  $[0, 1]$  [30-32] equation (5)

$$S_{ij}^{t+1} = \begin{cases} \text{Converted to Urban } (PC)_{ij}^t \geq Q \\ \text{Non Converted } (PC)_{ij}^t < Q \end{cases} \quad (5)$$

The 2010-2020 land-cover maps were first used as inputs in Markov module to generate a transition matrix and a set of conditional probability images between the two dates of the

thematic maps. These resulting outputs were later loaded in the CA-Markov module to generate the 2020 predicted map. Afterwards, the predicted 2020 land-cover map was compared with actual land-cover map of 2020 for validation. Following the validation, the 1990-2020 land-cover maps were used to predict the 2040 land-cover map.

**Flow chart for the study**

All the GIS and remote sensing processes are summarized in Figure 2.

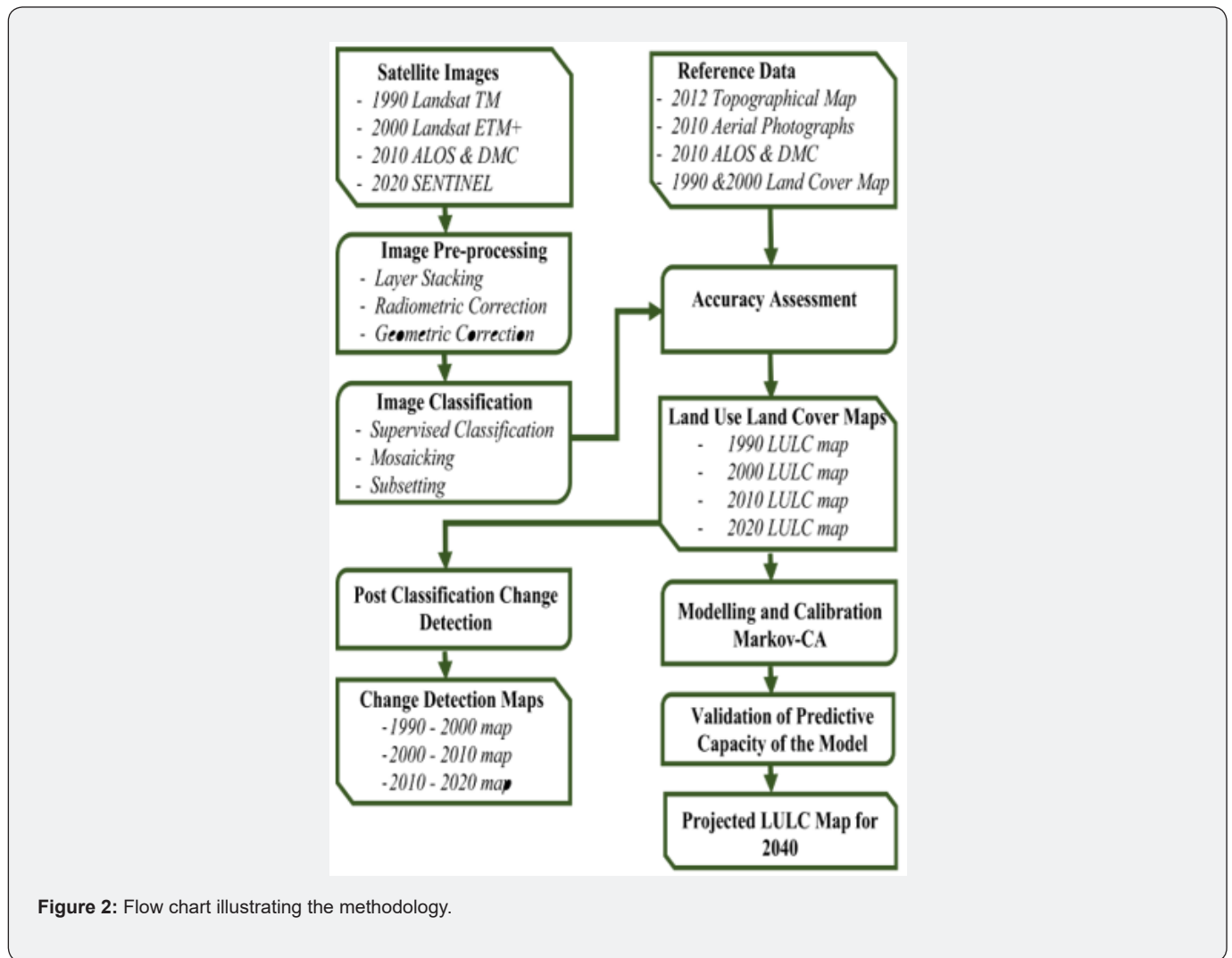


Figure 2: Flow chart illustrating the methodology.

**Results**

**Image classification and accuracy assessment**

Foody [33] and Behera et al. [34] intimate that accuracy assessment is essential, and particularly so, when using post-classification change detection methods Accuracy assessment of

the LULC Maps produced from the 1990, 2000, 2010 and 2020 were performed and assessment report was generated. Total classification accuracy of 80.00% was attained. Overall Kappa statistics of 0.7375 was realized for 2020 LULC. The Ghana Forest Preservation Program -report [35] Ground truthing and verification data was used for this activity. Accuracy assessments

for 1990, 2000, 2010 images were undertaken through 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.

**LULC maps assessment**

**Table 3:** 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	27545	10.78	22805.98	8.93	28811.25	11.28	30863.5	12.08
Open_forest	134618	52.71	117263	45.91	130689	51.17	96723.5	37.87
Agriculture	74985.7	29.36	85520.1	33.48	51748.2	20.26	53598.8	20.99
Built_up	13109	5.13	24542.1	9.61	38662.1	15.14	69031.11	27.03
Water	5148.85	2.02	5275.37	2.07	5496	2.15	5189.64	2.03
<b>Total</b>	<b>255406.6</b>	<b>100</b>	<b>255406.6</b>	<b>100</b>	<b>255406.6</b>	<b>100</b>	<b>255406.6</b>	<b>100</b>

The Table 3 shows the extent of the area of the individual LULC in hectares (ha) and expressed in percentages. Five (5) LULC classes were produced based on supervised classification - Closed

Forest, Open Forest, Agriculture, Built Up and Water. Figure 3A-3D display the four thematic maps generated for 1990, 2000, 2010 and 2020 LULC Maps respectively.

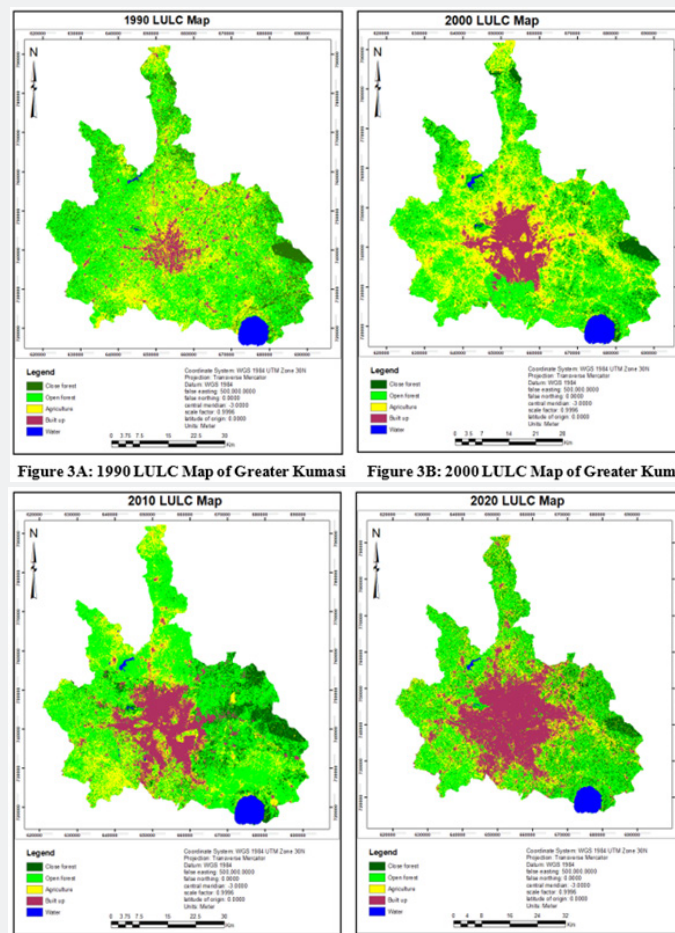


Figure 3A: 1990 LULC Map of Greater Kumasi

Figure 3B: 2000 LULC Map of Greater Kumasi

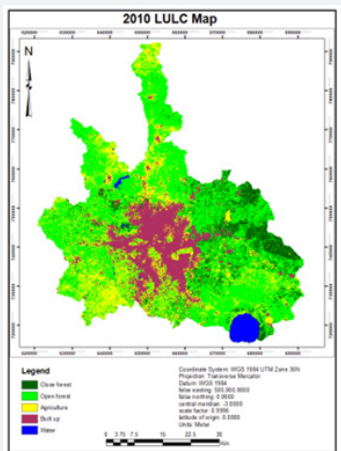


Figure 3C: 2010 LULC Map of Greater Kumasi

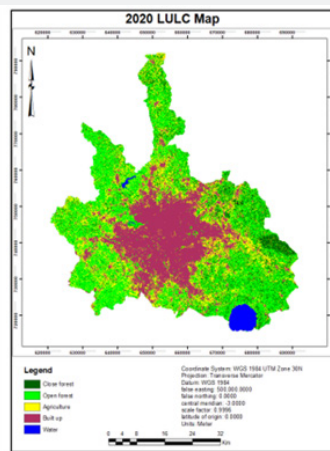


Figure 3D: 2020 LULC Map of Greater Kumasi

Figure 3:

Figure 3A displays the LULC map for 1990 where Close and Open forests constituting a little over 63%; Agriculture constitute next dominant LULC category at 29%; Built-Ups is displayed at 5% of the LULC and Water share of the LULC aggregating 2%.

The LULC map (Figure 3B) for 2000 shows Close and Open forests plummeting to 53% Agriculture increases slightly from 29% in 1990 to 33%; Built-Ups doubles from 10% from 5% in 1990. Water part of the LULC remains same.

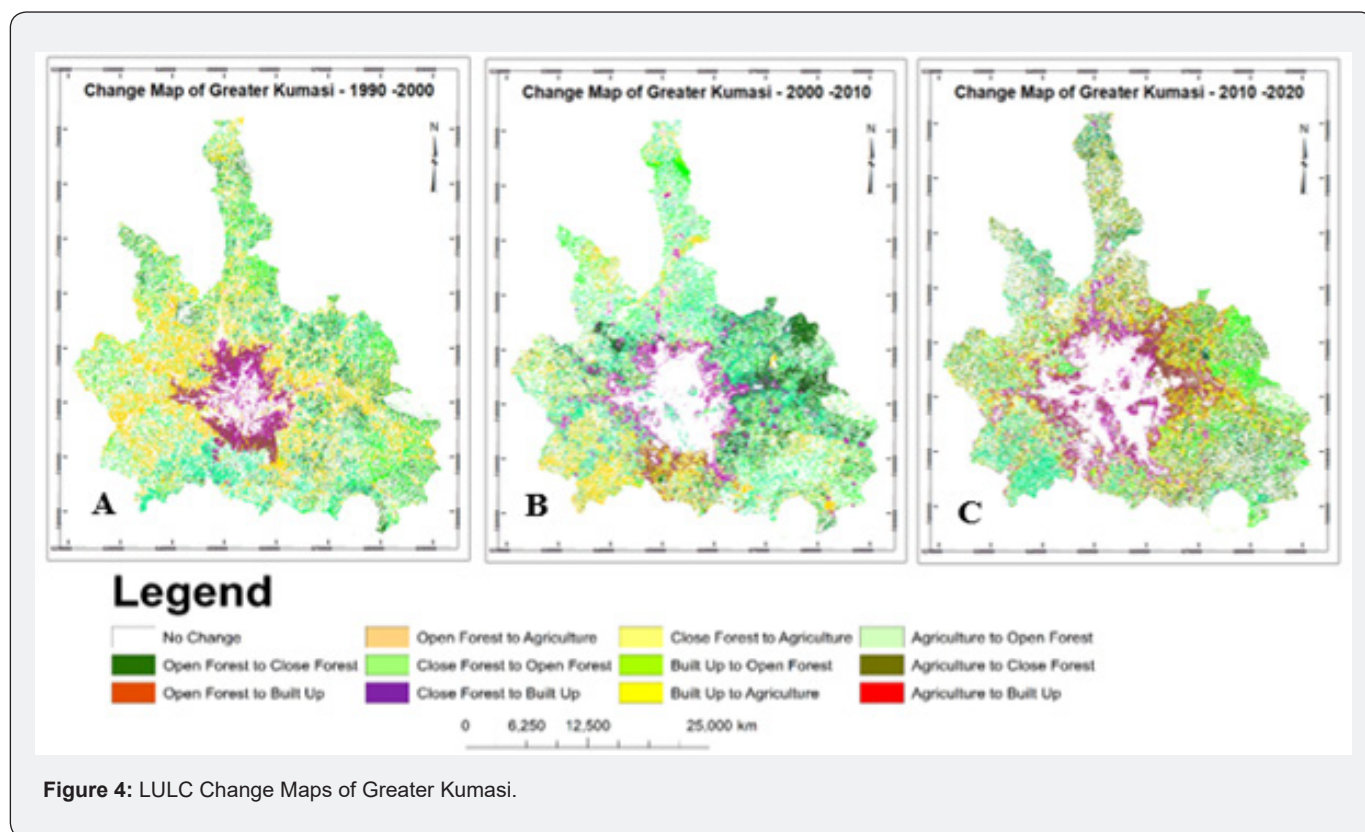
LULC map for 2010 (Figure 3C) portray Close and Open forests bounce to 62% from 53% in 2000 as results of considerable reforestation efforts. Agriculture drops to 20%; Built-Up to increases at the expense of Agriculture to 15%. Water share of the LULC remains constant.

The LULC map for 2020 (Figure 3D) shows Close and Open forests plummeting to 50% Agriculture remaining stable @ 20%; Built-Ups surge endures from 15% to 27%. Water share of the

LULC remains same.

### LULC change detection

The Table 4 show the scope of change in the area of the individual land cover classes in hectares (ha) and the percentage they occupied for 1990–2000, 2000 – 2010 and 2010 – 2020 respectively. Figure 4A-4C provide illustrations of the changes that have transpired. An overall scrutiny defines a severe change from 1990 to 2000 (Figure 4A) as Close and Open forests decrease whereas Agriculture and Built up area increase. The LULCC map incessantly changes from 2000 to 2010 (Figures 4B) as Close forest and Built up improves as Agriculture drops. This fast expansion illustrates positive influence headed for urbanization and reforestation. Incessantly, the LULC map continues from 2010 to 2020 (Figure 4C) as Open forest is used up mostly for Built up, while Agriculture remains stable. This development illustrates positive impact towards urbanization as in the previous decade.



### Validation of the 2040 LULC map

The validation used the computer-generated 2020 LULC map produced by the CA-Markov model and compared it to the actual present 2020 LULC map. Assessment of simulated and actual classified map for the year 2020. Close forest area and water bodies had the best agreement. The simulated LULC map showed

an overestimated share for Open at 51% while the Actual LULC map showed it to be 40%. The simulated LULC map showed that Agriculture and Built up areas were underestimated at 16% and 17% while the Actual LULC map put the figures at 20% and 25%.

Kappa coefficient was used as the main statistical evaluation based on the to measure the overall agreement of matrix, the

ratio diagonal values summary versus total number of pixel totals within matrix, and the non-diagonal elements is the optimum method to evaluate the model accurateness [36]. A kappa value of 0 shows the agreement between actual and reference map (equals chance agreement), the upper and lower limit of kappa is +1.00 (occurs when the is total agreement) and -1.00 (happen when agreement is less chance). The accuracy assessment process achieved by employing VALIDATE module in IDRISI Selva environment v.17 produced K values (Kstandard = 0.6595; Kno = 0.7313; Klocation = 0.7241; KlocationStrata = 0.7241) above 0.8 displaying reasonable level of accuracy [37]. The values were deemed to be within the standard values recommended by

Monserud & Leamans [38].

**LULC 2040 quantification**

Table 5 & Figure 5 show the amount of the area of the different LULC in hectares (ha) and expressed in percentages for the predicted LULC map for 2040. The aggregate forest cover comprising both the Close and Open forests had reduced as the area are being converted for agricultural use and built up purposes. Agriculture declines as the area is converted into Built up. Built-Up category is the main LULC. Water level remains stable. This fast expansion shows positive impact towards the urbanization.

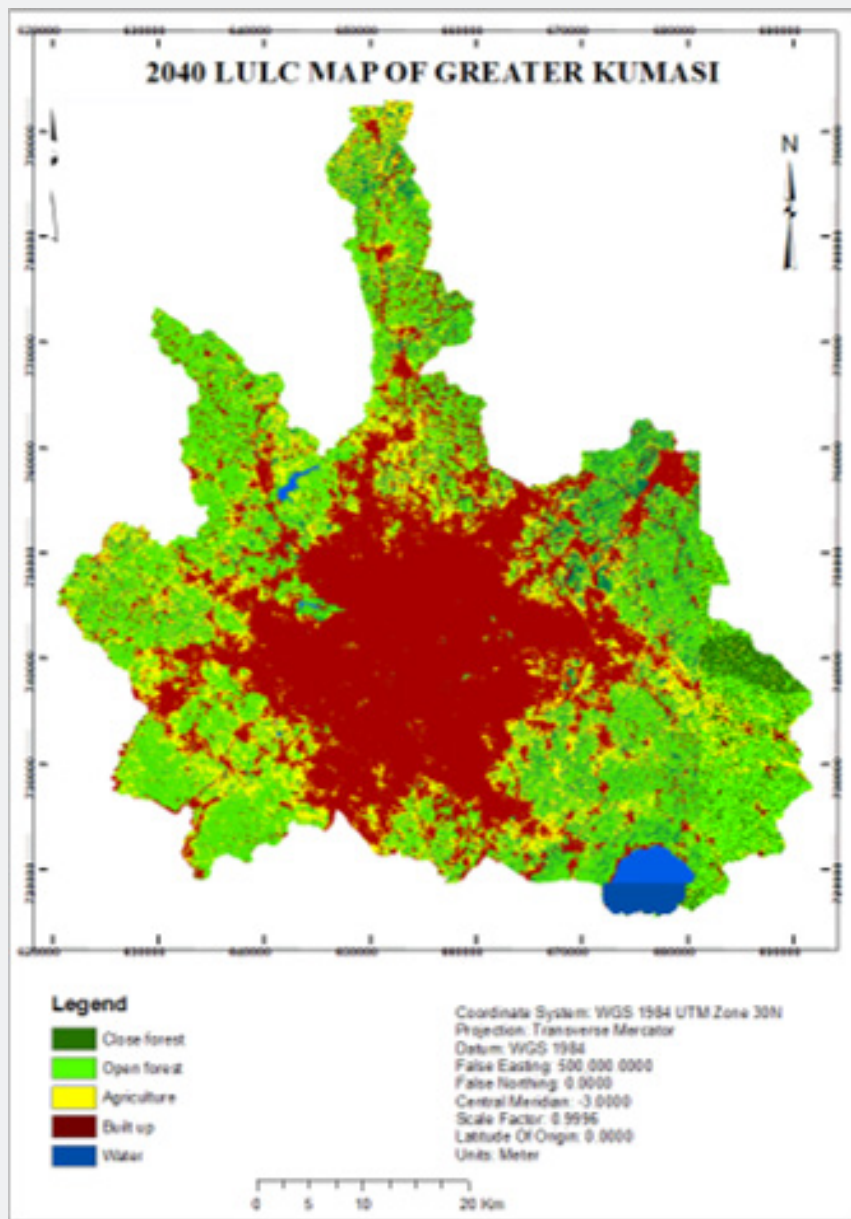


Figure 5: 2040 LULC Map of Greater Kumasi.



**Table 4:** Change detection 1990-2000, 2000-2010 and 2010-2020 for Greater Kumasi.

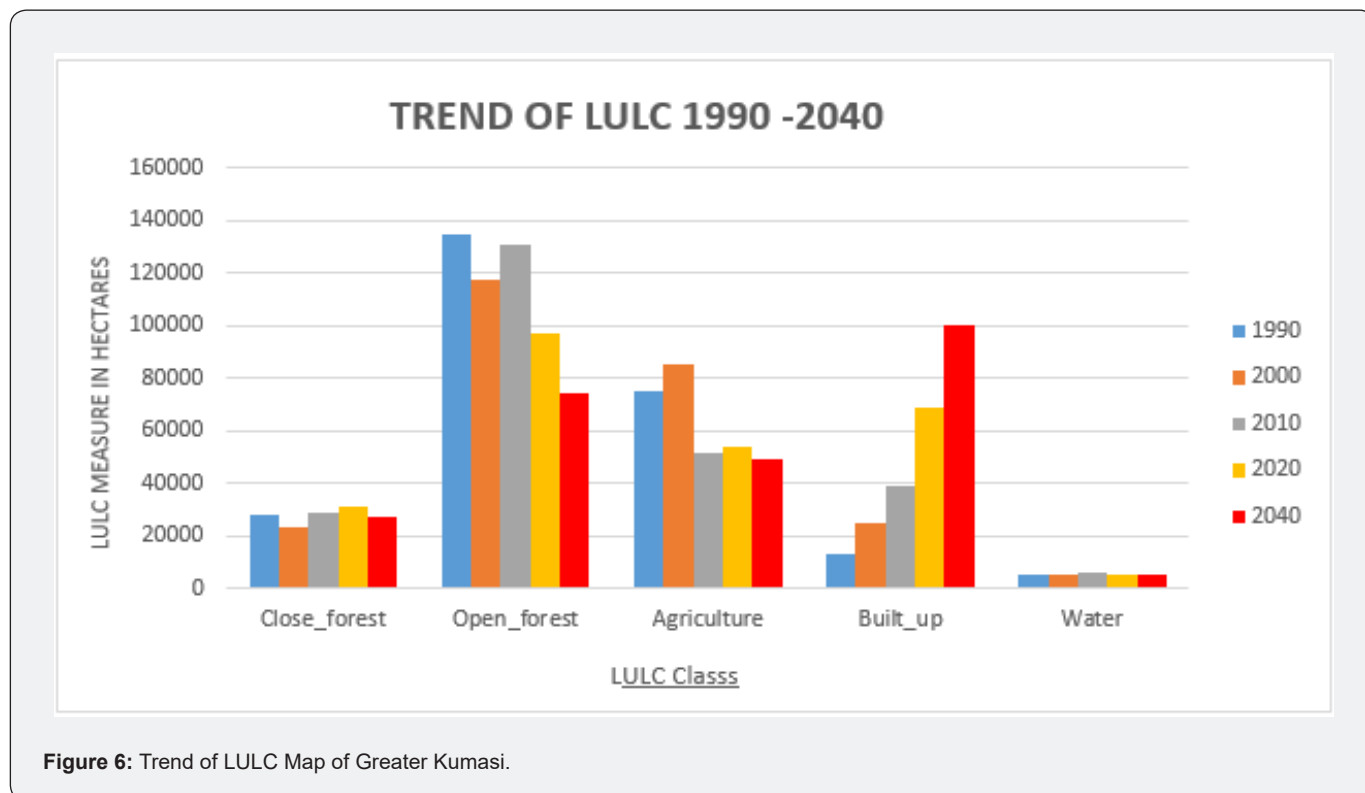
Land use Land Cover Change Trajectory	1990 -2000		2000 - 2010		2010 - 2020	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Close forest - Open Forest	15087.7	12.4	13840.6	12.2	10447	8.62
Close forest -Agriculture	3539.62	2.91	1579.11	1.39	6668.27	5.5
Close forest -Built up	106.1	0.09	52.92	0.05	3861.64	3.19
Open forest - Close forest	9614.96	7.9	12761.6	11.25	18932.1	15.62
Open forest - Agriculture	44671	36.72	22637.3	19.96	30064.7	24.8
Open forest - Built up	6670.05	5.48	3107.42	2.74	14589.9	12.03
Agriculture - Close forest	4343.69	3.57	8747.36	7.71	3942.24	3.25
Agriculture - Open forest	28262.1	23.23	37772.4	33.3	18691	15.42
Agriculture - Built up	9370.29	7.7	12916.7	11.39	14040	11.58
<b>Total</b>	<b>121665.5</b>	<b>100</b>	<b>113415.4</b>	<b>100</b>	<b>121236.9</b>	<b>100</b>

**Table 5:** 2040 LULC Quantification.

LULC CLASS	Area (ha)	Area (%)
Close_forest	26,796.84	10.49
Open_forest	74,100.28	29.01
Agriculture	49077.53	19.22
Built_up	100235.1	39.25
Water	5196.8	2.03
<b>Total</b>	<b>255406.6</b>	<b>100</b>

**LULC trajectory for 1990 - 2040**

Figure 6 shows the course of LULC from 1990–2040 covering 50years. The illustration defines a perturbing scenario for forests. There is forest loss (deforestation and degradation) from as high as 66% in 1990 by 2040 to 44%. Agricultural land will continue to decline paving way for more houses and social amenities to be provided. Built-ups share would continue be the fastest growing land use class from 4.8% in 1990 35.2% by 2040. The water share remains unchanging throughout the 50 year under consideration.



**Figure 6:** Trend of LULC Map of Greater Kumasi.

## Discussion

### Remote sensing and GIS in LULC appraisal

The optimal utilization of the land and its resources requires an in-depth information of the historical, current and possible future scenarios. RS and GIS provide the tools expedient for monitoring the dynamics of LULC ensuing out of both the changing demands of increasing populace and elements of nature acting to influence the landscape [39,40]. Processes emanating from natural and man-made activities cause the transformation of earth's atmosphere and land [41,42]. The assessment of the spatial-temporal patterns of LULC in forests, rural, urban and other land use forms are necessary to the understanding of the evolution of forest loss, urban systems and other critical ecosystem services. Consequently, information about LULC extent, change and forecasting are essential for appraising land cover maps and the management of natural resources [43,44].

Satellite imagery deliver a proficient means of obtaining information (data) on spatial distribution and temporal trends of LULC required for quantifying, appraising, forecasting and projecting land changes [45,46]. Additionally, in inaccessible (such as mountainous, marshy, glacial and many others) terrain, remote sensing technique is feasibly the only method of procuring the relevant data at a cost and time effective basis [47,48].

### LULC trajectory

In the selection of the training sites for the supervised classification of the Greater Kumasi stratified random sampling ensured quality results. This involved employing expert knowledge, as the area of interest was disseminated into strata that maximized the dissimilarities between units and minimize the difference within each unit. Strata designated (One or more) were appraised to be main drivers of the system under scrutiny. A random sample was then selected from each unit or stratum. As recognized variances occur between the strata, stratified random sampling with well-adjusted allocation gives enhanced estimation devoid of bias. The chief advantage of stratified random sampling is that results are generally unbiased and precise. It frequently produces data that is more illustrative of the entire population due to the special attention it gives to the smaller subcategories within the population. Additionally, it provides the best avenue to get results that mirror the diversity of the population under study [49,50]. Stratified random sampling is more effective for large and diverse populations as pertained in Greater Kumasi.

LULCC detection appraisals have quite a lot of inferences contingent on the range and concentration of the researcher. However, the widely accepted fact about Change Detection use is its capacity to deliver data on changes in LULC including the

magnitude, location and trajectory and the spatial dissemination of the change [50,51].

The LULCC maps for 1990 - 2000, 2000 - 2010 and 2010 - 2020 gives a great cause for concern in the light of climate change concerns. LULC changes of 141504.72ha (49.69%), 130354.25ha (45.77%), 138598.03ha (48.67%) for the respective epoch years had transpired transitioning mostly into other land use classes. Deforestation is prevalent outside of the protected areas while forest degradation is manifest in the protected areas as a result of logging (mostly illegal), illegal mining popularly called Galamsey and admitted agricultural activities. Cumulatively, urbanization is on rise as the population continues to rise. LULCC in this study is clearly caused by anthropogenic forces. These findings concur with earlier research undertaken [52-55].

### Predicting the future land use changes

Forecasting LULC has become critical in land and resource management [54,56]. The consolidative and combinative model of cellular automata and Markov chain were employed to forecast the future LULC pattern of the study area for the year 2040.

The forecast for the period 2040 indicates the human built up class becoming the dominant LU in the study area. Mostly, the measurements display a growing trend in human-built environment, which is attributed to increasing human population [19]. The Ashanti Region as the center of the country with its rich natural resources and strategic location attracts migrants from different communities in Ghana and other nationals from West Africa and the continents.

### Anthropogenic causes of the land use land cover trends

Greater Kumasi has undergone dramatic increase of built-up areas and agricultural intensification as revealed by the land cover change analyses. The sum of land cover change substantiates the trend and extent of urban growth resulting in sprawling unto the outskirts and additional densification in the inner parts as well. The upsurge of built-up and agriculture (mostly in the neighboring districts) have impacted negatively on forest cover and other open spaces. Essential service such as water supply from the Owabi and Berekese Headworks are under serious threat owing to wanton destruction of natural vegetation for human settlement and agricultural purposes [57]. The driver for deforestation and degradation is clearly anthropogenic in this study. The Ashanti Region has the largest population in Ghana and the fastest growing population [19]. The surge in population has direct consequence on the environment and the forests in particular. The rapid urbanization growth in study area is the consequence of natural increase in population, and migration [19]. Ghana's population was 24,658,823 in 2010. 6,726,815 was

recorded in 1960 and increased to 18,912,079 in 2000. Between 1960 and 2010, a period of fifty years, the population more than tripled. The Ashanti Region had the highest population in all the census years and most of the population in Ashanti Region resides in the urban centers [19]. The factors enumerated in Table 1 all apply in the study area. This unfortunate situation necessitates a quick and a well thought out plan to salvage what is left.

## Conclusion

The application of GIS, remote sensing, and statistical simulations techniques has shown in this study to be a cost effective and potent means for monitoring spatial and temporal LULCC. The study revealed that, built up area grew astronomically (fivefold) at the expense of forest cover and Agriculture in the Greater Kumasi area within the 30years (1990 - 2020). Most of the forest cover within the study area are under strict protection. These protected forests include part of the Bobri Forest reserve, the Barekese Headworks and the Owabi Headworks reserves. Forests cover outside these protected reserves are mostly gone or heavily degraded. Water share of the LULC remained stable as the main water bodies within the study area which includes the Bosumtwi late and the two headworks (Barekese and Owabi) are important national assets and are thus protected. The 2040 projected LULC map of Greater Kumasi estimates 40% of the LULC being built up, which was at 5% in 1990. The results of this study is consistent with studies by Addae & Oppelt [58]; Akubia et al. [59] and Toure et al. [60] in Ghana.

LULC maps derived from satellite data in this study are not without errors. As Robinove [61] stated, computer produced maps via digital operation of multispectral data is never 100% precise. The procedure of categorizing a wide spectrum of the World's landscapes into precise and frequently simplified categories brings error by delineating boundaries round geographically situated categories which are 'homogeneous' or suitably heterogeneous. Nevertheless, these limitations are rectified by comprehensive statistical scrutiny to give reasonably correct LULC maps [62].

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