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Multi-Temporal Landscape Dynamics, Driving Forces and Land Surface Transition Intensities of the Ankobra River Basin (ARB), S/W, Ghana

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Abstract

Understanding the characteristics of a degraded peri-urban watershed is crucial for sustainable ecosystem management. The study adopted the FAO LCCS and the Markov-Chain algorithm to evaluate the past, present, and future temporal variation of land cover classes in the Ankobra River Basin, Ghana. A 33-year Landsat imagery revealed that, between 1990 and 2023, there was an increased expanse in settlements, bare land and mining excavations, while forests and agriculture/farmlands recorded a decreasing trend. The research hypothesized no significant spatio-temporal land use land cover (LULC) changes using the Paired Sample t-test. The null hypothesis was therefore rejected, with evidence showing significant LULC changes over the study period. The study showed an increase in settlement/built-up from 159.90 km² in 1990 to 958.4 km² in 2023. Mining excavations also increased substantially from 6.81 km² in 1990 to 642.0 km² in 2023, while bare lands increased from 185.67 km² in 1990 to 784.3 km² in 2023. Contrary, agricultural/farmlands significantly decreased from 2472.38 km² in 1990 to 1892.20 km² in 2023 while forests also decreased from 5576.79 km² in 1990 to 3920.70 km² in 2023, demonstrating significant spatial LULC variability, largely affected by anthropogenic activities. Based on the driver-factor analysis using the AHP, the study indicates that agricultural expansion, population pressure, logging, mining activities and industrial expansion were the main drivers of LULC changes in the ARB. The findings presented, herein, prove that monitoring the dynamisms of ecosystem can serve as scientific references for the sustainability, protection and management of global tropical ecosystems.

Keywords: Land Use Land Cover; Ecosystem Sustainability; GIS/Remote Sensing; DPSIR; Galamsey; HumanWellbeing (HWB); Ankobra River Basin (ARB)

Introduction

The accelerating pace of land use change during the half past century, coupled with the externalities of modern industrialization, urbanization, agricultural intensification, unregulated mineral extractions and commercial activities are more profound in Africa and many other tropical regions (Ajakaiye & Page, 2012; Mir et al., 2025; Rudel, 2021). Environmental transformations in sub-Saharan Africa, compounded with modification in ecosystem structure and other intensified human, technological and political activities on land surfaces, are the principal causes of biodiversity loss and disruption in the core ecosystem process (Ellis, 2021; Okorundu et al., 2020). As such, land use land cover changes (LULCC) have been in the spotlight raising worldwide concern due to their significant impact on the earth's ecology (Ran et al., 2023; Verburg et al., 2006). The exponential growth of human activities (Herrmann et al. 2020; Kankam et al. 2023) has resulted in a substantial increase in land use practices that not only modify the characteristics of landscape patterns but also led to the creation of sinks and source pollution and pose significant landscape ecological risk (LER), with the latter being pivotal for ecosystem conservation and sustainable social development (Hussain et al., 2025; Li et al., 2024; Mataima & Gumbo, 2005). Land use has been a comprehensive reflection of human activities and if uncontrolled, could disrupts the basic functions and balances of several ecological variables (Chaudhry & Malik, 2017; Tahiru, Doke, & Baatuuwie, 2020). These disturbance in ecosystem functions influence surface water quality, organic pollution, soil carbon storage, pollutant loads, food web and plankton diversity in riverine and marine environments (Owusu et al., 2025; Schmidt et al., 2018; Vrebos et al., 2017).

Many parts of sub-Saharan African countries are still undergoing rapid urban and peri-urban expansions, with population growth averaging at 140% between the 1990's and the 2010's, at a rate that is 10 times faster than in the industrialized countries (Addo et al., 2022; Kusi et al., 2025; Osumanu, 2022). The 2016 West Africa Land Use Dynamics Project conducted by the USGS under the West Africa Land Use Land Cover Time Series represent an effort to map LULC, characterize the trends in time and space, and understand their effects on the environment across West Africa. Unfortunately, Ghana have been battling with illegal mining activities, referred to as "*galamsey*", unsustainable agricultural practices, together with the rate of migration and population pressure disrupts the functionality and productivity of environmental variables (Duncan, 2020; Kusimi, 2015). In mining areas, severe environmental harm and ecological degradation, such as the deforestation and eradication of native vegetation and other natural resources, are particularly prevalent (Ahirwal & Pandey, 2021; Mensah et al., 2015). Like most activities that support human life, mining has had the greatest impact on the ecosystem's structure and functioning in mining areas (Karaca et al., 2018).

From health and ecological perspectives, the Ankobra river basin is characterized with inflow migration (Kutir et al., 2023), rapid and spontaneous growth due to the "*rush for gold*" syndrome, resulting in negative health issues and environmental degradation. The basin has witnessed rapid growth of towns and total urban population which has led to extraction of large mineral wealth and consequent industrial growth, including rubber plantation. A number of towns including Tarkwa, Wiawso, Prestea, Dominase, Huni Valley, Nsuta, Gwira Banso, Gwira Eshiem have been greatly impacted by the rapid growth of mining activities and indiscriminate land use activities. Acquah (1993), Boakye et al. (2020), Donkor and Agyeman (2018; 2019) added that the recorded deforestation in the Ankobra catchment was influenced by local population growth, agricultural extensification, timber logging and increased surface mining activities since 1990's when the Government of Ghana triggered a memorandum of understanding for implementation of the structural adjustment programme of the World Bank, liberalized Ghana's economy and increased foreign direct investment in the mining, timber and agricultural industries.

Many studies have so far focused on LULC changes in the ARB over a span of time. For example, Schueler et al. (2011) used Landsat satellite images from 1986–2002 to map land cover change and implications of mining-related land cover change. It was confirmed the study of Schueler et al. (2011) that conversions from forest and farmland to mining pits were the two most widespread land cover changes, mostly due to the expanse of forest remnants. Overall, about 3,168 ha of forests were cleared for gold mining pits between 1986 and 2002. Similarly, Obodai et al. (2019) assessed the pattern of Land use/cover changes with Landsat images (1991-2016), and the possible drivers of change, in the Ankobra River basin. It was revealed that basin witnessed noticeable changes in LULC over the 25-year period. They revealed that Open Forest is the major LULC followed by Closed Forest and

this pattern remained unchanged for all the years selected for the study. In other studies, Cudjoe et al., [2023](#) and Kankam et al. ([2022](#)) investigated the suitability of a 32-year (1986-2018) Landsat data for a LULC trend analysis in a comparable basin with similar landscape conditions.

The aforementioned studies of Aduah et al. ([2015](#)) share a lot of things in common with Boakye et al. ([2018](#)), Obodai et al. ([2019](#)), and Schueler et al. ([2011](#)). Likewise, Aduah et al. ([2015](#)) have argued that the land cover/use changes in the aforementioned catchments can be attributed to anthropogenic drivers, which can be grouped into two broad categories, namely global and local factors. The global factors include globalization of agriculture, urbanization, international trade regimes and global politics, while the local factors include population growth, urbanization, immigration, economic development and government policy, which is also consistent with Barbier ([2007](#)), Lambin and Geist ([2008](#)), Meyfroidt, Lambin, Erb, and Hertel ([2013](#)), and Sonter et al. ([2014](#)). The LULC analysis by Boakye et al. ([2020](#)) revealed that closed forest and open forest consistently decreased in their spatial dimension while farm/grassland, settlement, and mining experienced an increase in spatial dimension. Further, viewing the Earth from space is now crucial to the understanding of the influence of man's activities on natural resource over time. In situations of rapid and often unrecorded land use change, observations of the earth from space provide objective information of intensified human utilization of the landscape. Over the past years, data from Earth sensing satellites has become vital in mapping the Earth's features and infrastructures, managing natural resources and studying environmental change.

It has been revealed by Duan, Feng, Zhou & Li ([2021](#)) and He et al. ([2000](#)) that despite the valuable functions of the watershed, the rate at which river basins are getting degraded due to human activities is alarming, necessitating area-wide watershed management that involves a host of actors and stakeholders. This study explores the use of geospatial techniques to identify the effects of mining activities generating the landscape metrics and numerical data in the region of interest. The research methodology was categorized as description of study area, sources of data, data processing, including data preprocessing, extraction of spectral indices, accuracy assessment, change detection, post classification and Markov-CA LULC prediction for 2056. In purview of the above, this study attempts to map out the status of land use land cover of the ARB between 1990 and 2023 with a view of (1) detecting the land cover changes and the trend that has taken place in the ARB from the Landsat satellite series, (2) Accuracy assessment with LULC transitions, notably trajectories and change intensity analysis. (3) Finally, the study further presents the analysis of land transformation in the future to ascertain the depletion of land use/cover types predicted for the year 2056 using CA-Markov chain model.

Methodology

Study Area

The study was conducted in Ankobra River Basin (henceforth, ARB) as shown in Figure 1. ARB is one of the south-western basins in Ghana, West Africa and occupies approximately 8,416 km². Geographically the basin lies within latitudes 4°52'– 6°27'N, and longitudes 1°42'–2°33'W, sharing boundaries separately with the Pra Basin to the east (Asare-Donkor et al. [2016](#)), to the west by the Tano Basin and South by the Gulf of Guinea. It is an extensive basin that spans across three political regions and eleven districts with Nzema East, Ellembelle, Wassa Amenfi, Wassa West, Prestea Huni-Valley (PHD) and Tarkwa-Nsuem districts making up 81% of the total area (Obodai et al., [2019](#)). It is approximately 8,416 km² in area and the metadata analysed from the digital elevation model (DEM) indicate that the basin is averagely 28m above sea level. The Ankobra River flows about 190 km (120 miles) from the northeast of Wiawso to southwards of Sanwoma near Axim, into the Gulf of Guinea on the Atlantic Coast. With a population of approximately 1.205 million people, of which 724,200 is peri-urban population and 525,900 is rural population (GSS, [2021](#)), the Ankobra River serves as the boundary between the Nzema East Municipal and the Ellembelle Districts. It takes its source from the hills north of Basin Dare (near Sefwi Wiawso and Bibiani) and flows for about 260 km mostly to the south before it enters the Gulf of Guinea at Asanta, a few kilometres west of Axim.

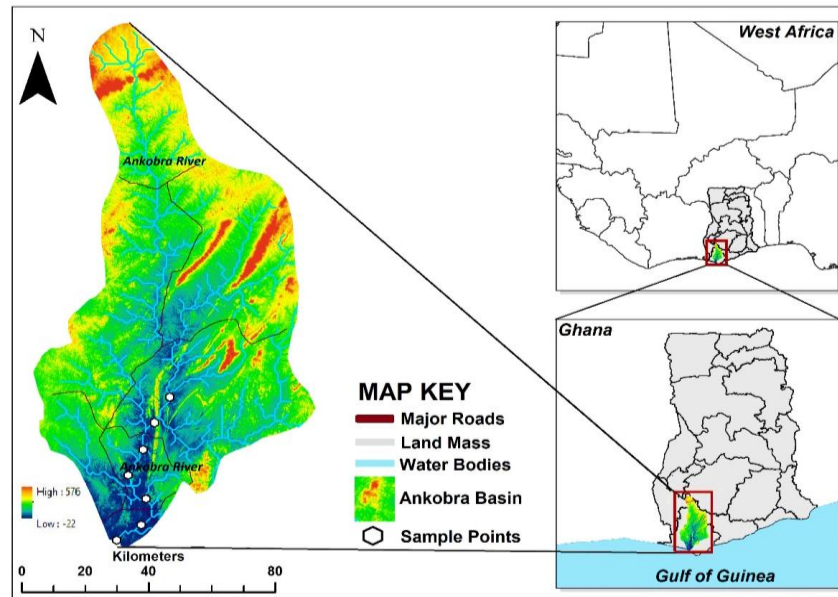


Figure 1: Map of Ankobra River Basin (ARB), Southwestern Ghana.

The geology of the area is of metamorphosed lava, pyroclastic rock and hypabyssal formed during the Birimian Era. The soil of the study area is underlain by metamorphosed sedimentary rocks and granites of the Birimian (middle pre-Cambrian) system with isolated basic intrusive rocks (WRI, 2003). In addition, a narrow belt of sedimentary rocks referred to as the Tarkwaian (upper pre-Cambrian) system is present in the valleys of the River Ankobra. Rocks of the Tarkwaian system consist of a thick series of shaly and sandy sediments, conglomerates, and phyllites which are younger than the Birimian rocks (Amponsah-Tawiah & Dartey-Baah, 2011; Eshun & Okyere, 2017; Minerals Commission Ghana, 2011). The Ankobra River Basin falls within the South-Western Equatorial and the Wet Semi-Equatorial climatic regions. The South-Western Equatorial is the wettest climatic region in Ghana with mean annual rainfall above 1900 mm. The study basin has a bi-modal rainfall (April to July and September to November) and a dry season from December to February within the year. The highest mean monthly temperature for the two climatic zones is 34 °C and occurs between March and April whilst the lowest temperature is approximately 26 °C and occurs in August (Tanu, 2009). The climate in the Ankobra Basin largely affects the geomorphic activities that influence LULC changes and ecological variables (Dickson & Benneh, 1980). Climate conditions of the ARB between 1995 and 2025 recorded at a district recording point of the Ghana Meteorological Agency is depicted in Figure 2.

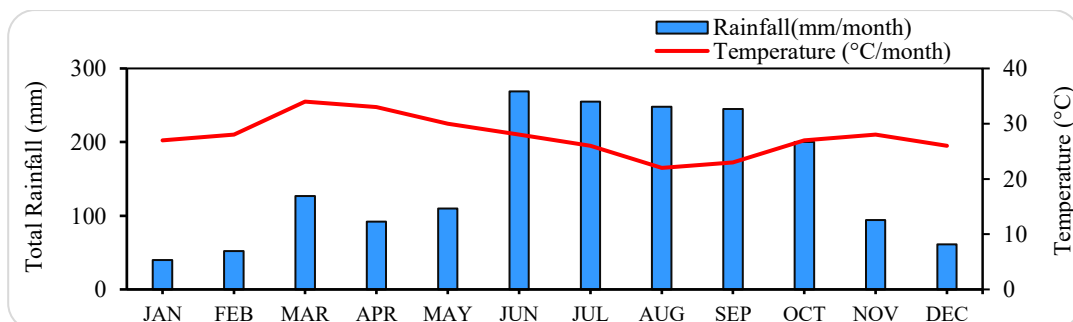


Figure 2: Mean monthly temperature and rainfall variations of ARB, S/W, Ghana between 1995 and 2025.

The settlement pattern of the study area is predominantly linear, highly influenced by the Ankobra River course and its tributaries. The benefits derived from closeness to the river cannot be overemphasised as most of the activities among the communities are water-dependent. The main occupation within the ARB is agriculture, employs about 65% of the entire population while fishing employs about 21% of the aforementioned population (GSS, 2021).

The majority of the people indulge in slash and burn or shifting cultivation on a subsistence scale. They grow staples such as plantain, cassava and cocoyam. However, companies like Ghana Rubber Estate Limited (GREL) as well as individuals in the basin cultivate cash crops like, rubber and oil palm, with a significant population also indulging in mining and other mineral extraction activities, referred to as “*gold rush*” or “*galamsey*”.

Over the years, the River Ankobra has played a significant role in the socio-economic activities of individuals and companies within its catchment area. It is one of the most important river basins in Ghana, in that it has some of the richest gold, diamond and manganese mines in the country (Appiah et al., 1993; Kortatsi, 2007). Also, it is a major source of revenue generation for national development (Karikari et al., 2021). Fishing and farming are the major source of livelihoods in the Ankobra area. About five small communities are located along the banks of the Ankobra River namely Sanwoma, Kukuaville, Eziom, Adelekazo and Eshiem. However, for some time, the pace of exploitation of the Ankobra Basin has been stretched to the point that if proper control mechanisms were not put in place, the Ankobra resources can no longer sustain the existence of its flora and fauna. There are numerous problems that have emanated in the Ankobra basin due to uncontrolled human exploitations mostly from illegal activities. Furthermore, illegal logging particularly the destruction of mangroves for both construction and domestic uses have directly and adversely impacted land surface area, water quality and livelihoods of people in the ARB area (GSS, 2021). Development of settlements and other human activities including unorthodox cutting of bamboo have degraded the riparian lands along the river, having an excessive impact on the basin, especially at the estuarine areas. The aforementioned problems and many more affect the ecological variables of the ARB. Figure 3 shows the diverse phases of LULC changes and the extent of land surface area transformation of the ARB over time, due to anthropogenic activities. Plates *a* & *b*, retrieved from MyJoyOnline on 21st October, 2023, plates *c* & *d* from a reconnaissance study by the Researcher on 11th Nov, 2021, while plates *e* & *f* is retrieved from CitiNewsroom on 16th January, 2024.

Currently, the basin supports an increasing population, together with industries from mining, quarry, tourism and rubber farms (Lawortey et al., 2020; Yidana et al., 2008). The ARB plays a vital role in maintaining ecosystem functions and biodiversity (Kutir et al. 2023), as well as promoting local economic development (Acquah, 1993; Anokye & Darko, 2025; Donkor and Agyemang, 2015). However, due to climate change and human activities such as illegal mining (locally referred to as “*gather and sell*” or “*galamsey*”), construction expansion, industrial activities, farming and grazing activities (Obodai et al. 2019), there is a risk of degradation of ecological functions in the basin (Faseyi et al., 2022). And as ecological risk increases, the human-terrestrial system is likely to become even more out of balance. Thus, there is an urgent need to analyze LULC changes in this basin to provide support for ecological management decisions.



Figure 3. Pictorial evidence of surface area transformation some sections of the ARB.

Source of Data

The study utilized four Landsat Collection 2 Level 1, 30x30 m in GeoTiff format, which comprises Landsat TM (Thematic Mapper) of 1990, Landsat-7 ETM+ (Enhanced Thematic Mapper Plus) of 2000 and 2010, and Landsat-9 OLI (Operational Land Imager) covering the year 2023. The tiles with path/row 196/55, 196/56 and 196/57 were obtained from the United States Geological Survey (USGS) database (www.earthexplorer.us.gov/) and complemented with google earth engine. This is because in cases where the study area is vast, the method gives ease of access and capabilities to leverage the platform for processing as it offers cloud computing functionalities in a free-to-use approach in the explorer web app. In selecting the satellite images, near-anniversary image acquisition dates were selected to minimize atmospheric influences and differences.

Satellite Image Processing Procedures

Landsat imageries were geometrically and radiometrically corrected to remove errors, including, cloud contamination, orbit, or sensing geometry issues were detected during image capture. This is to ensure image visibility and consistency. Geometric correction was used to convert the satellite image geometry to real world coordinates and projection, enabling the comparison of two or more images, the extraction of geospatial information, and the overlay of images with maps from different sources (Aggarwal, 2022; Maeder et al., 2002). Radiometric correction, on the other hand, corrects for the effects of the atmosphere on satellite images. The objective of radiometric correction in change detection is to ensure that available images are compared on the basis of similar radiometric properties (Badreldin & Goossens, 2014). FLAASH atmospheric correction module was utilized to compensate for various atmospheric and sensor inherent effects. For the Landsat 7 imageries, the gap filling technique was used to correct the distortions on the images. A mosaic was done to combine the different satellite tiles in their respective years and a subset of the region of interest was extracted. Image processing and analysis were done using the ARCGIS and ENVI applications.

Pre-LULC Classification and Visual Analysis

Visual interpretation is the first step in any LULC analysis. From a geospatial point of view, it is the simplest way to interpret an image, distinguish various land covers and change information over a particular area by a human interpretation. The goal of visualization is to identify image elements by recognizing the relationship between pixels and group of pixels, complemented with ground-based statistics.

A set of seven (7) primary Land Use classifications has been chosen for Land Use and Land Cover (LULC) interpretation. These classes encompass Water (WT), Agriculture/Farmlands (AG), Forest Land (FT), Settlement/Built-Up (ST), Bare Land (BL), Mining Excavations (MN), Mangroves/Wetland (MW). In order to gain supplementary information and synoptic view on land cover features, numerous ground-based campaigns were initiated. The motive for the ground-based campaigns was to gather evidence that complements the comprehensive reference dataset and observing the real interpretations for training the LCCS and Markov classification models (Wohlfart et al., 2016). Images were taken from the field to depict all seven (7) LULC classes used for LULC analysis and interpretation, as presented in Figure 4.



Figure 4. Images taken from the field to represent all the seven (7) LULC classes under consideration.

Extraction of Spectral Indices

Several spectral indices (NDVI and NDWI) and image operators were calculated on the Landsat images to be used either in the segmentation process or in the classification process in further steps (Maeder et al., 2002). Vegetative indices were analyzed in the study area to determine both quantitative and qualitative measures of vegetation cover, vitality, and growth dynamics. Some of them highlight certain surfaces, such as vegetation, built-up surfaces or water bodies, and certain thresholds were applied to these images to classify these surfaces (Capolupo et al., 2017; Ramos & Sappa, 2024). Others may highlight edges of objects and were used to guide the delineation of objects in the image segmentation process.

Training Signature Sampling for Classification

After sub-setting the image, the training data sets were created from the satellite images with the help of aerial photographic interpretation and ground truth data from the reconnaissance survey. The photographic interpretation information was used as a guide for defining the feature classes in the satellite images. For the LULC classification approach, the study adopted the FAO Land cover classification scheme (LCCS) West African Land Cover Reference System (Anderson et al., 1976; Jansen & Di Gregorio, 2022). By adopting these schemes, the 4-multi-temporal historical LULC (1990, 2000, 2010, and 2023) were classified into seven main classes, including Water (WT), Agriculture/Farmlands (AG), Forest Land (FT), Settlement/Built-Up (ST), Bare Land (BL), Mining Excavations (MN), Mangroves/Wetland (MW). To ensure accuracy in the analysis, Google Earth was used to select training samples in the classification process. These classes were sampled from the satellite image by using the polygon extraction method. The polygon extraction method simply allows drawing a polygon that defines the location of the pixels which represent the particular spectral class. Once the base training sets were established, each training set was stored in signature editor and assigned the colour desired for the particular feature class.

The training data sets were then used to generate class signatures and classify the rest of the image into meaningful information classes. To organize the classification more easily, FAO system used a dichotomous (divide into sub categories) approach in hierarchical levels and used eight classifiers to group all land cover types at the third level. In other words, any location on the earth surface can be categorized into one of the eight classes without having a conflict. Up to this third level, FAO used the presence of vegetation, edaphic (plant conditions generated by soil and not by climate), and artificiality of land cover for classification. Additionally, the third level of FAO

classification can be considered as a concept based on visual classification, which uses the directly visible and knowledge-based components on the ground. Lastly, data alignment was performed to ensure that all the data sources were in the same geographical reference system for consistency in spatial resolutions. Hence, all satellite images were projected onto the UTM zone 30N/WGS 84 coordinate system, respectively. In the absence of a direct auxiliary data for acquiring detailed LULC data, the study relied on the works by Aduah et al. (2015), Asante-Yeboah et al. (2022), and Obodai et al. (2019) as a decision support for the post classification.

Accuracy Assessment and Kappa Statistical Testing

The recommended good practice procedures by Olofsson et al. (2014), Radoux and Bogaert (2017) and Strahler et al. (2006) were adopted to robustly assess the accuracy and estimate the area of LULC maps. The analysis includes the construction of the error matrix by area proportion and accuracy indices assessment. The accuracy assessment of an image classification was done by creating the classification error matrix. In this confusion matrix, classification results were compared to ground truth data obtained during fieldwork. This was done by selecting the menu item classifier accuracy assessment, then importing the ground coordinates of the ground truth samples from an Excel file which was already saved in text format. According to Coppin and Bauer (1996), whatever the algorithm used, the spectral image classification always results in accuracies which range between 50% and 75%, depending on the number of available image registrations, the quality of the ground truth and the number of considered change classes.

To evaluate the performance of the classification algorithm, accuracies of the LULC maps were assessed by using 30% of the sample class data generated from each satellite image. The accuracy assessment was conducted by creating confusion matrices between the LULC maps for 1990, 2000, 2010 and 2023 and the test data involved calculating the overall accuracy, user accuracy, producer accuracy and the Kappa statistics coefficient. The Kappa statistic coefficient was based on the formula provided by Congalton and Green (2019), as shown in equation 1.

$$\hat{K} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} - x_{+i}) / N^2 - \sum_{i=1}^r (x_{i+} - x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} - x_{+i})} \quad \text{Equation 1}$$

where K is the Kappa statistic, N is the total number of observations in the matrix, r is the number of rows in the error matrix, x is the number of observations in row i and column i, x_{+i} and x_{i+} are the marginal totals of row i and column i, respectively.

Change Detection

In this study, the post-classification method was used to determine the cover area change, the percentage change, annual rate of change, and the percentage annual rate of change. Change detection analysis was performed between the baseline years 1990-2000, 2000-2010 2010-2023 and 1990-2023, to estimate the gains/losses and intensity levels of LULC types in the Ankobra river basin. These were estimated based on the following formulae used by Kashaigili and Majaliwa (2010) achieved using MS Excel software;

$$\begin{aligned} \text{Area Change} &= \text{Area}_{i\text{year } x+1} - \text{Area}_{i\text{year } x} \\ \text{Percentage Change} &= \frac{\text{Area}_{i\text{year } x+1} - \text{Area}_{i\text{year } x}}{\sum_{i=1}^n \text{Area}_{i\text{year } x}} \\ \text{Annual rate of change} &= \frac{\text{Area}_{i\text{year } x+1} - \text{Area}_{i\text{year } x}}{t_{\text{years}}} \\ \% \text{ Annual rate of change} &= \frac{\text{Area}_{i\text{year } x+1} - \text{Area}_{i\text{year } x}}{\sum_{i=1}^n \text{Area}_{i\text{year } x} \times t_{\text{years}}} \end{aligned}$$

Equation 2

$\text{Area}_{i\text{year } x+1}$ = area of land cover for the following year

$\text{Area}_{i\text{year } x}$ = area land cover of the current year

$\sum_{i=1}^n Area_{iyear\ x}$ = the total the land cover of the current year
 t_{years} = the years' difference between the first and second period

The area of transition between the periods were examined to determine the extent of transition from forest to bare land, settlement/built-up and mining/excavations as well as other land cover types in the study area. The extent of transition from forest to bare land, settlement/built-up and mining/excavations and other land cover types was determined by calculating the percentage yearly rate of change during the 33-year period (yearly rate of change (%/year) = area change for 33/33 * 100). Figure 5 shows the flow chart of the methods used in this study.

Post-classification and Predicting Future LULC with Markov Chain

After the image classification, the spatial extent of each land use class within each sub-basin was determined for the 1990, 2000, 2010, and 2023 multi-temporal images using the Modules for Land Use Change Evaluation (MOLUSCE) plug-in in the QGIS software.

The CA Markov chain model was also explored because it is technique that can predict accurately and precisely the long-term LULC dynamics in both spatiotemporal patterns. Markov Chain Analysis is a convenient tool for modelling land use change when changes and processes in the landscape are difficult to describe. For the purpose of this study, the Markov method was used to simulate the LULC map for the year 2056. Accordingly, in the first step, we simulated LULC for the year 2023 using the transition matrix generated from the thematic maps of the years 2000 and 2010 and the selected predictor variables (slope, aspect and HAILS) generated. To simulate future LULC, it is recommended that a number of predictor variables, which play a major role in LULC change and transition should be considered (Abass et al., 2023; Corner et al., 2013). Furthermore, we selected three (3) predictor variables to describe the LULC change processes in Ankobra basin between 1990–2023. These predictors include topographic variables such as slope, aspect and human activity intensity (HAILS) variables presented in *Supplementary Sheet, Table 11*. These variables are frequently used to predict LULC because they provide reproducible data on the natural and human disturbances in LULC processes (Muhammad et al., 2022).

This study set two assumptions for predicting the 2056 LULC map. The first-time scenario involves land use following the current (Business as usual) trends, with at least the prevailing LULC dynamics that have persisted between 2010 and 2023 being a contribution factor, and also without significant changes in population characteristics. Then, the second scenario is assuming an increasing population size and mining activities, coupled with the improvements in the income levels of the people who settle in the basin. The projection in scenario two anticipates more land to be demanded for mining/excavation activities, settlement/built-up and bare land uses than for other purposes, in the long term (1990–2023), with a 33-year projection (2023 + 33) from 2023, hence, pitching at 2056. The basic assumption in the model is that; the state (X) at some point in the future (t+1) can be determined as a function of the current state (t), in other words the future change will only depend on the existing change, so the transition between two times can be modelled mathematically as (Iacono & Levinson, 2012);

$$X_{t+1} = f(X_t)$$

This model was initially used by socioeconomic researchers in 1950s. Following the 1960s it gained popularity in urban studies. Additionally, it was employed in LULC modelling in the late 1970s (Iacono et al., 2012). The first application of this model was on parcel level. Later, Bell (1974) expanded its use to include remote sensing sources and pixel-based analysis.

Implementation of Markov Chain to Study Area

The variables used for the model summarized in Table 1 and procedures presented in Figure 5. In the study area the “t” is LULC map of 1990 and “t+1” is LULC map of 2023, which resulted in a difference of 33 years. This difference is added to 2023, to predict the 2056 LULC map. According to MARKOV model the relation between 1990 and 2023 has been modelled to be used in the 2056 simulation map. The results of the MARKOV model are based on the transition matrix, which contains the probability of each land use/cover category changing to every category. It also based on the transition area matrix, which also contains the number of pixels expected to change

from one land use/cover type to another over the specified time period (Gidey et al., 2017). Last results include the conditional Probability Images: This reports the probability that each land use/cover type would be found at each pixel after the specified time period (Corner et al., 2013; Gidey et al., 2017; Selmy et al., 2023). After obtaining adequate validation metrics, we utilized LULC data from 1990 and 2023 maps to simulate future LULC for the year 2056.

Table 1: Markov Chain variables used in the prediction of 2056 LULC.

Variables	Value
t	1990 LULC Integrals
t+1	2023 LULC Integrals
Time Period (2023-1990)	33
Prediction (2023+33)	2056

Driver-factor analysis using the Analytical Hierarchy Process (AHP) technique

Subsequently, to identify and categorize the drivers of land use change of the ARB, we applied the AHP on thematic and other geospatial data as previously described by Jhariya et al. (2021). The Analytical Hierarchy Process (AHP) technique was used to determine the weights of each land use class to help examine factors that drive LULCC (Bagheri, 2013; Guo et al, 2022). The weight of each potential driving factors of LULC change for the ARB were analyzed using the AHP model developed by Saaty (2004; 2013; 1990; 1982), which draws on experts' judgment and a literature review as components in the AHP model (Kundu et al., 2017; Mahiny & Clarke, 2012; Nath et al., 2020; Shareef et al., 2020). Since human judgement can be inconsistent, the six AHP analytical steps formulated by Saaty (1982), and enhanced by Danumah et al. (2016) was employed. These steps include (i) breaking a complex unstructured problem down into its component factors; (ii) formulation of hierarchical structure using the Analytical Hierarchy Process (AHP) technique; (iii) conduct a paired comparison matrix determined by coercing results; (iv) allocating weights to subjective judgments and measuring the relative weights of each criterion; (v) systemize results to determine the priority driver of change variables, and (vi) derive the consistencies in assessments and judgments based on statistical tools such the consistency index (CI) and consistency ratio (CR) using Random Index (RI) for $n=9=1.45$.

Consistency is checked based on Consistency Index (CI) and Consistency Ratio (CR) using the Equation of Cai et al. (2016) and Rahmati et al. (2014) in equations 3 and 4, respectively.

$$CI = (\lambda_{\max} - n) / (n - 1).$$

Equation 3

$$CR = \frac{CI}{RI}.$$

Equation 4

where, CI: consistency index, $\lambda_{\max}$: highest matrix Eigenvalue, n: number of variables (thematic layers), CR: consistency ratio and RI: Random Index value based on the number of variables.

A perfectly consistent decision maker should always yield $CI = 0$ but small values of inconsistency may be tolerated if the $CI < 0.1$ (Saaty, 1990). With a matrix of nine variables, the ratio index (RI) is 1.45, per the 9th position on the RI table (see [Supplementary Sheet, Table 8](#)). We obtained an acceptable CI value of 0.0794. Also, if the CR is greater than 0.1, the pairwise comparison judgments must be re-evaluated. The applied weighting yielded a CR of 0.05 (Table 7). Accordingly, the values for CI and CR shows that the weights assigned to GIS thematic layers of potential drivers are consistent (Danumah et al. (2016). The output of the AHP model used in this study focused on the use of evidence of weighted factor or the interactive priority weight and/or eigenfactor values to determine the driving factors and spatial heterogeneity among the coefficients of the explanatory variables based on the Saaty's pairwise criteria assignment and random index (RI) matrix in Tables 9 and 8, respectively. The priority

weight or eigenfactor values were obtained, where higher values indicate significant contribution and lower values indicates low contribution to a particular LULC driving factor in a chronological order.

In all, nine (9) independent thematic layers such as elevation (EL), distance from settlement (DS), soil type (ST), Agricultural Expansion (AE), Logging (LG), Mining Activities (MA), Industrial Activities (IA), Population Pressure (PS) and Weak Laws (WL), were generated using data mining approach, expert consultation and geospatial techniques in ERDAS imagine and ArcGIS software. These independent thematic layers, considered as driving factors of LULC in the ARB, were subjectively ranked from equal importance to relatively greatest hierarchical importance across the full breadth of the 9-point Saaty scale (Saaty, 1990) based on their likelihood of impacting land use land cover change. A pairwise matrix constructed from these driving factors and their reciprocal values in [Supplementary Data, Tabel 9 & 10](#) were used to estimate a mean normalized weight for each priority factor. These normalized weights were applied to each of nine factor classes that were identified by natural breaks in the data using the Jenks method. LULC categories were numerically scored as potential driving factors based on their linkage to LULC using human judgement protocols as mentioned by Saaty (1990). Finally, the Quantitative Relative Importance Index (QRII) ranking approach in Q-GIS was used in ranking the key drivers of the LULCC. QRII helps to prioritize which driving factors are most influential and important to LULC change alongside with the ANOVA p-values to determine their sensitivity and score ranking. Methodological steps are shown in Figure 5.

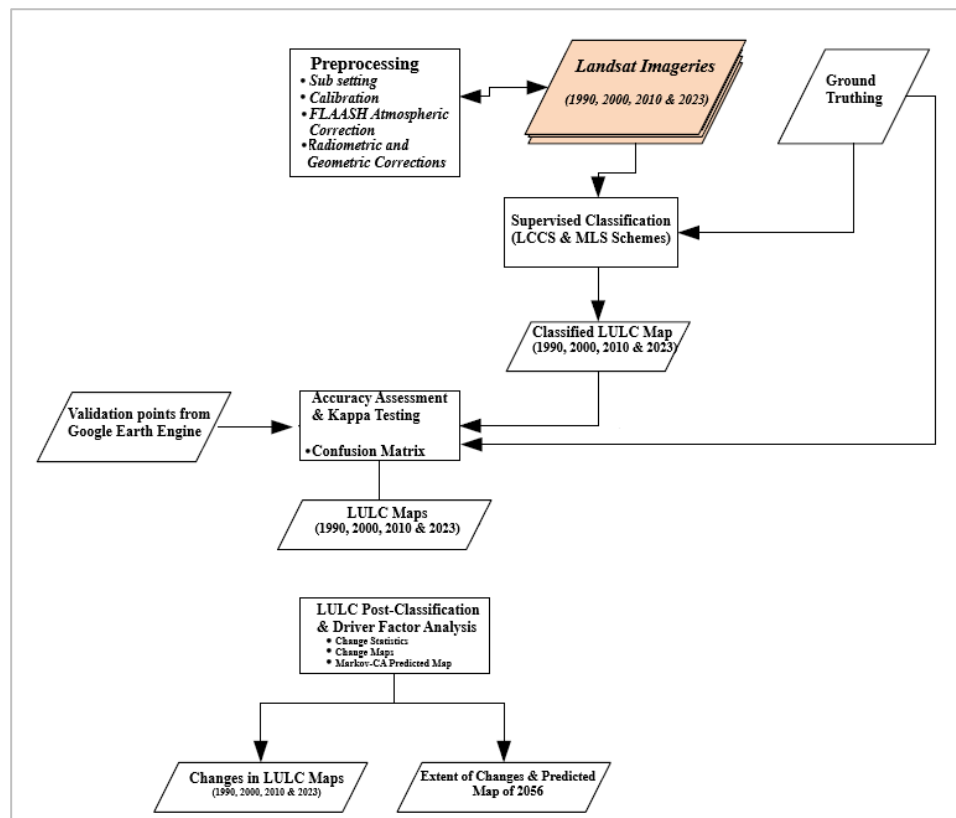


Figure 5: The flow chart of the research data and methodological steps.

Results and Discussion

Land Use/Cover (LULC) Status within the River Ankobra Basin, 1990-2023

The ARB have gone undergone various stages of land use land cover alterations over a period of 33 years (Figure 6, Table 2). Seven LULC classes were identified. They are: water bodies (WT), agriculture//farmlands (AG), evergreen forest (FT), bare lands (BL), mining excavations (MN), settlements/ built-up ((ST) and mangrove/wetlands (MG). The 2000 map overestimated mangroves/wetlands, settlement and bare land due to commission errors. Water and mining excavation areas were underestimated due to omission errors.

Notwithstanding, the overestimations and underestimations, the map area values of the LULC categories fall within the tested lower and upper bound of the true areas at the 95% confidence level. The statistics of LULC distributions for each study year as derived from the maps are represented in Table 1.

Evergreen forest is the major LULC followed by Agriculture/farmlands, settlement/built-up and bare land. This pattern remained unchanged for all the years gap selected for the study. Nevertheless, Evergreen Forest and Agriculture/farmlands consistently decreased from 5576.79 km² in 1990 to 3920.70 km² in 2023. In 2000, Evergreen Forest (61.6%) recorded a relative decrease to the former years but declined again in 2023 (46.6%). There was a gradual and consistent decrease in Agriculture/Farmland with an area of 2472.38 km² in 1990 to 2293.77 km² in 2000. However, this change was not significant in the year 2010 and 2023. Mining excavations witnessed a tremendous increase in its coverage by the year 2023 (7.6%) with an area of 642.0 km², more than seventy times its area in 1991 (6.81 km²). The increase in Mining excavations was sustained through the subsequent years under study with the area in 2010 (150.1 km²) being thrice as much as that in 2000 (39.17 km²).

The area covered by Water did not show any significant variability in the area from the year 1990-2023, it almost increased in fivefold by the year 2010 with an area of 0.7 km². The decrease in the area covered by water in 2023 was due to the distinct vegetation which acted as canopy cover for the water body losing quantity via evaporation. This also accounts for the unusual conversion from Water to mangrove/wetlands and Evergreen Forest especially for the period 2000-2010. Settlement/built-up increased continuously from 1990 (159.9 km²) through to 2023 (958.49 km²). This pattern was similar for Bare land classes, increasing to 784.3 km² in 2023 from an initial coverage of 185.67 km² in 1990. All the LULC classes except Evergreen Forest and Agriculture/Farmland recorded different net gain intensities by the year 2023. Evergreen Forest and Agriculture/Farmland which correspondingly occupied 66.2% and 29.4% of the total basin area in the initial year (1990) reduced drastically to 46.6% and 22.5% in 2023. Similar trend was observed in the work of Kutir et al. (2022), Obodai et al. (2019), and Schueler et al. (2011) in the ARB and also in comparable watersheds in studies conducted by Appiah et al. (2015) and Boakye et al. (2020). It was detected that the impact of mining on evergreen forest, agriculture/farmlands, mangroves, and other existing non-forest areas of ARB was severe between the period understudy. The clearing of the top soil to make room for mining over the years has created conditions favourable for shrubs capable of growing in the hash edaphic condition. This confirms the studies conducted by Adu-Poku (2010), Awotwi et al. (2018), Coulter et al. (2016) and Rogan and Chen (2004) who concluded that the upsurge of mining activities and the changes in land use/cover types were correlated to each other.

Table 2: Land use/land cover areas for the period under study in square kilometers derived from Landsat imagery.

Land cover class	Area in (Sq./km) 1990	%	Area in (Sq./km) 2000	%	Area in (Sq./km) 2010	%	Area in (Sq./km) 2023	%
WT	12.42	0.2	20.46	0.3	62.24	0.7	117.2	1.40
AG	2472.38	29.4	2293.77	27.3	2097.8	25.0	1892.2	22.5
FT	5576.79	66.2	5192.05	61.6	4670.6	55.4	3920.7	46.6
BL	185.67	2.2	471.21	5.6	496.2	5.9	784.3	9.3
MN	6.81	0.1	39.17	2.2	150.1	1.8	642.0	7.6
ST	159.90	1.9	386.73	2.8	857.9	10.2	958.4	11.4
MG	2.18	0.08	12.76	0.2	81.1	1.0	101.2	1.2
Total	8416.15	100	8416.15	100	8416.15	100	8416.15	100

Abbreviations: *WT*= Water; *AG*= Agriculture/Farmlands; *FT*= Evergreen Forest; *BL*= Bare land; *MN*= Mining/Excavation; *ST*= Settlement/Built-Up; *MW*= Mangroves/Wetlands.

Land Use Land Cover Change for the year 1990

Land use land cover maps of 1990 (Figure 6a) serves as the baseline time for the decadal satellite images analysis process. The 1990 image showed that forest and agriculture land were the most predominant land cover classes which occupied 66.2% (5576.79 km²) and 24.5% (2472.38 km²) of the area in the basin. Forest spread from

the central part of the basin to the east and while agriculture was seen dominating the western part of the study area. The overall vegetative cover in the basin added up to 8,051.35 km². This translated to 95.68% of the total basin area (Table 2). This were indicative of the occurrence of evergreen and semi- deciduous forest of the basin that lies in the South-Western Equatorial and the Wet Semi-Equatorial climatic zone. In addition, the high forest cover was attributed to the fact that some areas within the basin had not been opened for agriculture and urbanization hence remained under indigenous forest cover. This could be due to the fact that there was little human and economic activity, including mining activities going on at the time to warrant new settlement/build up and mining concessions. A study conducted by Donkor and Agyeman (2015) as well as Kutir et al. (2022) made the same assertion to confirm this statement from our result. Bare land (2.2%) and settlement (1.9%) classes occupied some portion of land cover representing 185.67 km² and 159.19 km² respectively. Bare lands and settlement cover types are barely scattered across the south eastern and northern part of the Ankobra basin area (Figure 6a).

Water, mining excavation, and mangrove/wetlands occupied 12.429 km², 6.81 km², and 2.18 km², representing 0.2%, 0.1% 0.08% of the lowest class proportions, together occupying an area of 21.40 km² which is in line with findings by Aduah et al. (2015) and Obodai et al. (2019) in a related study of the same study area. Although, the area covering mining excavations were recorded at this time period, they were hardly observable with intermittent spots and not easily recognized in the classified 1990 LULC images. This could be due to the low-resolution characteristics of the TM and ETM+ images used for the 1990 image classification or the thick tree canopies shielding these spots. Aduah et al. (2015), Obodai et al. (2023), and Schueler et al. (2011) indicated similar sporadic appearance of mining/excavations in their studies. Thus, for this period settlement/build up, mining excavations and bare lands and concreted areas did not cover a large area, unlike evergreen forest, agriculture/farmlands and bare lands.

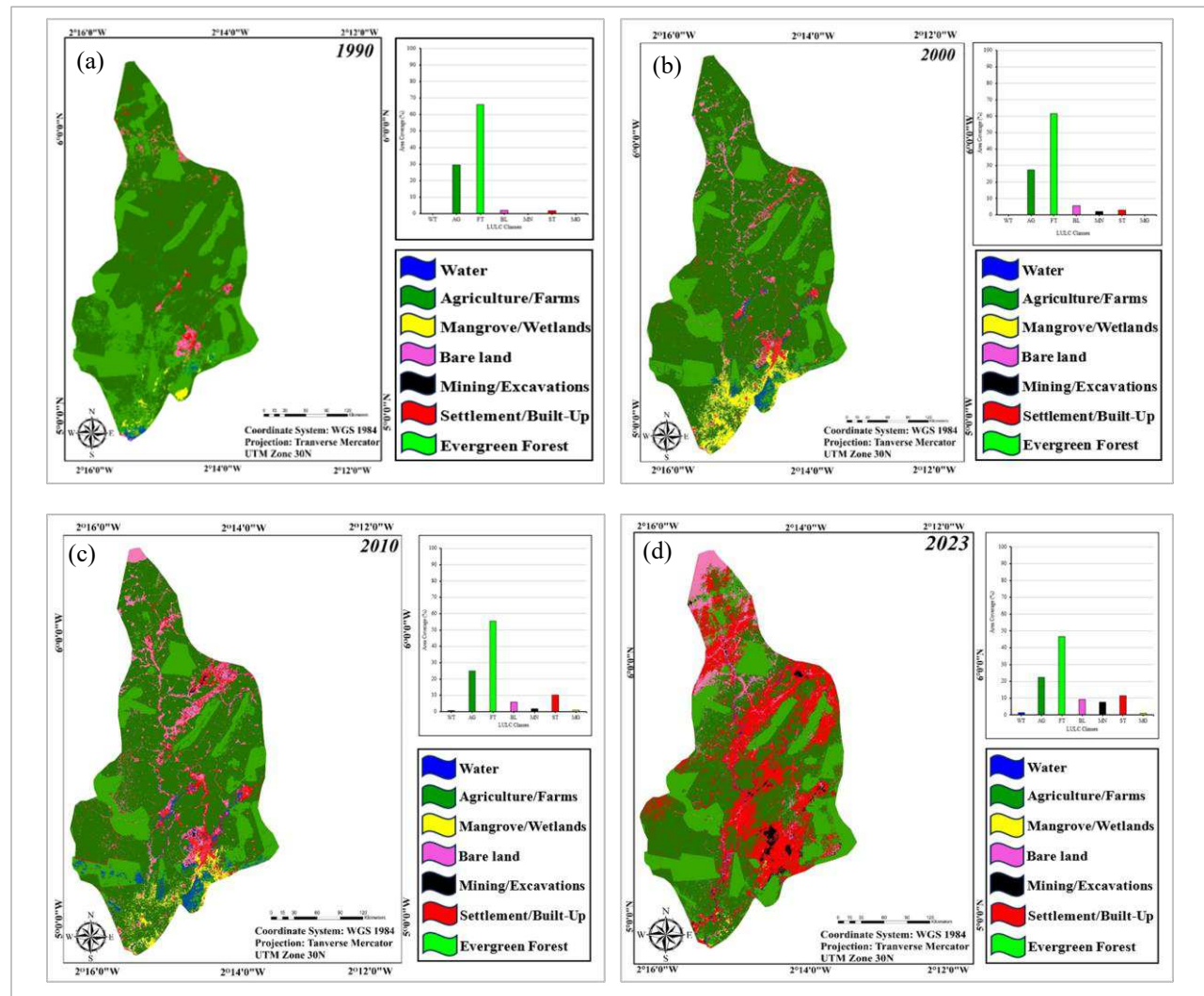


Figure 6. Land-use and land-cover (LULC) map for 1990 (a), 2000 (b), 2010 (c), and 2023 (d).

Land Use Land Cover Change for the year 2000

In the year 2000, the LULC map in Figure 6b indicated that land cover classes had not changed substantially. However, the particular spatial distributions and proportions of these seven land cover types had changed. Evergreen forest had reduced to 5192.05 km² (61.6%), agriculture/farms had also slightly reduced to 2293.77 km² (27.3%), while mining excavations had increased to 0.4%. Evergreen forest now occupied an area of 61.6%, with a significant increment in bare land area to 5.6%. Settlement/built-up had increased to 2.8%, alongside mangrove/wetlands covering an area of 0.2%, while exposed waterbodies in the Ankobra river basin covered only 0.3%. However, the mangrove vegetation showed some form of resilience through regeneration in the year 2000. The Appiah (2001), FAO (2012), as well as FAOSTAT (2015) has reported that the annual deforestation rate for Ghana and the ARB has been estimated to decline at a rate of 0.6% and this may have contributed to the state of the forests cover decline reported in the current study since the year 2000. In Figure 6b, study has shown that evergreen forest cover and agriculture farmland reduced, while there was an increase in open spaces including bare land, settlement and mining/excavations at an annual rate of change of 4.6%, 6.2% and 8.8% for evergreen forest cover and 2.1%, 2.3% and 2.5% for agriculture farmland between 1990 and 2000, 2000 and 2010 as well as 2010 and 2023. These results from the current study are not surprising and supports the claim by Acquah (1993), Donkor (2018; 2019), and Konadu-Agyemang (2001) that deforestation occurred more in the most forested areas in Ghana due to implementation of the World Bank's structural adjustment programme (SAP), which liberalized Ghana's economy and increased foreign direct investment in the mining, agricultural industries etc (Donkor 2018; Hilson, 2004; Konadu-Agyemang, 2018; Kusimi, 2015).

Land Use Land Cover Change for the year 2010

Figure 6c depicts the extent to which the vegetation cover was degraded as a result of the deforestation and galamsey phenomenon. Similarly, there was no change in land cover types in 2015, although there were differences in the spatial extent and area proportions of the land cover types. Evergreen forest had decreased to 55.4%, representing 4670.6 km² of the area proportion in the year 2010. This loss was noticeable at the middle and areas around the estuarine sections of the Ankobra due to the inception of illegal mining (rush for gold/galamsey) activities in this tear-period, in pretence under community mining. As well, agriculture/farms had further decreased and now covered an area of 25.1%, representing 2097.8 km². Though agriculture/farms recorded significant loss in the three oldest mining concessions areas (Schueler et al., 2011), it increased in the basin as a whole in this study. Particularly within these mining concessions, agriculture/farmland loss caused farmers to extend farmlands into near-by forest areas with its associated "spill-over effect" into wetlands (Schueler et al., 2011; Sonter et al., 2014).

In contrast, settlement/built-up and bare land areas had also increased to 10.2% and 5.9%, representing 857.9 km² and 496.2 km² respectively. Areas covering mining excavations had also increased to 1.8%, with more open pits visible in smaller patches compared with the larger bare land patches. The smaller patches of mining excavations and pits were seen dominating the north-eastern and south-eastern part of the study area, with some scattered patches across the northern section as well. Mangroves/wetlands increased significantly (from 0.2%, representing 12.76 km² in the year 2000 to 81km², representing only 1% in the year 2010). Exposed water bodies had a slight increase to from 0.3% in 2000 to 0.7% in 2010 (Figure 6c). This does not show a significant change in water bodies across the basin. As indicated in the study conducted by Debebe et al. (2023), Aduah et al. (2015) and Hughes et al. (2017) and highlighted by Chazdon (2008), the removal of forest covers in the basin, also leads to loss of indigenous plant species, the destruction of animal habitats and reduction in biodiversity of the forest ecosystem. Planting rubber trees and other non-native tree species for example in replacement for native tree in this region, can reduce groundwater recharge and baseflows significantly (Kortatsi, 2007), because exotic plants consume more water than the native species. The study findings also conform to that of Ferring, Hausermann and Effah (2016).

Land Use Land Cover Change for the year 2023

In the same way, in Figure 6d, no new land cover types found in 2023. Nonetheless, significant changes had occurred in the area extent and spatial distribution of the land cover types, compared to the baseline year of 1990. Evergreen forest had significantly decreased to 46.6%, representing a covering 3920.7km² of the total area of the Ankobra basin. The remaining agriculture/farms on the study landscape dominated the western part of the study landscape but there was consistent decrease in this particular class from 29.4% in 1990 to 25.5% in 2023 and shared an immediate border with settlement. Bare land had also increased to 9.3%, with a slight increase in settlement/built-up to 11.4% from a previous percentage of 10.2, making settlement the highest dominant land cover type in 2023. Settlement and bare land had increased with much dominance in the central and northeastern part of the study landscape due to the livelihood opportunity that the areas offer to local folks (Asante-Yeboah et al., 2022; Minerals Commission, 2011). Acheampong et al. (2022) and Sarfo et al. (2020) reported that between 1990's and 2020's, a significant proportion of the evergreen forest within the ARB region was converted to agriculture and farmlands, stating that these practices have caused approximately 78% of the forest lost in reserves while expansion of settlements and other human activities has caused 6% of the deforestation. This study established that there is a proportional relationship between population increase and anthropogenic activities. That is, as population increases anthropogenic activities are also bound to automatically increase as well. Thus, population growth and the lack of enforcement of forest protection laws have led to the expansion of farms, unregulated settlements and mining excavations within the forest landscapes (Ankomah et al. 2022) of the ARB. It must also be noted that the settlement/built-up and bare lands areas were dominant partly due to the prolong exposure of the surface soil to erosion after deforestation, lumbering and subsequent mining by both legal and illegal miners.

Mining excavations, including open pits, found in mining areas had also increased significantly to 7.6%. The increase in mining excavations dominated the south eastern and north-eastern part of the study landscape in 2023. Exposed water (0.7% in 2010 to 1.4% in 2023) and mangrove/wetlands (1.0% in 2010 to 1.2% in 2023) did not significantly change in area (9.1%). Though mangroves are a source of fuel energy for the estuarine communities (Donkor and Agyemang, 2015), the depletion of forest cover at the estuary of the basin can be ascribed to immense mangrove and bamboo logging. Additionally, conversion of more forested lands to agriculture can increase soil erosion and loss of soil fertility, thereby making it more difficult to produce enough food and cash crops to meet the demands of the growing population in Bonsa catchment. Land degradation and the loss of soil fertility has the potential to reinforce more land cover changes through the extensification of agriculture and introduction of pollutants into water systems (Barbier, 2007; Meyfroidt et al., 2013). Since agriculture in the Bonsa catchment is of the low-input type, the only means to increase production will be to increase the area under cultivation, which can further cause changes in land cover. The decline in forest cover for the period 1990–2000 occurred mainly in the Wassa West District. The main drivers of deforestation were deforestation, mining and farming activities from artisanal, large-scale and illegal mining (*galamsey*) activities (Schueler et al., 2011). An estimate of the deforested areas concurs with mining activities in the area. This mining activities in the Ankobra basin has led to the conversions of Forest land to Mining Area/Excavations for the period between 1990 and 2000 (Kusimi, 2008). All trends in the of the LULC changes within the 33-year span are shown in Figure 7. Within these mining concessions and communities, agriculture land loss caused farmers to extend farming into forest areas with its associated “spill-over” effect (Schueler et al., 2011; Sonter et al., 2014). In addition, the depletion of forest and agricultural cover at the lower part and estuary of the basin as shown in Figure 7 can be attributed to vast mangrove, wetlands, shrub and bamboo logging for fish smoking and mongering, since mangroves and wetlands are a source of fuel energy for the estuarine communities (Donkor and Agyemang, 2015).

Deforestation in the ARB has been mainly due to the overexploitation of natural resources and poor land use practices (Appiah, 2009; Appiah, 2015, Goswani et al., 2024; Obodai et al., 2019; Schueler et al., 2011). Several factors contribute to the rapid deforestation and associated LULC changes, however the most important of these are urbanization, industrialization, mining activities and slash-and-burn agriculture production (Appiah et al., 2009; Goswani et al., 2024; Kalame et al., 2009; Sonter et al., 2014).

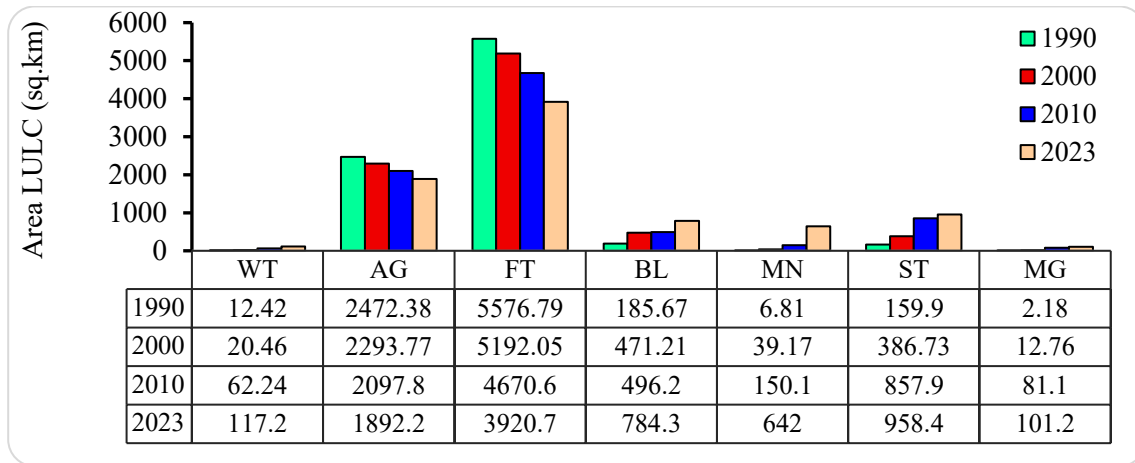


Figure 7: Grouped bar graphs showing trends in major (AG, FT, ST and BL) and minor (WT, MN and MG) LULC classes in square km from 1990 to 2023.

Accuracy Assessment and Change Detection

The overall accuracy gives probability of correctly mapped points in the map with field and user accuracy which compares map with field data. Producer accuracy, however, compares field data with maps. In this case, the field data was collected using GPS and noting the attribute of the associated point. The overall accuracy of the classification results from the confusion matrix and the kappa statistic is 85.7% and 81.2% respectively (Tables 3, 4 and 5). These values fall within the range described by Congalton & Green (2019) and Iacono et al. (2012) as strong agreement and implies that a significant proportion of the discriminated classes/units represent the true feature classes.

Land Transition from 1990 – 2000

As shown in Table 3, 126.3 km² of settlement/built-up areas remained unchanged, with 3.72, 3.46, 5.56 and 2.39 km² of the land covers transitioned from ‘settlement/built up’ in 1990 to Agriculture/farmlands in 2000 respectively, while 3.46 km² of evergreen forest was also transformed to agriculture/farmland within the same period. Within this period, 5.56 km² of ‘settlement/built-up’ area also transitioned into ‘bare land’. In that same time, 2.39 km² of ‘settlement/built-up’ areas transitioned into Mining excavations. Besides, 4822.16 km² of ‘evergreen forest’ stayed unchanged; 376.01 km² of ‘evergreen forest’ was converted into ‘agriculture/farmlands’ and 35.04 km² was converted to ‘settlement/built-up’ areas. Within the same period, 25.48 and 6.85 km² of land surface were converted to bare land and mining excavations.

Within this same period, an area of 2420.76 km² for Agriculture/farmlands remained unchanged, whereas 237.24 km² of the same land cover transitioned into ‘Evergreen Forest’ and approximately 6.184 km² was converted to Bare land areas. In furtherance, 4.28 km² of ‘Agriculture/farmlands’ as well as 2.91 km² of the same land cover type was converted into Settlement/Built-up and Mining Excavations respectively. Again, while an area of 143.78 km² remained unchanged for Bare land, an estimated 7.82, 5.92, 3.74 and 3.26 km² of Bare lands were converted into Agriculture/farmlands, Settlement/Built-up, Mining Excavations and Evergreen Forest in 2000, respectively. However, the conversion of classes for water and Mangrove/Wetland to other LULC types were slightly noticed and not significant. This did not differ too much from findings by Kumi et al. (2023). The overall Kappa accuracy analysis for the classification period between 1990 and 2000 was 87%. The matrix information in Table 3 below shows the land cover classes distribution of the basin with the level of both producers and users’ accuracy.

Table 3: Land use and land cover change matrix table between 1990 and 2000.

Conversion Matrix: 1990-2000 (km ²)									
LULC Class	WT	AG	FT	BL	MN	ST	MG	Total	UA (%)

WT	8.43	0.18	0.73	0.06	1.02	0.04	2.28	12.74	0.6617
AG	0.52	2420.8	237.24	6.18	2.91	4.28	0.03	2671.9	0.906
FT	0.4	376.01	4922.2	25.48	6.85	35.04	0.4	5366.3	0.9172
BL	0.36	7.82	3.26	143.78	3.74	5.92	0	164.88	0.872
MN	0.14	1.95	0.61	2.57	32.14	0.81	0.05	38.27	0.8398
ST	0.23	3.72	3.46	5.56	2.39	126.3	0.01	141.67	0.8915
MG	0.04	0.25	0.03	0.03	1.08	1.11	18.28	20.82	0.878
Total	10.12	2810.7	5167.5	183.66	50.13	173.5	21.05	8416.6	
PA (%)	0.833	0.8613	0.9525	0.7829	0.6411	0.728	0.8684		

Overall Accuracy = 0.97, Kappa Coefficient = 0.87

Abbreviations: The diagonal (shaded) values indicate the persistence (unchanged) land cover types across the analysis years, 1990 to 2000. **UA**= Users Accuracy; **PA**= Producers Accuracy; **WT** = Water; **AG** = Agriculture Land; **FT** = Forest; **BL** = Bare land; **MN** = Mining/Excavations; **ST** = Settlement/Built-Up; **MG** = Mangroves/Wetlands.

Land Transition from 2000 – 2010

Findings in Table 4 revealed that an area size of 612.01 km² of settlement/built-up remained unchanged, with 50.06 km² of the land cover transitioned from built up areas in 2000 to Bare land in 2010, while 9.58 km² of built-up area was also transformed into Agriculture/farmland in the same period. In the same Ankobra basin, 1.45 km² and 1.81 km² of built-up area was also transitioned into Mining excavations and Evergreen Forest. In that same time, classes that transitioned from built up into water and mangrove/wetlands were below recognition, a finding similar to the those observed by Aja et al. (2022), Awty-Caroll et al. (2019) and Kutir et al. (2022). Also, 3378.31 km² of Evergreen Forest stayed unchanged, with 702.30 km² of this land cover converted into Agriculture/farmland, while 144.41 km² and 123.21 km² of Evergreen Forest were converted to Bare land areas and Settlement/built-up respectively. Another significant transformation was the conversion of 82.12 km² of Evergreen Forest land into Mining excavations. At this point, transition of Evergreen Forest into Mangrove/wetland and Water was recorded as 0.01 km² and 0.11 km² respectively, below the recognition level on the LULC images.

A total of 1991.15 km² of Agriculture/farmland remained untouched, whereas 210.02 km² of the same land cover transitioned into Evergreen Forest; and 35.22 km² was converted to Settlement/built-up areas between 2000-2010 transition period. However, 40.20 km² of Agriculture/farmlands was converted Bare land as 17.06 km² of Mining excavations was regained from Agriculture/farmland. Water and mangrove/wetland gained 0.19 and 0.01 km² from Agriculture/farmland concurrently. Again, 52.03 km² of land in the basin was changed from Bare lands into Settlement/built-up areas while an estimated 8.06 and 8.02 km² of land were converted into Mining excavations and Agriculture/farmlands. During this period, 478.38 km² of Bare land remained unchanged, with 1.40 km² and 0.14 km² of Bare land been converted Mangroves/wetlands and Water in 2010 (Table 4). Similar transition trend occurred between water and mangrove/wetland with other LULC classes, as also comparably reported in the studies of Aja et al. (2022), Akbar et al. (2024), and Gnanappazham et al. (2021).

Table 4: Land use and land cover change matrix table between 2000 and 2010.

Conversion Matrix: 2000-2010 (km ²)									
LULC Class	WT	AG	FT	BL	MN	ST	MG	Total	UA (%)
WT	19.91	0.13	0.22	0	3.63	0.02	1.01	24.92	0.79
AG	0.19	1991	210	40.2	17.06	35.22	0.01	2294	0.86
FT	0.11	702.3	3728	144.4	82.12	123.2	0.01	4780	0.78
BL	0.14	8.02	2.04	478.4	8.06	52.03	1.4	550.1	0.87
MN	1.38	2.41	2.13	3.88	169.1	3.4	0	182.3	0.92

ST	0.01	9.58	1.81	50.06	1.45	500	0.02	563	0.88
MG	0.1	1.01	0	0.07	0.1	5.05	15.71	22.04	0.71
Total	21.84	2715	3945	717	281.5	719	18.16	8416.15	
PA (%)	0.91	0.73	0.94	0.66	0.61	0.69	0.86		

Overall Accuracy = 0.82, Kappa Coefficient = 0.89

Source: Satellite Image Analysis, 2023.

Abbreviations: The diagonal (shaded) values indicate the persistence (unchanged) land cover types across the analysis years, 1990 to 2000. **UA**= Users Accuracy; **PA**= Producers Accuracy; **WT** = Water; **AG** = Agriculture Land; **FT** = Forest; **BL** = Bare land; **MN** = Mining/Excavations; **ST** = Settlement/Built-Up; **MG** = Mangroves/Wetlands.

Land transition from 2010 to 2023

A pictorial view of all LULC transition from one class to another is shown in Figure 8 and Table 5. Here, 627.28 km² of Settlement/built-up area remained unchanged. Amidst this, 23.11 km², of the land cover transitioned from built ups in 2010 to Bare land in 2023, although higher (50.06 km²) in 2010, while 15.17 km² (9.58 km² in 2010) of built ups were also transformed to Agriculture/farmland in the same period. In the catchment, 7.05 km² (1.45 km² in 2010) of built ups also transitioned into Mining Excavations. In the same period of time (2010 to 2023), 1.65 km² (1.81 km² in 2010) of built up transitioned (+/-) into Evergreen Forest. Mining excavations increased tremendously in fourfold from 169.09 km² in the 2000 to 2010 transition period to 687.56 km² between 2010 and 2023, but this class feature shared portions of its land of 16.84 km², 10.34 km², 6.16 km² and 2.83 km² with Evergreen Forest, Settlement/built-up, Water and Agriculture/farmland respectively. However, no area coverage was gained for mangroves/wetlands (MG), like wise in 2000-2010 period when mining/excavation areas remained unchanged. Same 0 value was recorded for mangroves/wetlands when Bare lands remained unchanged in the 1990-2000 and 2010-2023 transition periods.

Furthermore, as 3030.48 km² of evergreen forest (FT) remained unchanged, about 538.17 km² (702.30 km² in 2010) of this land cover transitioned (+/-) into Agriculture/farmland whereas 256.89 km² (82.12 km² in 2010) was converted to Mining excavations. Bare land remained stable and did not change as this class feature recorded 144.41 km² both in the 2000-2010 and 2010-2023 transition periods. Other classes such as Settlement/built-up also substantially regained 149.57 km² of land from Evergreen Forest while 0.35 km² and 0.01 km² of land from Evergreen Forest were marginally transformed into Water and Mangrove/wetland respectively. The conversion of significant forest changes was said to have been attributed to various underlying factors such as deforestation, mining and decline or inadequacy forest conservation efforts, rapid socio-economic developments, and institutional changes (Ankomah et al., 2022; Asante-Yeboah et al., 2022; Obodai et al., 2019).

Again, an estimated 1376.82 km² of Agriculture/farmland remained stable, whereas 164.36 km² (previously, 210.02 km² in 2010) of the land cover transitioned into Evergreen Forest and 123.06 km² (17.06 km² in 2010) was transformed into Mining/excavation areas in 2023. However, 117.17 km² (35.22 km² in 2010) of Agriculture/farmland was converted into Settlement/built-up. In furtherance, 97.37 km² (40.20 km² in 2010) was transited from of Agriculture/farmland into Bare lands while an estimated 1.08 km² (0.19 km²) and 1.06 km² (0.01 km²) of Agriculture/farmlands were transformed into Water and Mangroves/wetland in the 2010-2023 transition period. Similar results were discovered within the ARB Forest Reserve in the Nzema East, Ellembelle, Prestea-Huni-Valley and Tarkwa localities (Adarkwah et al., 2024; Lawortey et al., 2020; Obodai et al., 2019).

Table 5: Land use and land cover change matrix table between 2010 and 2023.

Conversion Matrix: 2010-2023 (km ²)									
LULC Class	WT	AG	FT	BL	MN	ST	MG	Total	PA
WT	29.25	0.17	0.13	0.03	8.16	0.37	0.03	38.14	0.7669
AG	1.08	1376.8	164.36	97.37	123.06	117.17	1.06	1880.9	0.732
FT	0.35	538.17	3030.5	144.41	265.89	149.57	0.01	4128.9	0.734

BL	0.23	12.66	2.31	792.15	51.72	92.03	0	951.1	0.8329
MN	6.16	2.83	16.84	6.86	687.56	10.34	0	730.59	0.9411
ST	0.13	15.17	1.65	23.11	7.05	627.28	0.02	674.41	0.9301
MG	0.3	0.74	0.01	0.02	0.5	1.07	9.67	12.31	0.7855
Total	37.5	1946.6	3215.8	1064	1143.9	997.83	10.79	8416.4	8416.4
PA	0.78	0.7073	0.9424	0.7445	0.601	0.6286	0.8962	5.3001	

Overall Accuracy = 0.78, Kappa Coefficient = 0.98

Source: Satellite Image Analysis, 2023

Abbreviations: The diagonal (shaded) values indicate the persistence (unchanged) land cover types across the analysis years, 1990 to 2000. **UA**= Users Accuracy; **PA**= Producers Accuracy; **WT** = Water; **AG** = Agriculture Land; **FT** = Forest; **BL** = Bare land; **MN** = Mining/Excavations; **ST** = Settlement/Built-Up; **MG** = Mangroves/Wetlands.

Transition Level Intensity Analysis

With reference to the transition matrix (Table 3, 4 and 5), intensities of a loss or gain have been constructed for each class for 1990-2000, 2000-2010 and 2010-2023 (Figure 8). Transition intensities for Evergreen Forest, Agriculture/farmland, Settlement/built-up, Bare land and Mining/excavations were the focus of analysis because they correlate easily with surface water systems. The hypothetical uniform intensity (U) thresholds calculated from the summation and differences in the means and standard deviations from yearly transition values are represented as vertical dash red lines on the chart which assesses class thresholds that should be targeted and avoided. To the left is the uniform intensity (U) which explains the hypothetical uniform value in the intensity of transition that accounts for the losses in the respective land cover category. To the right represent the gains in transition intensity. In between are unchanged classes that needed to be avoided.

From 2010 to 2023, the transition to evergreen forest mainly targeted agriculture/farmland and avoided mining/excavations, bare land and settlement/built-up (Figure 8a). Similarly, losses in evergreen forest were targeted by mining/excavations, bare land and settlement/built-up. Expansions in evergreen forest between 2000 to 2010 transition period targeted agriculture/farmland while losses in evergreen forest targeted settlement/built-up in addition to mining excavations. From 1990 to 2000, reductions in evergreen forest similarly targeted settlement/built-up, bare land and mining excavations and marginally targeting agriculture/farmland (Figure 8b). In furtherance, the transition intensity showed that the all expansions in agriculture/farmland in the periods between 1990-2000, 2000-2010 and 210-2023 targeted evergreen forest and mining/excavations only and losses in agriculture/farmland were targeted by settlement/built-up, bare land and mining/excavations as shown in Figure 8b.

Likewise, as indicated in Figure 8c, the transition to settlement/built-up between 1990-2000 did not target any class feature but avoided the other LULC categories such as evergreen forest and agriculture/farmland, while the losses in settlement/built-up slightly targeted evergreen forest and mining excavations. In 2000-2010, losses in settlement/built-up mainly targeted evergreen forest and mining excavations, whereas the gains in the settlement/built-up category targeted bare land only (Figure 8c). The reductions and expansions in settlement/built-up between 2010 and 2023 followed a similar trend to that of 1990–2000, where this category targeted evergreen forest and mining excavation areas as a loss (Asante-Yeboah et al., 2022). In addition, the expansions in settlement/built-up in the same period marginally targeted bare land only (Figure 8c). Again, bare land shared similar intensity trend as evergreen forest. For example, between 2010-2023, the conversion to bare land mainly targeted settlement and mining/excavations while it avoided the other land cover categories such as mining/excavations and settlement/built-up in smaller proportions. Similarly, in Figure 8d in the same period between 2010-2023, losses in bare land targeted agriculture/farmland and evergreen forest. Lastly for the period between 1990 and 2000, reductions in bare land marginally targeted mining excavation and evergreen forest while avoided some classes, with expansions marginally targeting agriculture/farmland only (Figure 8d). Similar results on the impact of human activities on land use intensities were observed a study conducted by Asante-Yeboah et al. (2022) in the Ahanta

West Municipality, which is a similar landscape very close to the Ankobra River Basin. However, both studies did not differ from HAIL analysis conducted by Dembélé et al. (2024).

Lastly, expansion in mining excavation targeted bare land and agriculture/farmland while losses in mining excavation marginally targeted evergreen forest and settlement/built-up for the period between 1990 and 2000. Again, for the period between 2000 and 2010, mining excavation targeted settlement/built-up and bare land and losses targeted evergreen forest, while in the period between 2010 and 2023, mining excavations slightly targeted only evergreen forest and avoided agriculture/farmland and bare land (Figure 8e). These finding, unfolding the pace land use transition level in this study, is underscored by FAO's (2019) and UNEP's (2017) support of the relevance of keeping forest covers sustained for sustainable livelihoods development, at least among forest- dependent communities. This is due to the resource base in tree species, and biodiversity, which sustains both the natural and human ecosystem nexus.

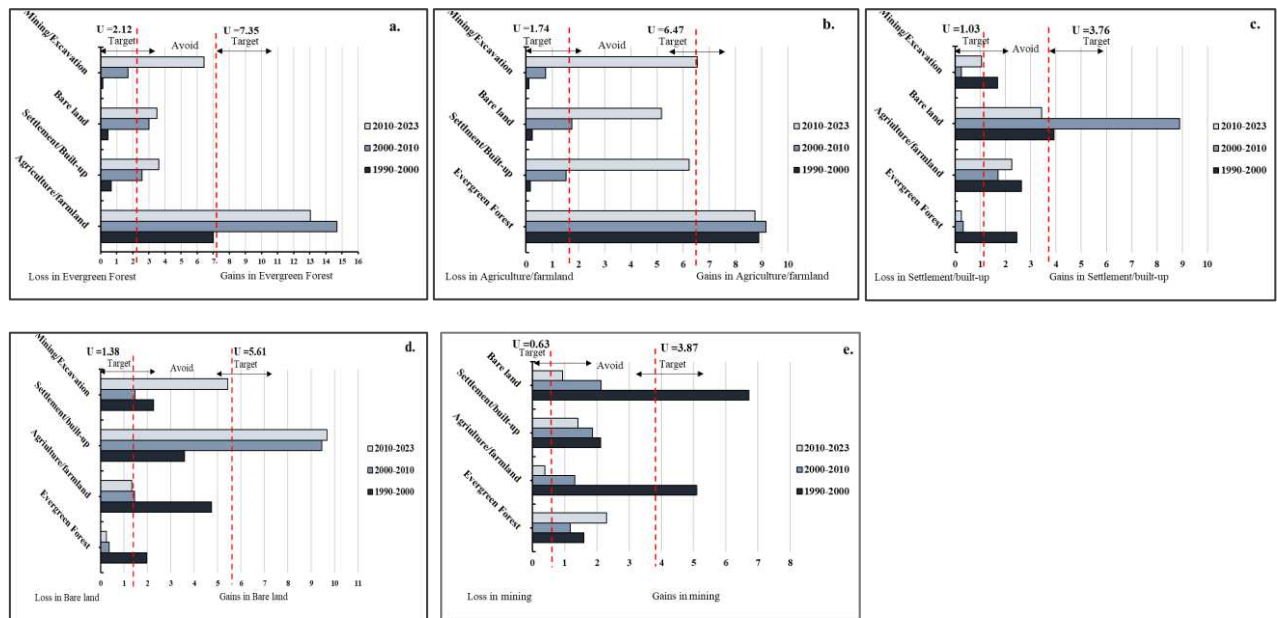


Figure 8. Transition level intensities for evergreen forest (a) and agriculture/farmland (b), settlement/built-up (c), bare land (d) and mining (e) for the periods 1990–2000, 2000–2010 and 2010–2023 (gains on the right, losses on the left).

Time Interval Level of Change Intensity

Time interval level of change analysis revealed that the periods between 1990–2000, as first interval, and 2000–2010, as second interval, experienced slow land cover transitions, while within the last ten-year period (2010–2023), experienced fast and intensive land cover transitions set at a uniform intensity threshold of ($U = 0.37$) (right of the bar in Figure 9). This implies that, considering the duration of each of the three-time interval periods, the rate of land change within the last ten years (third interval) is much faster compared to the rate of land change in the first- and second-time intervals. This makes land cover change in the period 2010 to 2020 very rapid compared to the previous two time periods (Figure 9). For the purpose of our study, we seek to understand the impacts of LULC changes on surface water systems. Hence, we did not present and analyse the results of land use intensity analysis for water.

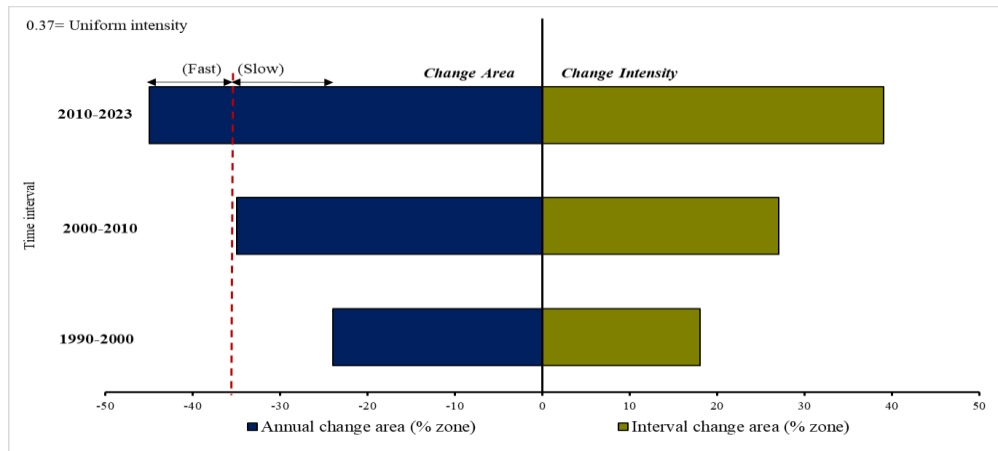


Figure 9. Time interval level intensity analysis. The dashed line indicates the uniform annual change speed/percentage during the temporal extent.

Source: Satellite Image Analysis, 2023.

In furtherance, the results of time interval of change level intensity in Figure 9 shows that the annual change percentage (bars on the left of the central axis) was greater and faster during the third time interval (2010-2023) than during the second time interval (2000-2010), in which 1990-2000 was observed to be very slower as compared to the first-time and second-time intervals, respectively. This time interval level of analysis does not show specific changes of whether there is an increase or decrease in the land categories (Asante-Yeboah et al., 2022; Dembélé et al., 2024). The interval level analysis indicate that land change was fast (45.7%) during the third time interval (2010-2023) and slow during the first (24.4%) between the year 1990-2000 and second (33.1%) time intervals for the year 2000-2010 with a uniform change (U) of 36%. Time interval intensity analysis corresponds with the recent accelerated loss of forest cover and wetlands due to socio-economic activities of increasing clearing of natural vegetation for mining, uncontrolled construction, land development, and smallholder rubber farming, driving a population increase on the landscape of Ankobra. Forest-to-bare land/built-up/mining excavations were observed. These rate of rapid land cover changes agree with the findings of Otchere-Darko and Ovadia (2020) and Bugri and Yeboah (2017). GSS (2021) report also noted a rapid population increase from 680,270 in 2000 to 867,800 in 2010, through to 950,134 in 2021, corresponding to 39.7% in the ARB between 2010 and 2023. These statistical presentation population increase denotes more lands for socio-economic activities and infrastructural developments (Iaquinta & Drescher, 2000; Obeng-Odum, 2014)

Changes at the category level, on the other hand, were obtained from the interval level of analysis. The percentage loss in closed forests exceeded that of its gains at the category level in the first interval. In both times, bare land, as well as other non-vegetated land, were more likely to increase than decrease (Appiah et al, 2015). The rapid expansion of bare land>settlement/built-up>agricultural land and mining excavations at the expense of forests and wetland/mangrove indicates that extensive mining activities (*galamsey*), and other related anthropogenic pressures as a result for rush for gold are the major cause of landscape changes and higher intensity of change in our study area. In addition, agricultural practices such as clearing forest and some sections of the wetlands for the cultivation or planting of rubber, teak and oil palm (Donkor and Agyeman, 2015) and population density (Obodai et al., 2019) are the dominant drivers affecting the landscape dynamics in the study area. In this study, the intensity analysis was used to assess LULC changes over a temporal extent of 33 years (1990–2023). The intensity and trajectory analysis provides a good understanding of the transition intensities among land categories and also provides complementary information, namely the spatial distribution of changes over different time intervals.

Gains, Losses and Net Change in LULC

With reference to the LULC analysis, the net change and magnitude of change in terms of gains and losses for each LULC class (1990 – 2000, 2000 – 2010, 2010 - 2023 and 1990 – 2023) were obtained and presented in Figure 10. Between 1990 and 2023, the majority of the loss were observed in forest cover (1,656.09 sq.km), followed by agricultural/farmland cover (580.18 sq.km), while settlement/built-up areas, mining/excavations, bare lands and

mangroves/wetlands progressively gained by 798.50, 635.19, 598.5 and 99.02 sq.km, respectively. Likewise, 1990 and 2023, forest and agricultural land consistently experienced the highest loss while mining settlement/built-up and bare land gaining some significantly classes between 1990 and 2000, 2000 and 2010, 2010 and 2023.

In general, there were both noticeable rates of changes in agriculture/farmland, forest, settlement/built-up, bare land and mining/excavation classes, with exception of mangrove/wetland and water classes. Similar trend observed in the studies conducted by Aduah et al. (2015), Bugri and Yeboah (2017), and Obodai et al. (2019). This was as a result of the quick increase of ‘Settlement/built-ups’ from 226.83 km² to 471.17 km² as well as Mining excavations also increasing from 32.36 km² to 491.90 km² not forgetting how Bare land which substantially contributed to loss of Evergreen Forest and Agriculture/farmland, due to the growth of peri-urban growth and rush for gold syndrome (galamsey activities) in relation to population increase from 680,270 in 2000 to 867,800 in 2010 through to 950,134 in 2021 and projected to increase to 1,452,589 in 2031 which indicates a percentage increment of 569,864 (13.8%) (Ghana Statistical Service, 2021; Kusimi, 2008).

The present study shows that between 1990 and 2023, evergreen forest and agriculture/farmland reduced by 21% and 8%, respectively, while mining areas increased over four-fold and settlements and bare land increased more than three and four-fold, respectively. The decrease in forest cover for the period 1990–2023 occurred mainly in Hiawa, Tarkwa, Beppoh and Prestea (South-Western) and Aiyim, Nzema Jukwa and Nsuaem (Northern) part of the basin (Figure 10). In fact, many farm lands were given out to miners with high purchasing power due to the high demand of land for the mining activities and other extractive activities, as well citing of constructional sites and industries and so on (Aduah et al., 2015; Forkuor et al., 2020; Kumi-Boateng et al., 2012; Kutir et al., 2024; Obodai et al., 2019).

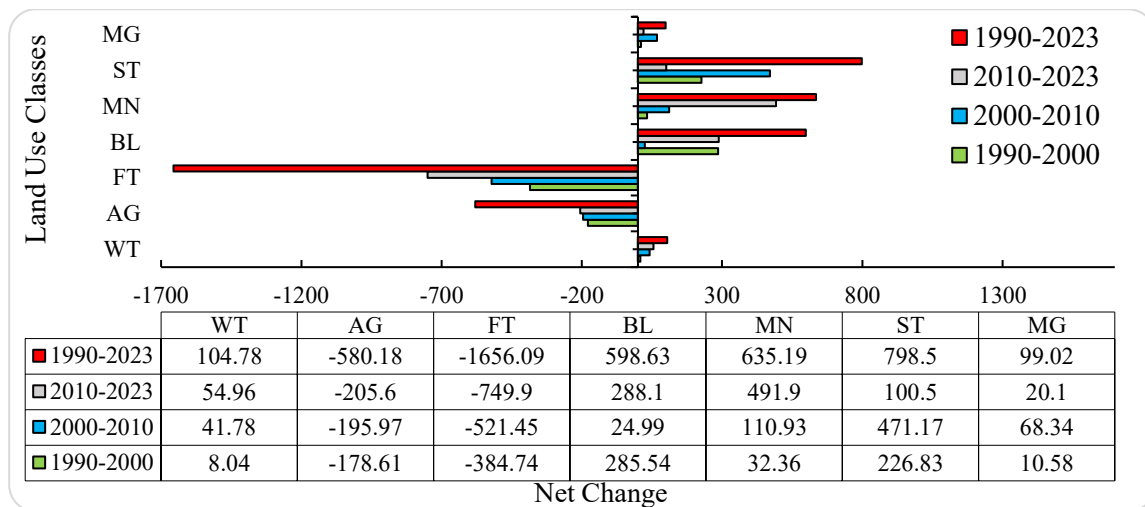


Figure 10. Annual rate of land cover changes.

WT = Water; **AG** = Agriculture Land; **FT** = Forest; **BL** = Bare land; **MN** = Mining/Excavations; **ST** = Settlement/Built-Up; **MG** = Mangroves/Wetlands.

Markov-CA Predicted LULC for the Year 2056

The land use transition dynamics did not deviate significantly under the first-time scenario assumption of the “business as usual” trend for the future prediction (Hamad et al., 2018; Larbi et al., 2019). By the year 2056, which is more than three decades from 2023, present land use land cover activities are proceeding at a rather increasing rate, transforming forest cover, being mostly targeted by settlement/built-up, bare land and mining/excavations. The validation results of the Markov-CA algorithm showed that the model adequately simulated the future LULC pattern in the Ankobra river basin with an overall correctness of 89% and a kappa coefficient of 0.87. A comprehensive evaluation of Markov Chain LULC projection against 2023 reference data with five important statistical metrics and performance ratings is shown in Table 6. All performance metrics exceeded 0.80, demonstrating excellent agreement

between the 2023 LULC classification and Markov Chain 2056 prediction. This indicates that the simulated LULC map of the year 2056 was highly comparable to the actual 2023 produced in this study, indicating an accurate model performance (Khan et al., 2024). The high Kappa value (>0.8) further confirmed the model's reliability, indicating strong predictive capability with minimal classification errors (Aldwaik and Pontius Jnr, 2013; Khan et al. 2024). These results align with findings from Kumi et al. (2023), who similarly validated LULC projections using comparable statistical approaches.

Table 6: Comprehensive evaluation of Markov Chain LULC projection against 2023 reference data.

Metric	Value	Rating
Overall correctness (Accuracy)	0.89	Excellent
Precision	0.96	Excellent
F1 Score	0.91	Excellent
AUC-ROC	0.83	Excellent
Kappa (κ)	0.87	Excellent

The predicted results in Figure 11a revealed that by 2056, settlement/built-up and bare land are expected to increase to 14.07% and 11.80%, respectively, compared to 11.4% and 9.3% in 2023. Similarly, the mining excavation might increase from 7.62% to 10.85% between 2023 and 2056. This is partly attributed to the expansion of illegal mining activities, rapid population migration, including the influx of illegal migrants and growth due to gold rush syndrome, logging of timber in the study area (Aduah et al., 2015; Donkor, 2018). Whereas the evergreen forest and agriculture/farmland acreage are anticipated to decrease from 46.62% and 22.57% in 2023 to 40.20% and 19.18% in 2056 (Figure 11b). This could be linked to illegal cutting of trees, overgrazing and mechanised agriculture since the population in Ankobra River basin depends mainly on farming activities for livelihoods (Nasirudeen and Allan, 2014; Obodai et al., 2019; Shueler et al., 2011). The model prediction showed that the trend of mangrove/wetland and water, as indicated in Figures 11, would increase by an insignificant proportion of about 0.823% and 0.373% respectively.

The model validation according to Appiah et al. (2017), indicated that there is a little degree of variability from the observed LULC trends between the initial and the predicted years (Reis, 2008). This trend implies that, the Ankobra basin, given the current rate of LULC change dynamics would continue to remain a predominantly rural district, with peri-urbanism activities concentrated in limited portions of the district especially areas that are in proximity to the main urban city centres such as Tarkwa, Prestea, Gwira Bansa and Sawoma-Asanta-Ankobra township near Axim (Obodai et al., 2019). However, there is the propensity for mining concessions (open pits/excavations), settlement/build-up, bare land and concrete surface land uses to increase consistently in the future given the transition probability matrix comparison (Figure 11b). Although we have used a robust and efficient Markov-CA algorithm in our future LULC classification experiment, the method has some limitations. For instance, we simulated the future (2056) LULC predictions using the current natural (selected topographic) and anthropogenic factors that might considerably change in the future. In addition, other factors that could play a significant role in the future LULC shift like fire, flood, conflict, and other geopolitical and socio-economic variables were not considered in our study.

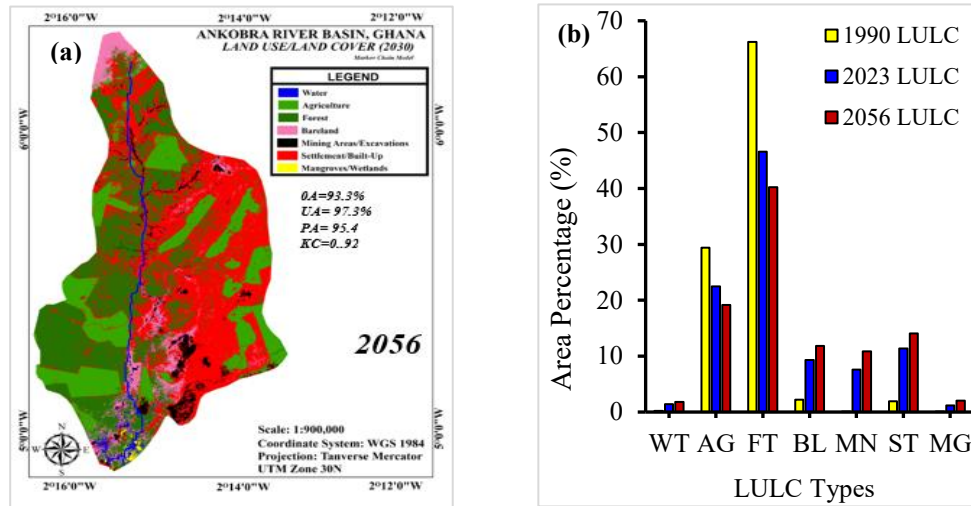


Figure 11: Predicted LULC map of 2056 (a) and statistical projections ed of 2056 LULC (b) based on 1990 and 2023 data.

AHP Model Validation and Consistency Metrices

Saaty's pairwise comparison matrix (1–9 scale) facilitated the calculation of normalized weights (for priority ranking), which were aggregated using GIS-based spatial multi-criteria modelling. According to Lambin et al. (2003) and Muhati et al. (2018), drivers of LULC changes at the local level vary over time and are anthropocentric and biophysical in nature, so are their impacts as the local landscape changes. The relationship between LULC changes and their driving forces are complex and dynamic. In this study, nine (9) major factors (proximate, underlying and physical) that drive LUCC change in the ARB, Ghana, were identified. For the driver-factor analysis (DFA), the pair-wise matrices were normalized for their eigenfactor values (priority weights) for interpreting the AHP results and the overall ranking assessment of driving factors as shown as Figure 12, along with their generated priority weights, level of consistencies, CI, CR and principal eigenvalue ($\lambda_{\max}$) in Table 7. The value of consistency ratio (CR) and index (CI) of the drivers on the pair-wise matrix were 0.00547 (0.547%) and 0.00794 (0.794%) for AHP which is below the acceptable threshold of 0.10 (10%). This indicates that the outlined drivers in the pair-wise matrix are reasonably consistent, acceptable and statistically reliable, that can be used for ranking purposes from the pairwise comparisons (Guria et al., 2024; Yadav et al., 2022).

The principal eigenvalue ($\lambda_{\max}$) of 9.064 is very close to $n=9$, in which only 0.064 exceeds “ n ” indicating a logically consistent expert judgement and criterion factor selection is very close to perfect consistency. In fact, the principal eigenvalue ($\lambda_{\max}$) is expected to be equal to or greater than “ n ” with a small a small desirable deviation. However, large deviations could be indicated logical contradictions in human judgements, problematic and requires revision of pairwise comparisons (Malczewski, 1999; Saaty, 1990; Zghibi et al., 2020). Although individual eigenvalues ($a \times b$) in Table 7 were computed during the eigenvalue estimation process, they were not interpreted separately, as their sole purpose is to aid in the derivation of the principal eigenvalue ($\lambda_{\max}$) for consistency checks, validation, and judgement assessments (Shekar et al., 2023). The relative influence of drivers was, however, evaluated using the normalized eigenfactor values (priority weights) in Table 7.

Table 7: Pairwise relative weight and eigenfactor/priority weight calculation for ranking contribution of potential drivers and consistency (CI and CR) assessment based on AHP.

S/N	Criterion/ Drivers	Pairwise Relative Weight (a)	Normalized Eigenfactor (Priority Weight) (b)	Eigenvalue ($a \times b$)	QRH	CI	CR
1	AE	2.165	0.320	0.692	1st	0.00794	0.00547
2	PS	4.635	0.225	1.041	2nd		

3	LG	7.593	0.150	1.139	3rd		
4	MA	11.45	0.106	1.209	4th		
5	IE	16.283	0.073	1.182	5th		
6	ST	22.083	0.050	1.111	6th		
7	DS	28.833	0.035	1.013	7th		
8	EL	36.5	0.024	0.888	8th		
9	WL	45	0.017	0.787	9th		
Sum		$\sum_{(a)}$ =174.542	$\sum_{(b)}$ =1.000	$\sum(\lambda_{max})$ Principal Eigenvalue =9.064			

Abbreviations: *AE* is agriculture expansion; *PS* is population pressure; *LG* is logging; *MA* is mining activities; *IE* is industrial expansion; *DS* is distance from settlement; *EL* is elevation; *ST* is soil type, and *WL* is weak laws. *CI* and *CR* represent consistency index and consistency ratio, respectively.

Implications of Driving Forces assessed with AHP-MCA-Based Relative Weighting on LULC Change

The driving factors responsible for the LULC changes in the Ankobra River Basin (ARB) in south-western Ghana were obtained from the AHP multi-criteria analysis (AHP-MCA) and presented in Table 7. The AHP-MCA revealed that driving factors comprises physical, proximate and underlying drivers (Figure 12). The overall ranking results based on Quantitative Relative Importance Index (QRII) showed that the alterations in land use/land cover (LULC) patterns in the Ankobra River Basin over the past 33 years has been driven by agricultural expansion (AE), population pressure (PS), logging (LG), mining activities (MA), industrial expansion (IAE), soil type (ST), distance to settlement (DS), elevation (EL), weak laws (WL) in a sequential order (Figure 12).

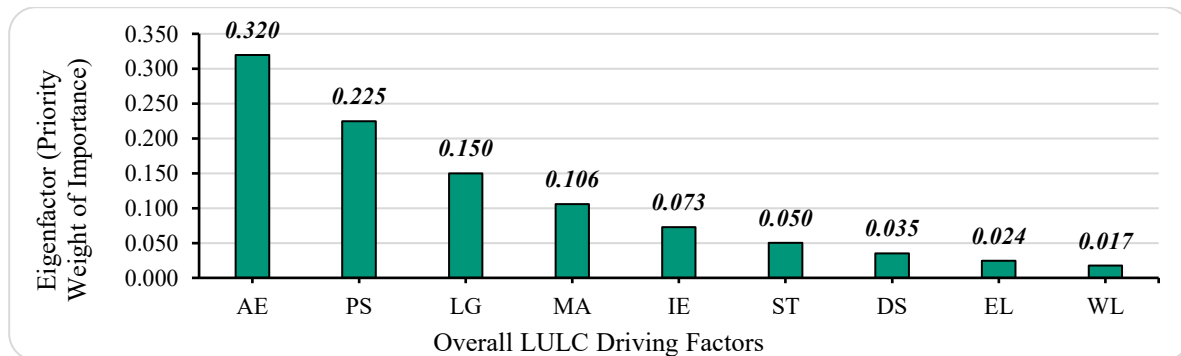


Figure 12: Overall weight of importance to different driving factors influencing LULC in the ARB, SW, Ghana. See Note 1 above for full meaning of *AE*, *PS*, *LG*, *MA*, *IE*, *DS*, *EL*, *ST* and *WL*.

It is worth noting that agricultural expansion (AE), the primary source of livelihood, accounted for the most dramatic form of landscape change in the ARB. From the AHP analysis, AE obtained an eigenfactor value of 0.32, ranked 1st per the QRII and significant value of ($p=0.0026$), respectively. According to the Water Resources Commission of Ghana (2019) and other studies conducted Mireku (2024), Obodai et al. (2019) and Yidan et al. (2008), the Ankobra River Basin has 94% of its total area in the Western region of Ghana, where pervasive farming is practiced and produces the largest quantity of cocoa in the country, as well as other cash crops including oil palm, and timber. In the current study, agricultural expansion was observed between 1990 to 2023, with much sharper agricultural expansion recorded from 2010 to 2023 and evident in Dominase, Hiawa, Kokofri, Atababo, Aiyim, Prestea, Tarkwa and Ankwaoso areas. The LULC results from this study, as reflected in Figures 6a-6d and 8a-8e are in-line with studies conducted by Assede et al. (2023), Faseyi et al. (2023), Eva, Brinks & Simonetti (2006), and Obubu et al. (2022), all indicating that in West Africa the trends in land-use change are dominated by intensification of agriculture in the areas already settled. Donkor (2018) and Nin-Pratt & McBride (2014) also explains that government's intervention in the south western areas, including the ARB, explains why agricultural land covers a substantive area of the basin after forest cover.

Traditionally, opportunities for agriculture and mineral exploration in the more humid coastal areas, have encouraged steady migrations from the outlying areas towards the coast, with the Ankobra River Basin not an exemption. Much of the coastal rain forest has been cleared to make way for agricultural plantations, mining and urban development and what remains is decreasing at an annual rate of between 2 and 5 % (Maitima et al., 2009). Rubber plantations are also gaining ground among various cash crops farmed in the study area due to their security and ready market. Ghana Rubber Estate Ltd. (GREL) and other private individuals usually buy the raw latex across the ARB, making it a major cash crop, replacing oil palm and cocoa. The cost of a tonnage of rubber latex was between GHS2,200-3500 (equivalent to USD\$200–300) as at 2022, and the pricing varied depending on the season. The price could be between USD 300–400 during the dry season. This makes rubber plantations the most secure industrial tree compared to oil palm, cocoa, and other crops. These development events in the Ellembele and Jomoro municipalities cause LULC, as Sarfo et al. (2022) confirmed in a similar study in southwestern Ghana. Studies by Assede et al. (2023), Mabogunje (1995), Malhi et al. (2013), and Obubu et al. (2022), conducted from the SSA and other developing countries with similar landscape characteristics have shown similar results, citing agriculture expansion and population pressure as active drivers that are currently facilitating LULC changes especially local communities surrounding the water resources.

This is closely followed by population pressures (PS), with an eigenfactor value of 0.225, ranked 2nd per the QRII and PS having obtained a significant value of ($p=0.0047$), highlighting its substantial driving factors to land use and land cover (LULC) of the ARB. Adarkwah et al. (2024), Lawortey et al. (2020), Obodai et al. (2019), and Sarfo et al. (2022) explained that population pressures are among the factors that have and continue to contribute to considerable resource depletion in the coastal zones of resource-endowed basin in Ghana, West Africa. This claim is not different from the records by Ghana Statistical Service population estimations for the ARB, which has been increasing at a growth rate of 4.5%, since 2010. The driver-factor analysis (DFA) findings conducted by Obodai et al. (2019) and Sarfo et al. (2022) also mentioned similar results across the ARB landscape. In relation to the aforementioned factors, rapid population increase resulting in population density per given land, together with mismanagement of land resources could destructively change land use patterns, affect land use patterns, which trigger the quality water resource components and biodiversity (Mataima et al., 2009). Several studies conducted in the Ankobra river basin by Arthur et al. (2025), Jain et al. (2016), Obodai et al. (2019), and Pielke et al. (2002) states that lack of alternative livelihood options and government incentives and flexible policies on agricultural practices may have motivated people to engage effectively agriculture, which may result in indiscriminate and unsustainable agricultural practices, contributing to LULCC.

Notably, logging (LG) is ranked the third most significant contributors to LULCC. Logging as a driving factor recorded an eigenfactor of 0.150 in the AHP model at a significant level of 0.008 across all location in the ARB a statistically significant contributor to LULC changes. Deforestation caused by both legal and illegal logging activities affects forest covers, biodiversity, and carbon compositions. Sites such as Ankwaoso, Nzema Jukwa, Tarkwa, Dompim, Prestea, Dominase and Gwira Bansa, located in the ARB, are among those areas where logging activities are predominant to effect LULC change as provided in the Human Activity Intensity of Land Surfaces (HAILS) (*Supplementary Sheet, Table 11*). Forest, agriculture and farmlands which are the major land cover types reduced substantially in coverage size as a result of logging, lumbering and other related mining activities as mentioned in similar studies conducted by Kusimi (2008), Obodai et al. (2019), and Schueler et al. (2011). Within these mining excavations in the ARB, farmland loss caused farmers to extend their farm boundaries into forest areas with its associated “spill-over” effect (Schueler et al., 2011; Sonter et al., 2014). Again, there was a noticeable depletion of forest and agriculture land cover at the lower section and estuarine area of the ARB that can be ascribed to immense mangrove and bamboo logging to pave way to illegal mining activities. Mangroves were depleted also because they serve also a source of fuel for the estuarine communities in the ARB (Donkor and Agyemang, 2015; Fatawu and Allan, 2014).

More importantly, mining activities (MA) also showed a very strong statistical association with LULC changes within the ARB. Supported by a p -value of 0.0037, with an AHP, GWR and QRII value of 1.11, 1.26 and 2.37, it is evident that the expansion in mining and excavation from mineral extraction related activities, concessions and open pits are associated with illegal small-scale and large-scale mining (*galamsey*), especially in resource-rich areas such as Tarkwa, Nsuem, Prestea, Dominase, Heman, Bonsaso, Gwira Bansa and Aiyim. The mining activities

played a significant role in altering land use change patterns (Aduah et al., 2015; Obodai et al., 2019; Schueler et al. 2011). Comparing the 2023 classified map in Figure 6d with the 1990 map in Figure 6a shows that mining areas have significantly increased around the south eastern and north eastern part of the basin, as well as along most tributaries of the river in the north western part of the basin towards the downstream. Fragile coastal ecosystems, such as the entire stretch of coast between south-eastern (Keta and Accra) and south-western part (Ankobra basin and Half-Assini), all in Ghana, are under further stress because of increasing demand for resources compounded by industrial and peri-urban development and their associated pollution loads. Donkor (2018), Konadu-Agyemang (2018), Ajakaiye and Page (2012) and Rauch et al. (2004) linked the drastic landscape changes due to mining to the implementation of the structural adjustment programme (SAP) of the World Bank, which liberalized Ghana's economy and increased foreign direct investment in the mining sector. According to the study's findings, mining areas as presented in Figures 6a and 6b, increased by a slight margin between 1990 and 2023. Mining activities in the ARB led to changes in land cover. They have a negative influence on the ecosystem, including deforestation, digging of pits, deviating water courses and obstructing another river network, having a variety of influences on ecosystem classes such as water bodies, plankton species, forest cover and alteration of soil profiles. While just taking up a small portion of the land's surface as revealed in Figures 6a to 6d, mining does have major and frequently irreversible repercussions on the environment (Snapir et al., 2017)

Industrial expansion (IE) is ranked as the fifth most statistically significant driver of LULC change, with a p-value of 0.0039 and an eigenfactor value of 0.073 from the AHP model, indicating a highly significant relationship with LULC change patterns in the ARB respectively. This underscores the role of increasing industrial activities and development, such as siting of factories and expansion of commercial infrastructure in areas such as Tarkwa, Prestea, Dompin and Ankobra in transforming land cover which often results in the loss of vegetation and an increase in impervious surfaces like concrete and compacted bare land. Industrial expansion as one of the major driving factors causing changes in LULC has been mentioned in several studies conducted by Asenso et al. (2020), Kutir et al. (2022), and Obodai et al. (2019). Their results show that large-scale industrial investments in the case study area led to substantial land use change, an appropriation of agricultural land, and an increase in the number of landless farmers, as well as farmers with small farmland holding sizes as reported in the study of Donkor and Agyemang (2015) and Sarfo et al. (2022). Similar findings were reported in the study of Assede et al. (2023), Guria et al. (2024) and Meyfroidt et al. (2013). At the same time, the total agricultural/farm land in the area decreased.

Soil type (ST), although obtained a minimal eigenfactor value of 0.050 at a significant value of 0.0346, was also identified to be contributing driver of LULCC. This has a pull factor that attracts migrants into the ARB in search gold and other mineral resources as other economic opportunities as highlighted in the works of Asare-Donkor et al. (2018), Donkor (2018), Konadu-Agyemang (2018), Kusimi (2015) and Kutir et al. (2024). In furtherance, the least drivers of LULC were identified as distance from settlement (DS), elevation (EL) and weak laws (WL), all returned a lower eigenfactor with varying insignificant values of 0.0732, 0.0519 and 0.1815 respectively. This infers that among the LULC driver criterion the DS, EL and WL has the least influence on the changes in LULC in the ARB. Elevation as closely related to slope is considered to be one of the dominant topographic factors affecting LULC change. However, the sensitivity analysis indicates that with a p-value of DS, EL and WL were above the conventional significance confidence level of 0.05. Elevation is considered marginally significant but may influence LULC indirectly by affecting distance to settlement, accessibility, climate, and vegetation type, though its role appears secondary to more immediate human activities. Elevation affects the pattern of built-up areas, vegetation, mining, and the conversion of forest into agriculture land. In addition, local authorities, governments, non-governmental organisations and other stakeholders responded to the effects by diversifying the livelihoods and raising awareness of the ARB, south-western Ghana. However, the use of environmental policies and laws to manage impacts was determined to be inadequate. The findings conform with the studies conducted by Kusimi et al. (2015), Lawortey et al. (2020), Obubu et al. (2022), and Wubetie et al. (2025).

The authors of the "Environmentalism's Paradox" and "DPSIR Framework" in their argument on land use practice (LUP), land use change (LUC), ecosystem services (ESs), and human wellbeing (HWB) nexus concluded by saying that the trade-offs that exist among the aforementioned variables could account for the indirect link that exists between some of the LUP, LUC ESs and HWB (Duraiappah, 2011). There is much concern about these trade-offs, and informed management or policymakers are expected to improve both land use and ecosystem services by

mitigating the negative trade-off between LUC and other ESs (Braat and Groot, 2012). Our findings supported our supposition that controlled LUP could have a positive effect on ecological indicators. With regards to LUP and LULC changes, even though we noticed a positive causal relationship, we did not have strong evidence to present in this paper. To some extent, these relationships give us a reason to suggest that the multiple socio-cultural and economic factors that determine individual LULC changes are tied to healthy ecosystems in a socio-ecological landscape like ARB.

Conclusion

The study concluded that, the settlement/built-up area increased from 159.90 km² in 1990 to 958.4 km² in 2023. Mining excavations also increased substantially from 6.81 km² in 1990 to 642.0 km² in 2023, while bare land also increases from 185.67 km² in 1990 to 784.3 km² in 2023, demonstrating significantly outcompete other land use/ land cover classes. Contrarily, agricultural/farmland and forest land significantly decreased from 2472.38 km² in 1990 to 1892.20 km² in 2023 and from 5576.79 km² in 1990 to 3920.70 km² in 2023, demonstrating that these two classes were the land use which were largely affected concurrently by anthropogenic activities and physical by the expansion of peri-urban areas of the ARB. In this study, we further assessed the drivers affecting LULC of the Ankobra Basin, S/W, Ghana, where we used AHP to perform a dimensionality reduction of nine thematic datasets to create a single variable for the LULC driver factor analysis. To mitigate structural limitations to AHP, our approach brought together a suite of methods and produced a set of comparative metrics to identify and refine LULC driver-factor eigenvalue and evidence of weight scores. Based on AHP Eigenfactor (priority weight) or weight of importance (WoI) values, the study identified that six (6) major proximate and underlying factors, including agricultural expansion (AE), population pressure (PS), logging/lumbering (LG), as well as mining activities (MA) and industrial expansion (IE) and soil types (ST), were factors driving LULC in the ARB between 1990-2023. All of these drivers and pressures contribute to land degradation, forest conversion, soil fertility and carbon loss, poverty, high floods, poor water quality and availability, a scarcity of resources for construction and fuel, as well as urban - to- rural migration.

Considering the significant depletion of land cover features of the ARB, it is worth recommending that using a more localised approach to advocate for land use management policies or bylaws is essential. Similarly, a localised advocacy platform to advocate for biological diversity and ecological protection laws and policies in Ghana is likewise crucial. Environmental conservation is both an international and national concern. Every effort must be made at both levels to safeguard the natural resources upon which life depends. Effective monitoring and surveillance of mining concessions and forest reserves using high-tech early warning systems, artificial intelligence (AI) and geospatial technologies, is crucial in the fight against anthropogenic activities illegal mining (*galamsey*) and mitigating pollution. Strong environmental regulations on mining operations are advised, and initiatives to inform the public about the different facets of mining should be supported by the government. Environmental conservation is both an international and national concern. Adequate and informative tools and frameworks must be developed to monitor changes in land cover, biodiversity and land use in order to assess and inform decisions at policy and management levels.

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Authorship contribution

Study design, reconnaissance study, methodology, data sourcing, processing, formal data analysis, validation, visualization, writing, review of original draft of the manuscript: **C.K.O.** Conceptualization, supervision, additional methodology, software, writing, review, editing data funding acquisition: **B.K.N.** Christian K. Owusu. Writing,

review, editing, resourcing, supervision: **B.E.N and E.A.** Proof-reading of the manuscript: **C.K.O, B.K.N. B.E.N and E.A.**

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Data availability

Additional data and supplementary information are provided on supplementary sheet. This will also be made available upon request from the first author, Christian K. Owusu (chkowusu@gmail.com)

Declaration of competing interest

The authors declare that they have no conflict of interest.

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