# Assessment, Mapping and Prediction of Land use/Land Cover Changes and Urban Sprawl in the Ho Municipality of Ghana*

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## Abstract

Land use/land cover (LULC) changes and urban sprawl are now complicated concepts on the Earth's surface due to global urbanisation, which also impacts the natural environment, the economy, and social systems. LULC analyses have emerged as one of the essential techniques for tracking and analysing the effects of urbanisation. In this study, the LULC changes of the Ho Municipality in Ghana were evaluated using remote sensing (with Landsat data from 2000 to 2020) and GIS techniques in order to categorise the different types of land use/cover, quantify and predict the rate at which the changes are occurring, and also evaluate the impact of urban sprawl over the study area. The supervised classification algorithm generated suitable LULC maps from the Landsat 7 ETM+ image (2000) and Landsat 8 OLI/TIRS image (2020). Further, Cellular Automata - Markov (CA-Markov) Model was used for predicting LULC changes for 2040. The development in the area has increased from 30.69 $km^2$ to 224.05 $km^2$ during the 2000-2020 period under observation. According to the LULC prediction made with the CA-Markov model, the Municipality's urbanisation could rise from 224.05 $km^2$ to 240.85 $km^2$ between 2020 and 2040. The prediction model predicts that most vegetation covers and bare lands will dramatically decline throughout the observation period 2020–2040, leading to regional urbanisation. These signs may warn the authorities to take action and reduce the effects of possible urban heat islands as land use, and cover changes continue to occur.

**Keywords:** Cellular Automata, Urban Sprawl, Land Use/Land Cover, Mapping, Prediction

## 1 Introduction

Urban sprawl is a broad concept that involves the expansion of a city's boundaries into vacant, low-density areas. Urban sprawl can be likened to a leap-frog pattern of expansion around an already built-up area (Nechyba *et al*., 2004). According to the 2018 Revision of World Urbanization Prospects, about 68% of the world's population will reside in urban areas by 2050, with Sub-Saharan Africa recording about 55% urban population, which is higher than the estimated 42.5% in 2022 (Avis, 2019; Ritchie and Roser, 2018; Yadav and Ghosh, 2019). Urban sprawl has an uncontrolled irregular expansion pattern, whereas urban growth has a well-planned growth pattern. Demographers typically define urbanisation as the proportion of a nation's population living in cities to its overall population (Glenn, 1984). The fast rate of urbanisation, which has marked the haphazard physical growth and development of cities, particularly in developing nations, has been a defining characteristic of the twenty-first century. In Ghana, for instance, high rates of population growth due to natural causes and net migration to urban areas in search of job opportunities combine to create the country's rising rate of urbanisation (Burchfield *et al*., 2006).

Land use/land cover change is a common phenomenon in urbanised areas worldwide and represents how culture interacts with the natural world. Compared to its spatial expanse, urban sprawl significantly influences economic and environmental systems negatively (Clarke *et al*., 1998). This is because, when urban sprawl is improperly managed, changes in land use and/or land cover in these urban areas can cause various social, economic, and environmental disasters. These include floods, landslides, droughts, lack of access to safe drinking water, and reduced crop productivity. Land use/land cover changes as a result of urban sprawl creates high demand on urban regions to link the planning of land use, transportation, and the natural environment to reflect changes made on the terrain for industrialisation, agriculture, and residential uses.

Earlier research efforts on Land use/land cover change analyses applied techniques that enable the detection of change, measurement of extent and magnitude of change, monitoring of change for updating of existing maps, and estimation of the impact of change on environmental, economic, and political condition (Green *et al*., 1994; Rogan and Chen, 2004; Kumar, 2004; Deilmai *et al*., 2014). Some models have been developed to carry out land use/ land cover change prediction and urban growth expectation; these include Cellular Automaton (CA) (Syphard *et al*., 2005), Logistic Regression (LR) (Hu and Lo, 2007) and CA-Markov Chain (CA-MC) model (Memarian *et al*., 2012). Although CA has an open structure and can be integrated with other knowledge-driven models, it is only dependent on spatial data and, therefore, not appropriate for making realistic simulations (Gharaibeh *et al*., 2020). Integrating CA and Markov Chain Model has the advantage of modeling spatiotemporal dynamics

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with reasonable accuracy (Aburas *et al*., 2017; Gharaibeh *et al*., 2020; Hasani *et al*., 2020). The CA-Markov model is a dynamic and discrete system that operates on a regular network of cells and spatially analyses changes in vegetation indexes (Mokarram and Pham, 2022).

The CA-Markov model combines cellular automata with the Markov chain to predict how the characteristics and patterns of LULC change over time, provide a better understanding of the processes that lead to changes in forests, and generate future scenarios for land use and land cover to help with the planning of policy responses (Tegene, 2002; Fitzsimmons and Getoor, 2003). Additionally, the dynamics of LULC, forest cover, population increase, plant growth, and watershed management modeling are widely illustrated using this model. It is also suitable for long-term planning of land use growth, which is helpful for the design of land use policies (Hua, 2017). As a result, studying the chronological LULC is critical for understanding the long-term relationships between humans and the environment (Yang *et al*., 2014).

The effects of human activities in Ho Municipality of Ghana have significantly increased, changing the entire landscapes and, ultimately, causing the city to physically expand beyond its established borders in order to accommodate the growing demands of urban residents for land. Urban sprawl in the Ho Municipality has a variety of adverse effects on socioeconomic growth, including safety issues, environmental issues (green space consumption), social issues (increasing social segregation), and dependence on private cars which car leads to increased traffic congestion and energy consumption and its consequent pollutants emissions. This paper intends to measure the pace of urbanisation change in the Ho Municipality in relation to land cover types and forecast future indicators using remote sensing, Geographic Information System techniques, and integration of the CA and Markov Chain Model.

## 2 Resources and Methods Used

### 2.1 Study Area

The Ho Municipality, with Ho as it is administrative capital, is one of the twenty-five (25) Municipalities and Districts in the Volta Region of Ghana. The Municipality lies in the southeastern part of Ghana. The Municipality is located between latitudes $6^0$ 20'N and $6^0$ 55'N and longitudes $0^0$ 12'E and $0^0$ 53'E, and it shares boundaries with Adaklu and Agotime-Ziope Districts to the South, Ho West District to the North and West and the Republic of Togo to the East.

The general relief of the Municipality is made up of both mountainous and lowland areas. The mountainous areas are mainly to the north and northeast, which are part of the Akuapim - Togo Range and have heights between 183 to 853 metres above mean sea level. The notable areas are the Awudome stretch in the southwest and Matse and Klefe in the northeast. The lowland areas are to the South of the Municipality and are between 60 to 152 metres above mean sea level. The general drainage pattern is southwards and dominated by rivers like Tsawe (Alabo) and Kalapa, which flow into the lower Volta or Avu Lagoon. These rivers are seasonal and therefore do not provide all year-round dependable water supply sources to the communities for home use and irrigation for farming. In 2000, the statistical report of Ho Municipality's population was about 177 281, which represented 8.4% of the Region's total population and was estimated to be about 271 881 with a growth rate of 3.1%. The growth rate of Ho compared with the regional population growth rate of 3.4% and the national growth rate of 2.7% indicates a high growth rate (Anon., 2010). This has contributed to pressure on the available facilities and urban sprawl. The study area is shown in Fig 1.

### 2.2 Materials Used

The material used for the study includes ERDAS Imagine, and ArcMap software. Ho municipality Topographic data in shapefile format and satellite images from the Landsat 7 ETM+ and 8 OLI/TIRS missions from 2000 to 2020. The satellite images were all downloaded from the United States Geological Survey (USGS) online database via the Global Visualization Viewer (GloVis) (http://glovis.usgs.gov). Tables 1 and 2 show the data sources used and the classification scheme.

ERDAS Imagine 2013 and ArcMap were the software packages used in this study. ERDAS Imagine was used in the remote sensing image pre-processing, layer stacking, area sub-setting, image classification, accuracy assessment, post-classification, and change detection. ArcGIS 10.4 was also used for data analysis and development of the maps produced.

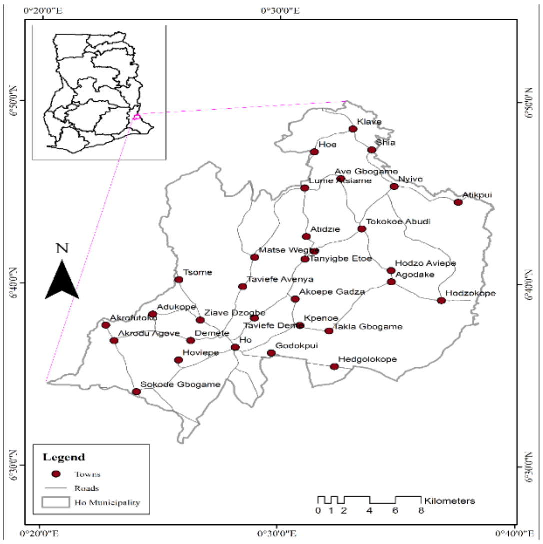


**Fig. 1 Map of Ho Municipality**

**Table 1 Data Source**

| Data Types | Date of Acquisition | Resolution (m) |
|---|---|---|
| Landsat7 ETM+ | 2000-02-04 | 30 |
| Landsat8 OLI/TIRS | 2020-01-02 | 30 |

## Table 2 Classification Scheme

| Class | Description |
|---|---|
| Vegetation | A mixture of all plant species in that particular area that includes grasses, trees and shrub (smaller plants) and sparingly distributed herbs. |
| Bare land | Exposed surfaces due to human activities or natural factors. |
| Built-up/Settlement/ Urban Area | Areas with intense infrastructural developments |

## 2.3 Methods Used

The methods used to obtain the results are show in the flow diagram in Fig. 2.

### 2.3.1 Image Pre-Processing

Data pre-processing of satellite data is essential for adjusting inaccuracies in the measured reflectance caused by changing electromagnetic radiation as it travels through the atmosphere (Lunetta and Elvidge, 1999). Using the spatial modeler tool in ERDAS Imagine, geometric and radiometric adjustments were performed to correct for altitude and attitude, scanner distortions, earth motion, varied detector response, etc., associated with the images. The images were already projected to the 1984 World Geodetic System Universal Transverse Mercator (WGS '84 UTM) Zone 30 North Projection, so re-projection was unnecessary.

### 2.3.2 Supervised Classification

Classifying an image's pixels, or its fundamental unit, is known as image classification in remote sensing. The images were classified using a supervised classification approach. This study divided land use into three categories using the maximum likelihood technique. Training samples were selected that reflect samples of the various surface land uses. Training samples were chosen based on their familiarity with the various land uses in the relevant study area (Ho). However, care was taken as samples wrongly chosen would affect the overall accuracy of the classification. From the training samples collected, signature files were generated with ArcMap. These signature files serve as a guide to the computer, as each pixel in the image is compared to these signatures and labelled as the class it most closely 'resembles' digitally (Mantey, 2017).

### 2.3.3 Post Classification and Accuracy Assessment

The Kappa test compares predefined producer ratings and user-assigned ratings (Hua, 2017), which can be expressed mathematically as in Equation 1.

$$K = \frac{P(A)-P(E)}{1-P(E)} \quad (1)$$

where, P(A) is the number of times the K raters agree, and P(E) is the number of times the K raters are expected to agree only by chance (El-Kawy *et al.*, 2011; Pontius and Millones, 2011).

The probability that a pixel on the image corresponds to a class on the ground was used to define user accuracy. The producer's accuracy demonstrates the possibility that a pixel will be correctly identified, and it is mainly used to assess how well a region may be categorised (Pontius and Millones, 2011). As previously said, the three classes, which comprise vegetation area, bare land, and built-up or settlement area, should have a minimum of 50 points for each measured category to enhance the percentage of accuracy assessment (El-Kawy *et al.*, 2011).

### 2.3.4 Change Detection

Change detection is the procedure by which possible changes that have occurred in the LULC over time are tracked. The difference between the two independently classified images over 20 years was evaluated using post-classification change detection (2000-2020). In order to simulate the land use and cover map for 2040, a change detection map (between 2000 and 2020) was created from the ERDAS imagine software. A cross-tabulation was used to compare classified images from two different datasets in order to identify the qualitative and quantitative aspects of change from 2000 to 2020. The magnitude and percentage of changes can be expressed in a simple formula, as shown in Equation 2.

$$A = \frac{F-I}{I} * 100 \qquad (2)$$

Where, $(F - I)$ is the magnitude of changes, A is the percentage of changes, F is the first data, and I is reference data (Hua, 2017).

Accuracy assessments on all the land use/land cover data were performed using field data captured on the field, and reference data were derived from carrying out the accuracy assessment on all the land-use/land cover maps in 2000 and 2020.

2.3.5 Markov Chain Analysis (MC)

Markov chain model is a stochastic model whose output is based on the transition probability, $T_{ij}$, between state $i$ and $j$. In a landscape with multiple land covers or land uses, the transition probability $T_{ij}$ would be the probability that a land cover type (pixels) $i$ in time $t_0$ changes to land cover type $j$ in time $t_1$. The transitions as probabilities can be expressed in Equation 3 as:

$$\sum_i^n T_{ij} = 1 \quad i = 1, 2 \ldots . n \qquad (3)$$

The transition probabilities are calculated using a sample of transitions within a specific time frame. These probabilities are illustrated in Equation 4 of the transition matrix

$$T.(B_i \times T_{ij}) = (B_1, B_2 \ldots B_n) * \begin{pmatrix} T_{11} & T_{12} & T_{1n} \\ T_{21} & T_{22} & T_{2n} \\ T_{n1} & T_{n2} & T_{nn} \end{pmatrix} \qquad (4)$$

where;

$(B_i \times T_{ij})$ is the proportion of land cover of the second date, $T_{ij}$ is a matrix of the probability of land cover transition, $B_i$ is the proportion of land cover of the first date (Vector), i is a type of land cover in the first date, j is a type of land cover in a second date, $T_{11}$ is the probability that a land cover *1* at first date will change into land cover *1* by the second date, $T_{12}$ is the probability that a land cover *1* at first date will change into land cover *2* by second date and so on and n is the number of land cover types in the study area.

This Markov chain analysis transition matrix may be used to forecast future land cover or land use at time $t_2$. As the Markov Chain model does not offer the geographical position of LULC future prediction, a hybrid CA-Markov model was employed to fix this. CA-Markov is a combined Cellular automaton, Markov chain, multi-criteria, and multi-objective land allocation model of the LULC prediction process (Parsa *et al*., 2016), where the projection is based on the Markov Chain process's transition area matrix and suitability maps.

2.3.6 Cellular Automata – Markov Prediction

The Cellular Automata (CA) are spatially dynamic models frequently used in studies of land use and land cover changes. The state of a cell's neighbours affects how it changes from one land cover to another in a CA model (Arsanjani *et al*., 2013; Mishra and Rai, 2016; Parsa *et al*., 2016). This is based on the concept that if a cell is closer to land-cover class 'A,' it has a larger chance of changing to 'A,' rather than 'B.' As a result, the CA model uses the past state of a landcover, as a Markov model does, and uses the state of neighbouring cells to determine its transition rules. For assessing changes in land use and land cover (LULC), notably in vegetation or forest cover change, CA models have been used frequently (Mishra and Rai, 2016). As a result, a CA model may add a spatial component to a Markov model, making it a dynamic spatial model. After creating a Markov chain matrix to establish a spatial weight-proximity factor to change the state of cells dependent on their neighbours. This study used CA-Markov to investigate and predict land use/cover for the Ho Municipality. The 2000 land use land cover map (Fig. 3) and the 2020 land use land cover map (Fig. 4) were used to simulate the 2040 land use land cover map (Fig. 6).

## 3 Results and Discussion

### 3.1 Land Use land cover

The classification scheme (supervised classification) of the various land-use/land cover of Ho municipality and its environs are shown in Fig. 3 to Fig. 5. Table 3 shows the extent of the various land use land cover classes in the study area. The overall accuracy was 80.65% and 72.58% for 2000 and 2020 LULC maps, respectively (Table 4). It can be observed from Fig. 3 and Table 3 that in 2000, urban areas were 30.69 km$^2$, covering about 5% of the entire study area, whiles vegetation covered 344.11 km$^2$, 60% of the study area. The land cover map of 2020, however, tells a different story. The urban areas occupy 224.05 km$^2$, representing almost 39% of the study area, an increase of 630% (Table 6). In addition, the vegetation cover had reduced to 294.34 km$^2$, a reduction of approximately 14% (Table 6).

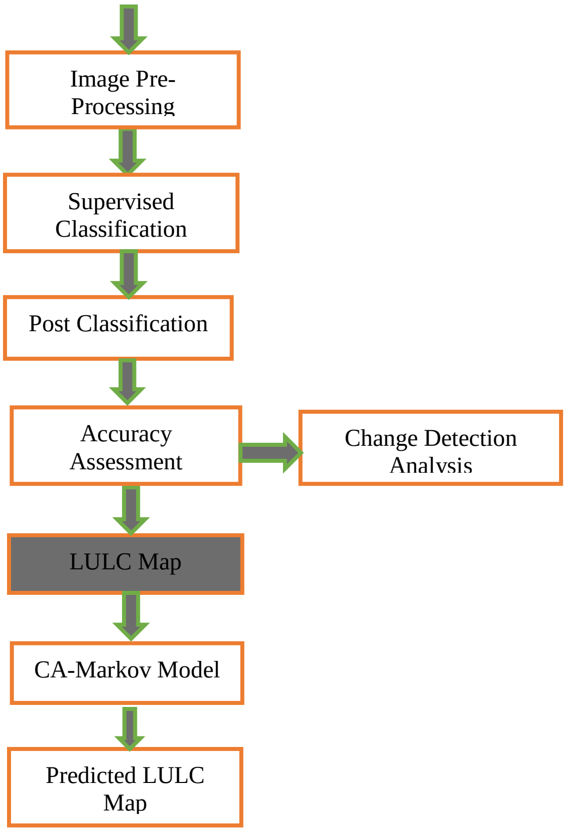


**Fig. 2 Flow Diagram of the Methods Used**

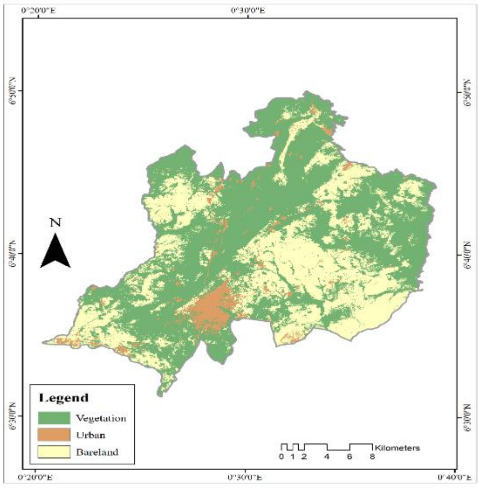


**Fig. 3 Land Use Land Cover Map for 2000**

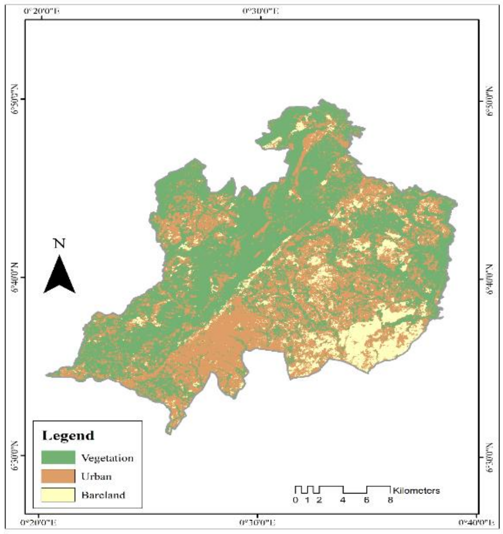


**Fig. 4 Land Use Land Cover Map for 2020**

**Table 3 Land Cover Statistics**

| | 2000 | | 2020 | |
|---|---|---|---|---|
| **Class** | **Area ($km^2$)** | **Percentage (%)** | **Area ($km^2$)** | **Percentage (%)** |
| **Vegetation** | **344.11** | **59.91** | **294.34** | **51.24** |
| **Urban** | **30.69** | **5.34** | **224.05** | **39.01** |
| **Bare Lands** | **199.59** | **34.75** | **56.00** | **9.75** |

Table 4 shows the overall accuracies and the Kappa values for the 2000 LULC and the 2020 LULC.

**Table 4 Classification Accuracy and Kappa Statistics**

| **Year** | **Overall Accuracy** | **Kappa** |
|---|---|---|
| 2000 | 80.65 | 70.52 |
| 2020 | 72.58 | 57.84 |

Fig. 5 represents the change detection map between 2000 and 2020 whereas Table 5 shows the land use land cover statistics for the change map

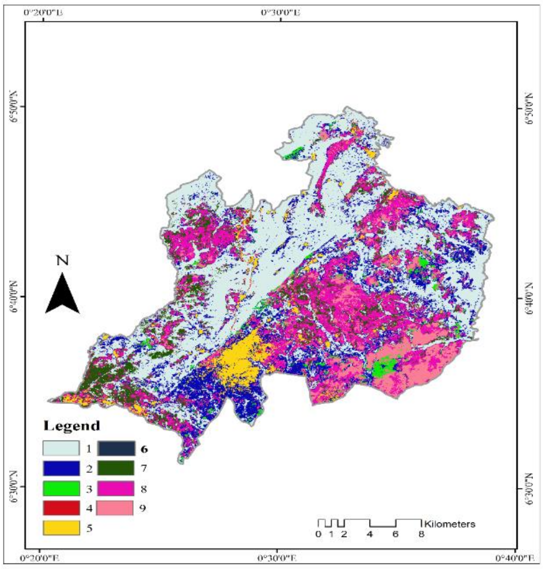


**Fig. 5 Changes of Map from 2000 to 2020**

The region's high urbanisation rate may be ascribed to the local population growth. According to the Ghana Statistical Service, 96 213 people lived there as of 2012. Demand for residential and commercial sectors will rise as the population grows. In order to accommodate the growing population, vegetation covers are consequently turned into residential or commercial areas for 218 650 people, thus decreasing the number of vegetative covers in the area.

**Table 5 Change Map Statistics between 2000 and 2020**

| Legend | Class | Area (km$^2$) |
|---|---|---|
| 1 | Vegetation unchanged | 243.51 |
| 2 | Vegetation to Urban | 88.35 |
| 3 | Vegetation to Bare land | 12.25 |
| 4 | Urban to Vegetation | 2.25 |
| 5 | Urban unchanged | 26.83 |
| 6 | Urban to Bare land | 1.61 |
| 7 | Bare land to Vegetation | 48.58 |
| 8 | Bare land to Urban | 108.87 |
| 9 | Bare land unchanged | 42.14 |

Fig. 6 and Table 7 represent the results from the simulated 2040 land use land cover.

**Table 6 Land Use Land Cover Changes between 2000 and 2020**

| Class | Area (km$^2$) | Percentage (%) |
|---|---|---|
| Vegetation | -49.77 | -14.46 |
| Urban | 193.36 | 630.04 |
| Bare land | -143.59 | -71.94 |

**Table 7 Land Cover Changes between 2020 and 2040**

| Class | 2020 | 2040 | Change | 2020% | 2040% | Change % |
|---|---|---|---|---|---|---|
| **Vegetation** | 294.34 | 290.89 | -3.45 | 51.24 | 50.64 | -0.60 |
| **Urban** | 224.05 | 245.85 | 21.80 | 39.01 | 42.80 | 3.79 |
| **Bare land** | 56.00 | 37.65 | -18.35 | 9.75 | 6.55 | -3.20 |

The simulated 2040 land use land cover map anticipated vegetation to reduce in size by 3.45 km$^2$ (0.6%). Bare land may shrink in size by about 18.35 km$^2$ (3.2%). Urban areas will increase to about 21.8 km$^2$ (3.8%) at the expense of both vegetation and bare land.

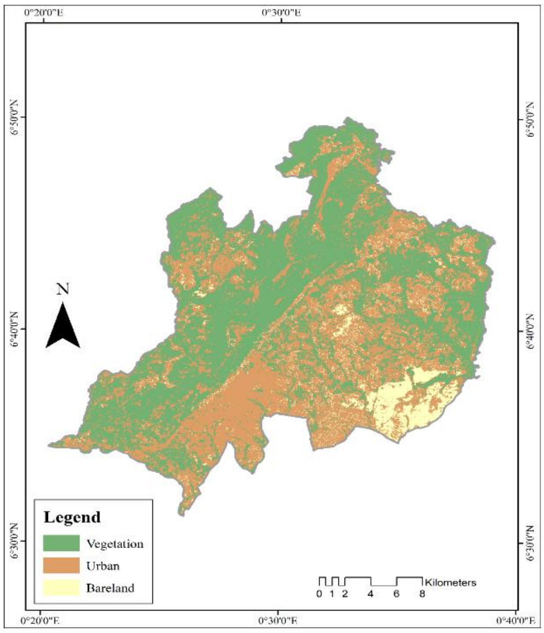


**Fig. 6 Predicted 2024 Land Use Land Cover Map**

## 4 Conclusions

Settlements, forests, grasslands, and bare land are the three categories into which the study region has been classified. Two land cover maps were created using ArcMap and ERDAS Imagine 2013. In order to create accurate land cover maps, accurate land cover classifications must be obtained. The rate of change of the various land cover types was successfully quantified by contrasting the two Landsat images (Landsat 7 ETM+ 2000 and Landsat 7 ETM+ 2020), and the changes in the various maps were determined for the period (2000-2020). The findings show that from 2000 to 2020, the urban area and settlements significantly increased, whereas vegetation significantly declined. The first land use/cover conversion pathway starts with gradual modification and eventual conversion of Forest reserves to degraded forest depending on the intensity and type of human activities involved. Degraded forest areas are either allowed to be converted to bare land and Settlement land as a result of surface mining and subsequently regenerated to Grassland.

In the second pathway, natural vegetation (especially in forests and degraded reserves) was completely and permanently changed into non-vegetated built-up or bare landscapes, with grasslands typically at the beginning. This is typically seen in proximity to existing towns and settlements, particularly in the northern parts of the study region. Additionally, the consequences of urban sprawl on the research region were evaluated.

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