TELEDETEKCJA ŚRODOWISKA
dawniej „Fotointerpretacja w geografii"
Tom 63 (2023) s. 5–17
ISSN 0071-8076
POLSKIE TOWARZYSTWO GEOGRAFICZNE
ODDZIAŁ TELEDETEKCJI I GEOINFORMATYKI
http://ptgeo.org.pl/teledetekcja/

# Forest loss and land cover land use change Dynamics in the peri-urban rural districts of Greater Kumasi – Ghana

*Wylesianie i zmiany w pokryciu terenu Dynamika zmian użytkowania gruntów w podmiejskich okręgach wiejskich Wielkiego Kumasi w Ghanie*

Addo KORANTENG
Kumasi Technical University
Institute of Research, Innovation and Development, Kumasi, Ghana
addo.koranteng@kstu.edu.gh

Isaac ADU-POKU
Kwame Nkrumah University of Science and Technology
Department of Geomatic Engineering, Kumasi, Ghana
i.adupoku@yahoo.com

Bernard FOSU FRIMPONG
Brandenburg University of Technology
Department of Hydrology, Cottbus, Germany
bengarzy007@gmail.com

Jack NTI ASAMOAH
Kumasi Technical University
Faculty of Engineering and Technology
Department of Civil Engineering, Kumasi, Ghana
jack.nasamoah@kstu.edu.gh

Tomasz ZAWIŁA-NIEDŹWIECKI
Coordination Centre for Environmental Projects, Warszawa, Poland
tzawilan@gmail.com

**Abstract**

The study evaluated the space-time fluctuations of the land cover land use changes (LULCC) in the peri-urban rural districts of Greater Kumasi in Ghana from 1990 to 2020. Several satellite images derived from medium to high-level spatial resolution (Landsat, Disaster Monitoring Constellation (DMC) and Sentinel) in decadal intervals of 1990–2000; 2000–2010 and 2010–2020 were analyzed. The multi-temporal satellite images were preprocessed (georeferenced, radiometrically, and geometrically corrected). The Land use land cover (LULC) maps were derived using the Maximum Likelihood Classifier (MLC) technique and the maps were validated. Comparisons were undertaken in post-classification for the LULCC detection analysis. Closed Forest, Open Forest, Agriculture, Built-up and Water were the five LULC categories defined. Accuracy assessments of the LULC maps were very satisfactory. The results displayed a disturbing forest loss trend. There was forest degradation in protected forests and deforestation in forests outside designated areas from 1990 to 2020. The land use class of Agriculture reduced over the period 1990–2020. For agrarian communities in the study area, this is cause for concern however, it still represented a sizeable land use. Built up category was the largest gainer from 2.27% in 1990 to 18.60% in 2020. Overall, from 1990 to 2020, 62933.20 ha (33.37%) of the study area had undergone an extensive LULCC. Temporal investigation shows that these variations occurred mainly between 1990 and 2000. There was a strong reafforestation in 2000–2010 and forest loss in 2010–2020. Closed forests were preserved, and Open forests were lost in the 30 years of study. This study adds to the endeavors of salvaging what is left of the natural environment and an effort to ascertain the proximate causes of LULCC in the area of study.

**Streszczenie**

W niniejszym artykule zbadano fluktuacje przestrzenno-czasowe zmian pokrycia terenu i użytkowania gruntów (LULCC) w wiejskich okolicach okręgu miejskiego Wielkie Kumasi w Ghanie w latach 1990–2020. Analizie poddano kilka obrazów satelitarnych o średniej i dużej rozdzielczości przestrzennej (Landsat, Disaster Monitoring Constellation – DMC i Sentinel) w interwałach dekadalnych 1990–2000, 2000–2010 i 2010–2020. Wieloczasowe obrazy satelitarne zostały poddane wstępnemu przetwarzaniu (korekcja radiometryczna i geometryczna). Mapy użytkowania terenu (LULC) zostały wygenerowane przy użyciu klasyfikatora największego prawdopodobieństwa (MLC), a następnie poddane ocenie dokładności. Porównania zostały wykonane poprzez analizę wykrywania zmian LULCC po przeprowadzonej klasyfikacji. Zdefiniowano pięć kategorii LULC: Lasy o zwartej strukturze, Lasy o luźnej strukturze, Tereny rolne, Tereny zabudowane i Woda. Ocena dokładności map LULC była bardzo zadowalająca. Wyniki pokazały niepokojącą tendencję ubytku powierzchni leśnych. Zaobserwowano w badanym okresie od 1990 do 2020 r. degradację lasów chronionych oraz wylesianie w lasach poza wyznaczonymi obszarami. Klasa użytkowania Terenów rolnych również zmniejszyła się w okresie 1990–2020. Dla społeczności rolniczych w obszarze badawczym jest to powód do zmartwienia, choć nadal tereny te zajmują istotną część analizowanego obszaru. Z kolei kategoria Terenów zabudowanych odnotowała największy wzrost z 2,27% w 1990 roku do 18,60% w 2020 roku, a obszar badawczy o powierzchni 62 933,20 ha (33,37%) przeszedł znaczną zmianę LULCC. Badania wieloczasowe pokazują, że te zmiany wystąpiły głównie między rokiem 1990 a 2000. W latach 2000–2010 obserwowano silne nasadzenia leśne, natomiast w latach 2010–2020 nastąpiła utrata lasów. Lasy o zwartej strukturze zostały zachowane, a Lasy o luźnej strukturze doznały znaczącego zmniejszenia pola powierzchni w analizowanym okresie. Niniejsze badanie przyczynia się do wysiłków mających na celu ocalenie tego, co pozostało z naturalnego środowiska oraz określenie bezpośrednich przyczyn LULCC w obszarze badawczym.

**Keywords:** Urbanization; Deforestation; Forest degradation; Anthropogenic pressure; Change analysis.
**Słowa kluczowe:** Urbanizacja; Wylesianie; Degradacja lasów; Presja antropogeniczna; Analiza zmian.

## Introduction

Anthropological socio-economic activities, environmental and biophysical factors are known to be the drivers of Land Use Land Cover (LULC) alterations (Makwinja et al., 2021; Liu et al., 2022). The adverse effects of LULC conversion are reckoned to substantially impact the abiotic and biotic sphere of the earth, these include climate, biotic diversity, biogeochemical cycles, hydrology soil, food security and quality of humans locally and globally (Ishiyama et al., 2021). Nevertheless, LULC conversions are known to provide critical support for communities and nations in the provision of food, the much-needed foreign exchange and a source of livelihood (Mekuria et al., 2020). Consequently, it is vital to track, monitor and document LULC fluctuations to comprehend their drivers and ramification in light of climate change, ecological changes, surging population and growing insistence for ecological sustainability concerns locally and globally (Le Boulzec, 2022).

Land Use Land Cover in Ghana and especially the Greater Kumasi area has undergone drastic changes in the last 30 years as a consequence of many causes which include rapid population expansion and other socio-economic activities. Several studies have endeavored to peruse and describe the LULC changes (Koranteng et al., 2020). These studies, nevertheless, analyzed changes and largely included Ghana's second city of Kumasi. These studies established that deforestation and other LULC had transpired and have resulted in several consequences. This study specifically addresses these issues in detail in the rural districts of the Greater Kumasi area only using a synergy of satellite images.

Geospatial analysis applied in this study involves remote sensing (RS) and geographic information system (GIS). It is explained as the assembly, exhibition, and use of images, GPS, satellite imagery and historical information, designated plainly in geographic coordinates (Zurmotai, 2020). Geospatial methods are vital means of acquiring precise and well-timed spatial data of LULC, in addition to investigating the modifications in a designated vicinity (Mhangara, 2011). Remote Sensing images effectively document LULC and provide a vast resource of data, through which current LULC details and variations are obtained, evaluated, and modelled effectively LULCC at varying levels (Khamaru et al., 2022). GIS conversely offers an open setting for gathering, saving, presenting, and examining digital information essential for change observation and other transformations (Li, 2020). There exist various techniques for identifying and studying LULCC (Liu et al., 2019) but RS and GIS methodologies make it conceivable to efficiently observe and predict the developments in LULC alterations through the analysis of past satellite imagery in a relatively shorter time.

This paper seeks to document the space–time fluctuations of the LULCC in rural districts of Greater Kumasi from 1990 to 2020. More precisely, the paper is intended to (a) categorize and map the key LULC categories in the rural districts of the Greater Kumasi in four-time intervals, including 1990, 2000, 2010 and 2020; (b) determine the space–time fluctuations of the LULCC over these three-time intervals (1990–2000; 2000–2010; 2010–2020) and (c) to integrate the resulting maps and classifications in a forestry oriented socio-economic comparative study to explain the changes and trend. These results will establish the basis for insight into the LULC development in this area of study. This paper is a contribution to the continuous insight into the sources and ramifications of LULCC, and it will additionally offer a more comprehensive contextual framework for the development of socio-economic and ecological strategies to safeguard the sustainable progress of the study area.

## Methodology

Steps used in this paper include the pre-processing of the satellite images (layer stacking, geometric and radiometric corrections, and image resampling), supervised image classification, LULC Maps, Post Classification Change Detection, LULCC Maps and Change Analysis. These steps are abridged in the flowchart in Figure 1.

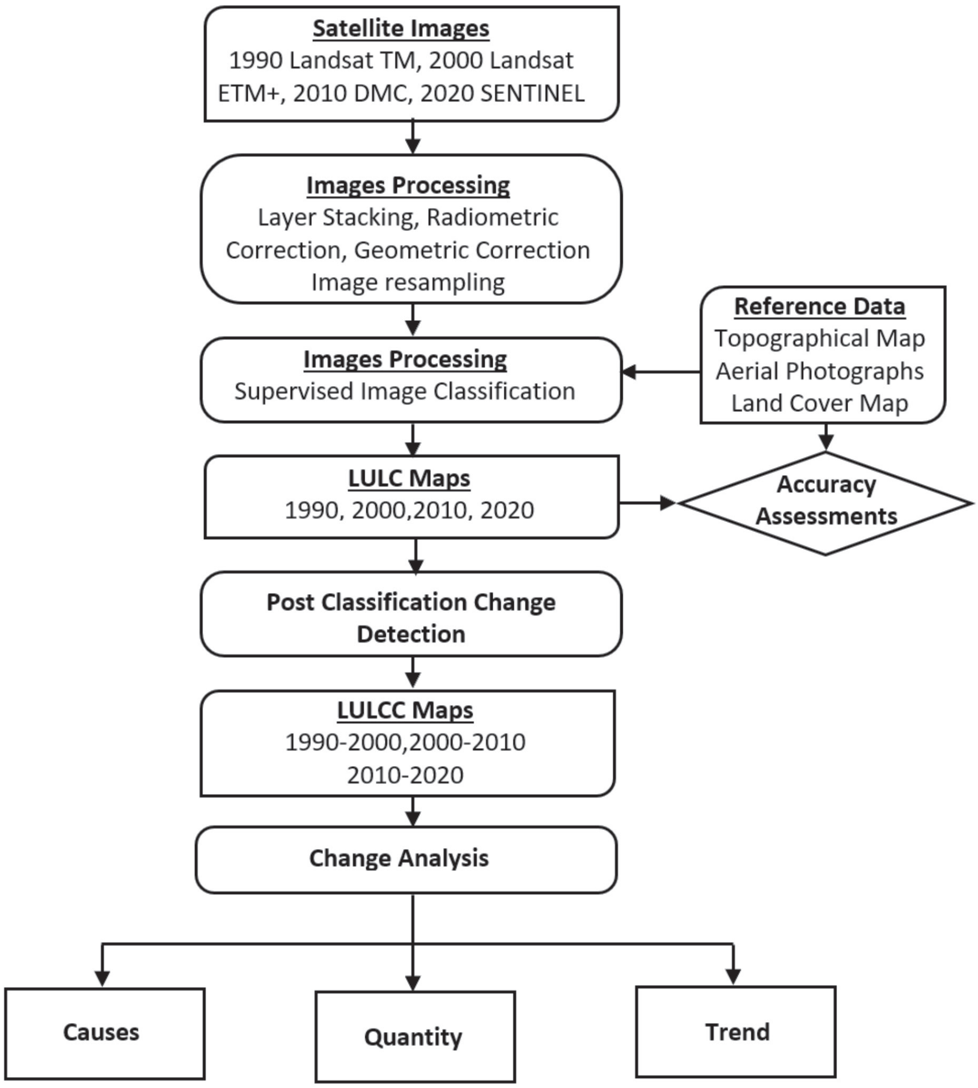


Fig. 1. Methodology flowchart adopted in the study

*Ryc. 1. Schemat metodyki przyjętej w badaniu*

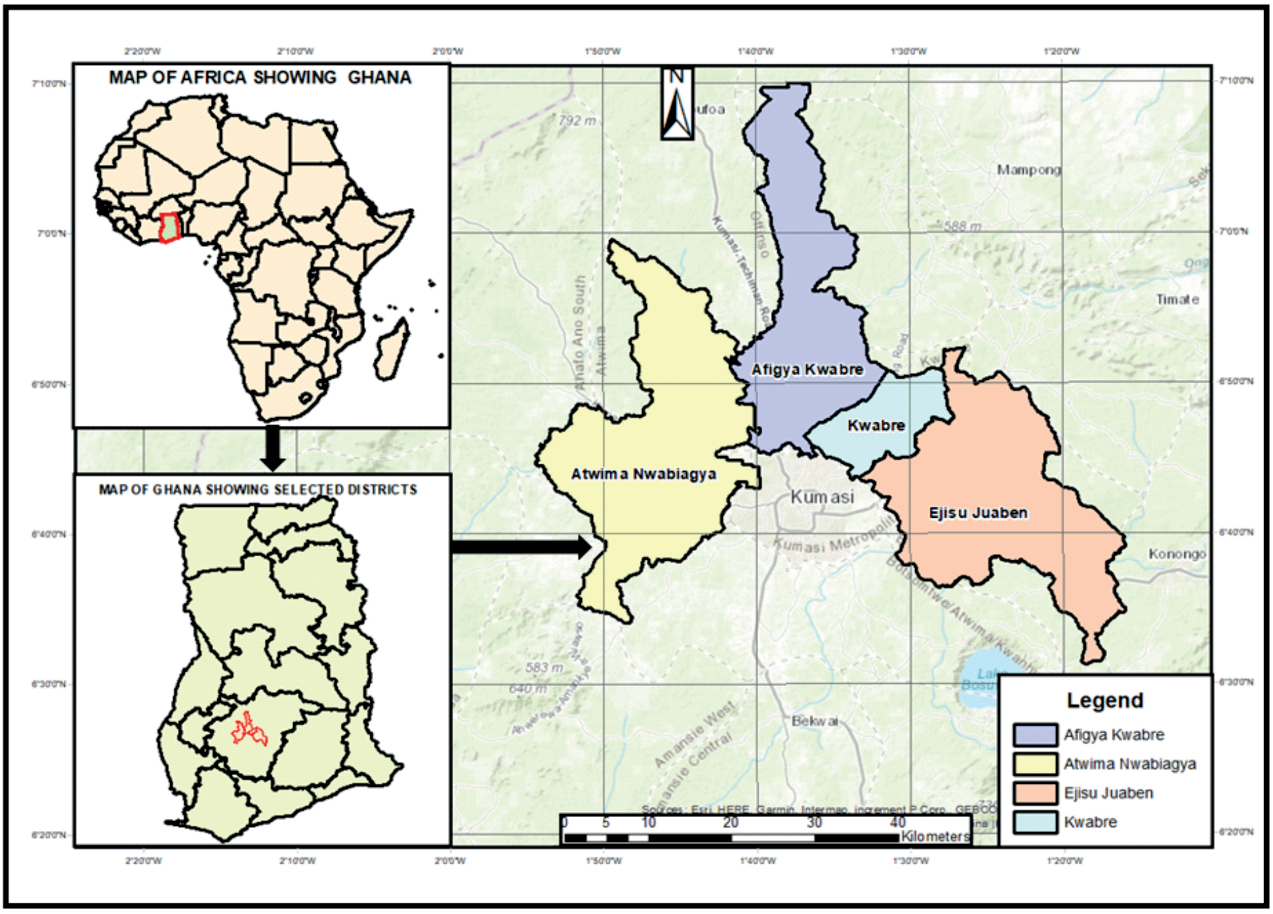


Fig. 2. Study Area comprising the Kumasi Metropolitan Assembly, Asokore Mampong Municipal and Atwima Nwabiagya Municipal

*Ryc. 2. Obszar badań obejmujący Związek Metropolitalny Kumasi, Asokore Mampong i Atwima Nwabiagya*

**Study Area**

This study was undertaken in the peri urban rural districts of the Greater Kumasi which includes the district administrative areas such as Atwima Nwabiagya, Afigya Kwabre, Kwabre and Ejisu municipality in the Ashanti Region, Ghana. These administrative districts share a common boundary with the Kumasi Metropolitan area and lie in the Deciduous Forest ecological zone in Ghana (Figure 2). The Owabi – Barekese catchment is situated within longitude 6°44'50"N and latitude 1°42'00"W is within the study area. Annual rainfall of approximately 1402 mm and an annual temperature of 24.6°C – 27.8°C characterized the area. These two dams (Owabi and Barekese established in 1920 and 1972 respectively) provide portable drinking water to the Kumasi Metropolitan area and surrounding communities (Forestry Commission, 2014). The catchment area of these two dams has a sizeable forest cover which has vital functions such as the protection of recharge areas, prevention of siltation and fast evaporation of water in the dam additionally, the improvement in rainfall. The forest cover and water resource of the catchment area has diverse vegetation and wildlife which play critical ecosystem services (Forestry Commission, 2014). Another important land-mark in the study area is the Bobiri Forest Reserve and Butterfly Sanctuary established in 1939. This 5460-hectare forest reserve (located on latitude 6°40′ and 6°44′N and longitudes 1°15′ and 1°22′W) is an important ecotourism site in Ashanti region, Ghana and is reputed to be the only butterfly sanctuary in West Africa with about 400 species of butterflies (Baffour-Ata et al., 2021).

**Data and software**

The major software employed in this study include ArcGIS, and ERDAS Imagine. Data sources listed in Table 1 were employed into this study.

**Image Processing and Classification**

Satellite imagery is best suited for analysis, when they are preprocessed to standardized data and signify the biophysical phenomena they represent (Parsa et al., 2020; Panuju et al., 2020). In this study the 2010 DMC and 2020 Sentinel satellite images were resampled to 30×30 meter pixel resolution (Landsat Images), this was undertaken to harmonize the precise analysis of the datasets and comparison possible.

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

*Tabela 1. Dane satelitarne wykorzystywane do klasyfikacji LULC i danych referencyjnych*

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

## Field Survey

An extensive desktop appraisal was carried out before the field survey was undertaken. Pertinent data and information regarding the study area were deliberated and evaluated. Data (Table 1) from the Survey and Mapping Division, Ghana and the Forestry Commission, Ghana were used. The subsequent image was employed to collect the ground truth and verification data. The study area was demarcated into grids and serially numbered for ease of sampling and identification of the sample zones. A GPS receiver and mobile GIS were employed extensively in the field survey. Stratified Random sampling was applied in the selection of the sampling units. 200 field sites traversing all the LULC types in the area under study were checked to determine the LULC types at their exact coordinates. The authors' knowledge and discussions with resident managers and indigenes of varying ages were undertaken to acquire vital information on the chronological development and the socio-economic circumstantial development of every spot (Koranteng et al., 2020; Frimpong & Molkenthin, 2021). Every single training site was defined on the images utilizing polygons covering multiple pixels. 100 points from the 200 field sites were used as ground truth data for image classification and the outstanding 100 data were used as verification data for the accuracy assessment. Five LULC categories – Closed forest, Opened forest, Agriculture, Built-up and Water (Table 2) were chosen and used in the image classification (supervised classification).

## Classification

All the satellite images for the respective epoch years (1990, 2000, 2010, 2020) were used for LULC classification. In classifying the 2020 image, the field data were brought into Microsoft Excel and then divided into two (2) groups (100 used as training data and the other 100 used as validation data). The training data together with the generated NDVI image were used to undertake the supervised classification premised on the maximum likelihood classifier in ERDAS imagine. The LULC classes and explanations are given in Table 2. The 1990, 2000 and 2010 epoch images were classified using ancillary data (Table 1).

The 2020 classified image was validated Accuracy assessment process in ERDAS imagine (error matrix and kappa statistics) are given in Table 3.

Table 2. Classification scheme of LULC used in this study

*Tabela 2. Schemat klasyfikacji LULC zastosowany w badaniu*

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

Table 3. Error Matrix and Kappa (K^) Statistics of Image Classification

*Tabela 3. Statystyka macierzy błędów i Kappa (K^) klasyfikacji obrazów*

| Class name | Reference Total | Classified Total | Number Correct | Producer Accuracy | User Accuracy | Kappa (K^) Statistics |
|---|---|---|---|---|---|---|
| Close forest | 17 | 20 | 15 | 88.24 | 75.00 | 0.6988 |
| Open forest | 33 | 30 | 25 | 75.76 | 83.33 | 0.7512 |
| Agriculture | 20 | 20 | 14 | 70.00 | 70.00 | 0.6250 |
| Built-up | 25 | 25 | 21 | 84.00 | 84.00 | 0.7867 |
| Water | 5 | 5 | 5 | 100.00 | 100.00 | 1.0000 |
| Total | 100 | 100 | 80 | – | – | Overall Kappa |
| **Overall Classification Accuracy** | **80.00%** | | | | | **0.7375** |

### Change Detection Analysis

The LULCC map covering a period of 30 years (1990–2020), was first calculated to peruse the overall change in the region and then LULCC of 10-year periods (1990–2000, 2000–2010, 2010–2020) were determined.

LULCC post-classification detection method adopted using the ERDAS Imagine, which entailed using two categorized images difference to obtain change information. Consequently, the differences between two images represent the change. The extent of change and proportion of changes are given in a straightforward formulation as used by Mahmud & Achide, (2012) and cited by Hua (2017):

$$K = F - I \quad (1)$$

$$A = \frac{(F - I)}{I} \times 100 \quad (2)$$

where $K$ is the extent of changes, $A$ represents the proportion of changes in percentages, $F$ is the first data, and $I$ is reference data.

### Rate of Deforestation

The annual deforestation rate was calculated for the 30 years (1990–2020) of study at a 10-year interval (1990–2000, 2000–2010, 2010–2020). This study adopted the formula of (Fearnside, 1993). This formula gives the essential information on the average speed at which deforestation occurs and it is stated in unit area per year.

$$R = \frac{A_1 - A_2}{t_2 - t_1} \quad (3)$$

where $R$ = rate of deforestation, $A_1$ = Initial value for forestlands in hectares, $A_2$ = Second yearly value of forestlands in hectares, $t_2$ = Second year, $t_1$ = Initial year.

## Results

### Image Classification and Accuracy Assessment

The classification of the LULC in the study area was done with five categories (Closed Forest, Open Forest, Agriculture, Built up and Water). The overall accuracies and Kappa indices for the years 1990, 2000, 2010 and 2020 were deemed very satisfactory (Table 2). Behera et al. (2012) advanced that accuracy assessment is essential, and principally so, when using post-classification change detection methods. The kappa statistics of 0.7375 was realized for 2020 LULC.

### LULC Maps

Figure 3 displays the four LULC thematic maps created for the study: 1990, 2000, 2010 and 2020 LULC Maps.

Closed Forest

Table 4 and Figure 3 illustrate the Closed Forest extent averages 17% of the study area. This category is principally made up of the designated and gazetted protected areas such as the Bobri forest reserve, Barekese and Owabi catchment areas. Other areas include burial, shrines and riverine forests. These are generally protected and off-limits because of enforcement of governmental and traditional enforcement activities. This LULC category remains stable at 17.18% in 1990, decreasing to 14.34% in 2000 (the largest decrease in the 30-year study period). The closed forest rebounded to 18.74% and 17.45% in 2010 and 2020 respectively.

Open Forest

As shown in Table 4 and Figure 3, Open Forest extent constitutes the largest LULC category in all the epoch years of study from 1990 to 2020. This is found in degraded Closed forests and formerly heavily forested areas outside the designated protected area from this large class. These areas used to be Closed forests and are liable to further degradation. In 1990 its extent was 55.22% of the entire study area but decreased to 46.93% in the year 2000. It regains 10% in 2010 to reach 57.12% and decline to 41.30% in 2020.

Table 4. Quantification of land use land cover classes

*Tabela 4. Kwantyfikacja klas pokrycia terenu użytkowania gruntów*

| LULC CLASS | 1990 | | 2000 | | 2010 | | 2020 | |
|---|---|---|---|---|---|---|---|---|
| | Area (ha) | Area (%) | Area (ha) | Area (%) | Area (ha) | Area (%) | Area (ha) | Area (%) |
| Close_forest | 32402.4 | 17.18 | 27036.4 | 14.34 | 35335.2 | 18.74 | 32898.1 | 17.45 |
| Open_forest | 104227 | 55.27 | 88497.6 | 46.93 | 107701 | 57.12 | 77873.6 | 41.30 |
| Agriculture | 47452.3 | 25.16 | 66723.3 | 35.38 | 30,154.10 | 15.99 | 42,339.10 | 22.45 |
| Built_up | 4282.38 | 2.27 | 5872.42 | 3.11 | 14,812.16 | 7.86 | 35,077.94 | 18.60 |
| Water | 202.77 | 0.11 | 437.13 | 0.23 | 564.39 | 0.30 | 378.11 | 0.20 |
| Total | 188566.9 | 100.00 | 188566.9 | 100.00 | 188566.9 | 100.00 | 188566.9 | 100.00 |

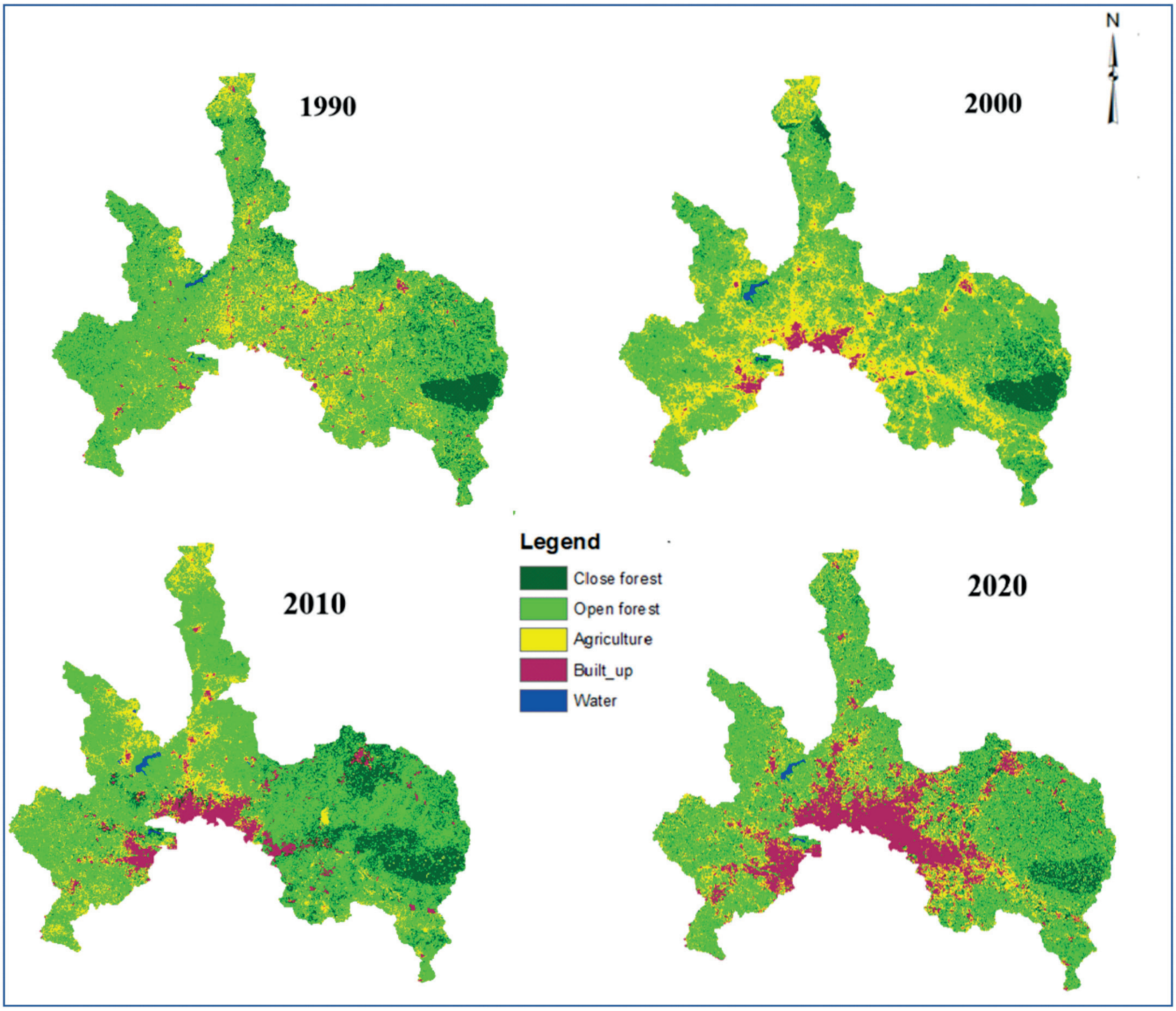


Fig. 3. LULC maps for the epoch years

*Ryc. 3. Mapy użytkowania i pokrycia terenu w poszczególnych latach*

Agriculture
This heavily mosaiced land use category is made up of cash crops such as Cocoa, Citrus, and Palm-nut to annuals such as maize, plantain, cassava, vegetables, and other local stable food plants. Agriculture is the second LULC in the study area as it is rural and farming is the main occupation of inhabitants. As depicted by Table 4 and Figure 3. Agriculture share was 25.16% of the LULC in 1990, increasing to 35.38% in 2000. In 2010 it was at 16% and by 2020 it had reached 22.45%.

Built Up
The built-up areas were dominantly observed in the southern portions and sparsely distributed in the study area. This category extent was the second least LULC class in 1990 at 2.27%. Ten years later in 2000, it had reached 3.11% but by 2010 and 2020 it had increased to 7.86 and 22.45% respectively. This category is constituted by towns, transport and sports infrastructure, farm settlements, peri-urban towns, hamlets, and surfaces without vegetation. The Built-up areas in 2010 and 2020 exposed a growing trend to the detriment of the other LULC classes, especially agricultural land use. Built-up areas increase throughout the study period (Table 4 and Figure 3).

Water
This LULC category had a spatial extent of less than 0.50% of the study area. The Barekese catchment area, Owabi catchment, rivers, river tributaries, dams and pools of water collected during the rainy season were the main constituents of this category. It ranged from 0.11% doubling 0.23% in 1990 and 2000 respectively. In 2010 it had 0.30% of the LULC type and 0,20% in 2020 (Table 3 and Figure 3).

## LULC Change Detection

Table 5 and Figures 4 and 5, show the spatial and thematic dispersal (in hectares) and the evolution of the proportion of each LULC class in the different periods of 10 years apart – 1990–2000, 2000–2010 and 2010–2020. The open forest remains the largest LULC type throughout the 30 years of study. Water was the least area throughout the 30 years while the built up category had increased more than 900% by the end of the study.

A total of 42 190.80 hectares which represented 22.37% of the total study area (188 566.90 hectares) had undergone some changes from 1990 to 2000. Closed forest and open forest decreased by 2.85% and 8.34% respectively. Agriculture increased within this decadal period by 10%. The built up and water recorded a marginal increase of 0.845 and 0.12% respectively.

For the period 2000–2010, 73 138.4 hectares representing 38.79% of the total study area had experienced some drastic changes. Unlike the period 1990–2000 which experienced forest loss, within this decade (2000–2010) there was increased forest cover of 4.40% and 10.18% respectively for Closed and Open Forest. There was a massive 19.39% of agricultural lands that had transitioned into Open forests and built-up areas. There was a rise in the built up category, indicating rapid urbanization. This decadal analysis indicates increasing urbanization and reafforestation (Table 5 and Figures 4 and 5).

The LULC change map for 2010 to 2020 (Table 5 and Figures 4 and 5) as 64901.56 hectares representing 34.42% had changed. There was a marginal Closed forest loss at 1.29%, another 15.82% of the Open Forest had been lost. There was an increase in Agriculture share at 6 at 6.46% and a whopping 10.75% increase in Built up category. Water land use class decreased by 0.10%. This decadal analysis specifies growing urbanization and forest loss (deforestation and degradation).

Cumulatively from 1990–2020 witnessed 62 933.20 hectares (33.37%) of the study area undergone LULC changes. This is very drastic and portrays very volatile LULC practices. Overall, there was forest loss (13.98%), loss of arable land (2.71%) and increased built up areas (urbanization) at 16.33% and water at 0.09%.

Table 5. Change detection 1990–2000, 2000–2010 and 2010–2020

*Tabela 5. Zmiany w powierzchni terenu w poszczególnych dekadach 1990–2000, 2000–2010 i 2010–2020*

| **LULCC Area** | **1990–2000** | | **2000–2010** | | **2010–2020** | | **1990–2020** | |
|---|---|---|---|---|---|---|---|---|
| | **(ha)** | **(%)** | **(ha)** | **(%)** | **(ha)** | **(%)** | **(ha)** | **(%)** |
| Close_forest | –5366 | –2.85 | 8298.8 | 4.40 | –2437.1 | –1.29 | 495.7 | 0.26 |
| Open_forest | –15729.4 | –8.34 | 19203.4 | 10.18 | –29827.4 | –15.82 | –26353.4 | –13.98 |
| Agriculture | 19271 | 10.22 | –36569.2 | –19.39 | 12185 | 6.46 | –5113.2 | –2.71 |
| Built_up | 1590.04 | 0.84 | 8939.74 | 4.74 | 20265.78 | 10.75 | 30795.56 | 16.33 |
| Water | 234.36 | 0.12 | 127.26 | 0.07 | –186.28 | –0.10 | 175.34 | 0.09 |
| **Total Area of Changes** | 42190.8 | 22.37 | 73138.4 | 38.79 | 64901.56 | 34.42 | 62933.2 | 33.37 |

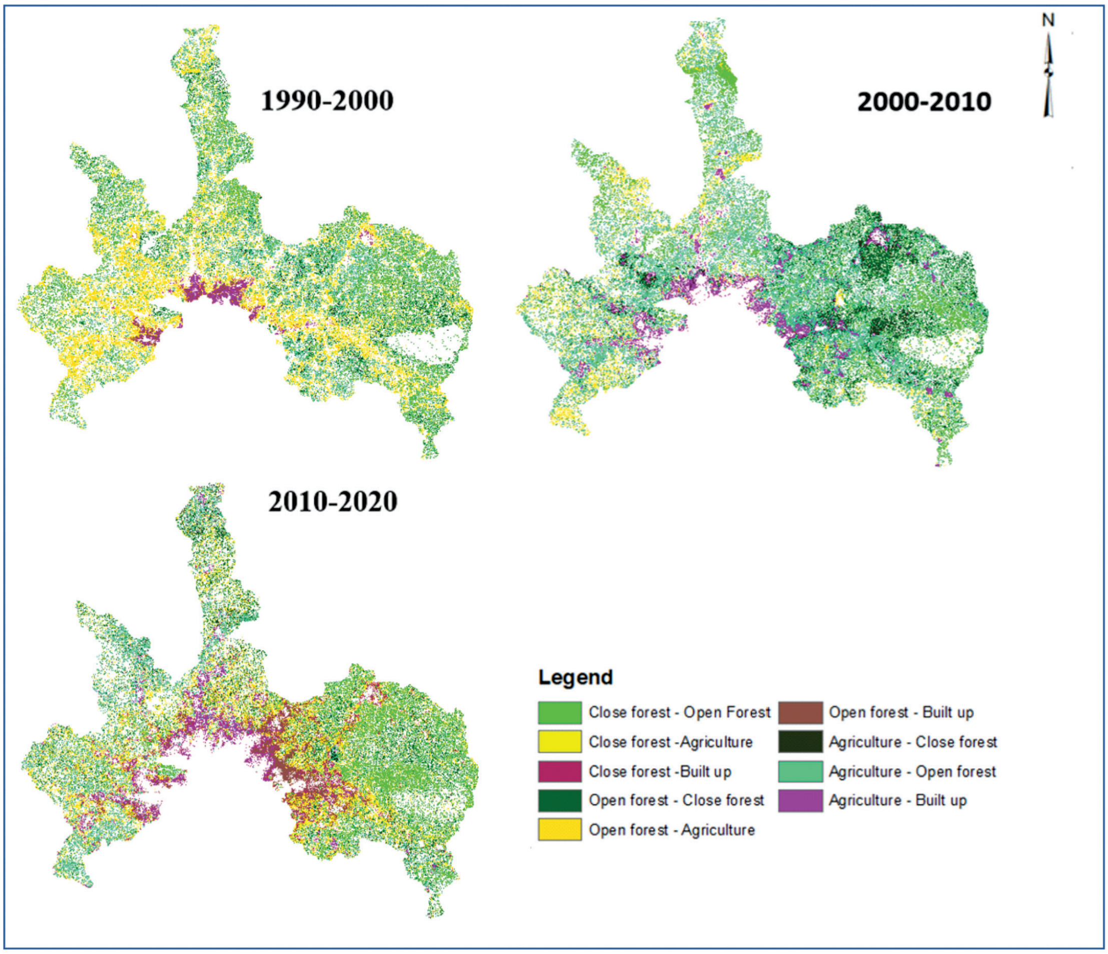


Fig. 4. LULCC maps for 1990–2000, 2000–2010 and 2000–2020

*Ryc. 4. Mapy zmian klas użytkowania i pokrycia terenu w latach 1990–2000, 2000–2010 i 2000–2020*

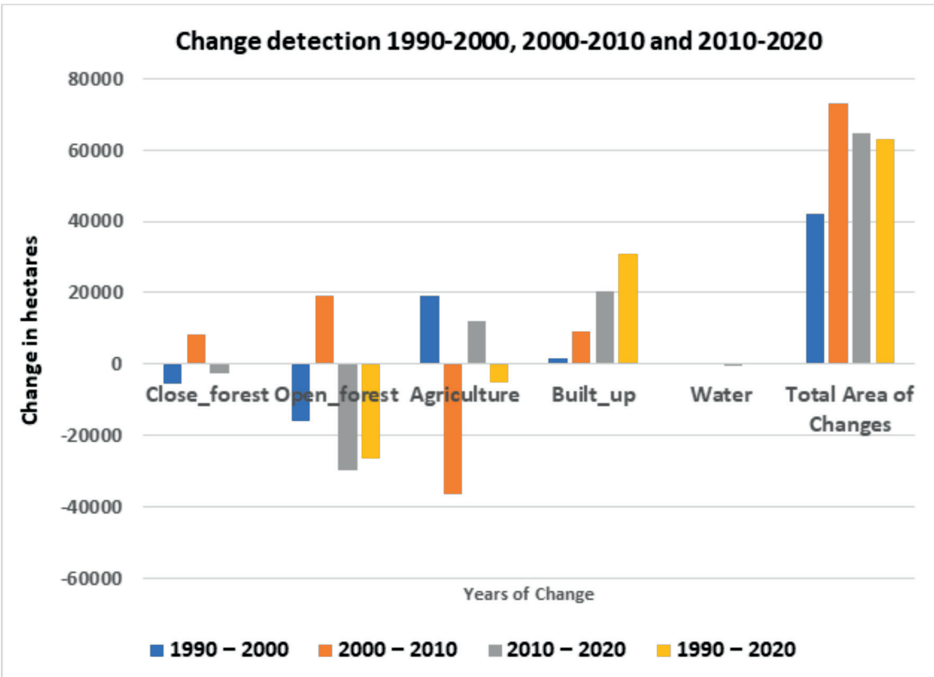


Fig. 5. LULC change in hectares

*Ryc. 5. Zmiany użytkowania i pokrycia terenu w hektarach*

**Annual rate of deforestation**

It was discovered that from 1990 to 2000, 2 109.54 hectares of forestlands (Close and Open Forests) were lost annually. However, from 2000 to 2010, there was an annual increase of 2 750.22 hectares per year. From 2010 to 2020, 3 226.45 hectares of forestlands (Closed and Open Forests) were lost to other LULC categories such as agriculture and built up (Table 6). A negative figure denotes forest loss, and a positive figure denotes forest gain.

## Discussion

**Satellite Imagery Datasets**

There exists substantial technical expertise in remote sensing to deliver tangible, practical, and relative solutions for environmental studies (Koranteng et al., 2020). Geospatial technologies such as RS and GIS are valuable and practical technologies for studying environmental modifications caused by anthropogenic influences or natural occurrences and are particularly excellent for LULC change assessment (Govender et al., 2022). The merits of satellite imagery comprise the capacity to traverse large expanses with extraordinary spatial features and high chronological regularity, the sturdiness of remote image sorting, enhancements on the spatial and spectral features, and the attainment of multi-temporal datasets containing diverse types of visual data (Yuan et al., 2020; Tong et al.,2020). GIS also has effective mapping and evaluating tools that offer many opportunities for evolving multi-varied phenomena (Cillis et al., 2021).

Satellite images such as the Landsat by the United States provide an uninterrupted data source for remote sensing studies and their global free data access policy makes them especially very useful in developing countries (Koranteng et al., 2020). The resolution and coverage of the Landsat images are good for studying large areas, but resolution inhibits sometimes very detailed studies (Hemati et al., 2021). The Sentinels of the European Space Agency (ESA) were made to provide a huge quality and quantity of data. These are also free of charge and has enabled serious studies to be undertaken by a scientist from deprived parts of the world. There are few issues with this satellite due to the relatively smaller coverage as compared to Landsat Images and there are no historical images as the program is fairly new (Tariq et al., 2022). DMC has a large coverage and relatively better resolution compared to Landsat TM and Landsat ETM+ but costly. The cost of obtaining the relevant satellite data for such studies is a challenge for researchers in developing countries as commercial satellite images are expensive. Scientists in developing countries consequently rely on Landsat images and Sentinel lately and benefactor-funded studies to provide access to datasets and other resources. These programmes come with their specified satellite images which may not essentially address some of the problems of the various places around the world.

**Accuracy Assessment**

Stratified random sampling was utilized in the choice of the training sites for the supervised image classification to obtain good outcomes. This (Stratified random sampling) is explained as utilizing expert information in sampling where the field area is scattered into divisions which optimizes the variations amongst units and reduces the difference within each component/unit (Snedecor & Cochran, 1989). A random sample is subsequently taken from each unit when established variations occur between the units. This method of sampling produces results that are both largely unbiased, accurate and more characteristic of the total population as it emphasizes smaller subcategories in a population. Stratified random sampling also gives the best way to get outcomes that is representative of the diversity of the population under consideration (Souza Jr et al., 2020). Stratified random sampling used in the selection of the training areas for the image classification ensured that all the range substrata were all aptly characterized and categorized accordingly. For a study area characterized by a wide variety of agricultural land categories (herbaceous plants, tree crops such as cashew, citrus, cocoa, Palm and shrubs), this method was excellent.

The accuracy assessment report was generated (Table 3) after the 2020 LULC image classification. The overall classification accuracy of 80% and 0.7375 as the overall Kappa statistics were attained. Accuracy assessments for later epoch years 1990, 2000 and 2010 were undertaken using data in Table 1.

**Land Cover Change Analysis**

LULCC detection has numerous extrapolations depending on the scope and intent of the study (Gomes et al., 2020; Clerici et al., 2019). LULCC spatial and temporal distribution such as the extent, location and trend is amply explained in change detection application studies (Verma et al., 2020; Mohan Rajan et al., 2020). The LULCC maps for the periods 1990–2000, 2000–2010 and 2010–2020 indicate a grim concern as climate change has emerged as a big challenge. LULC changes for the entire period of study (1990–2020) cumulatively was 62 933.2 hectares (33.37%), as LULC transitioned into other LULC categories. Deforestation is predominant outside of the designated protected areas. The forests have been permanently changed into other land use. Forest degradation is seen in protected forest reserves due to logging (largely illegal), illegal mining commonly named ‘Galamsey’ and the phenomenon of admitted farms. Admitted farms are farmlands permitted by Ghana’s Forestry Commission to remain within protected forest reserves (Brobbey et al., 2020; Acheampong et al., 2019). Some of these farms existed in the forests before they were declared as protected reserves or indigenes in the surrounding communities are allowed to farm in these reserves for certain silvicultural, traditional, or political reasons as well. Anthropogenic activities account for LULC changes in the study area and agree with earlier studies undertaken in the study area (Abass et al. 2019; Koranteng et al., 2020).

## Drivers of LULC Changes

Deforestation and Forest Degradations
Several studies have outlined and identified the major drivers of forest loss (degradation and deforestation) in Ghana (Abugre & Sackey, 2022). The key drivers of forest loss were established throughout the field surveys, communal interaction in the area of study and consultations with government officials and statutory bodies. The main drivers are anthropogenic-induced and include unrestrained urbanization, Mining and Unsustainable agricultural practices.

Increasing Urbanization
As depicted in Table 6, the population of Ghana surges every year of census and the most populous in all censual years is the Ashanti region with its capital city Kumasi and its adjoining districts housing most of the population. The rapid increase in the population of study area has grave consequences for the delivery of urban land for housing, infrastructural and other social services provision (GSS, 2021). The loss of forest lands is largely ascribed to the enlargement of urban, increasing rural built-up structures, the construction of roads and other developments that remove land vegetation as parcels of land are cleared to make way for the increasing population. The increasing population acting in sync with local migration is the reason for the increasing forest loss and loss of arable land. Land values have increased astronomically depriving local farmers of the much-needed land for farming activities and intensifying the production of food to feed the increasing population. Peasant farmers are inclined to suffer the most as they are forced into environmentally sensitive areas with low agrarian potential. As population rises, so too does the need for land, to expand settlement infrastructure and other utilities (Abass et al., 2020; Takyi et al., 2021).

Table 6. Annual Deforestation Rate

*Tabela 6. Roczny wskaźnik wylesiania*

| Period | Annual rate of deforestation (ha per year) |
|---|---|
| 1990–2000 | –2109.54 |
| 2000–2010 | 2750.22 |
| 2010–2020 | –3226.45 |

Uncontrolled expansion is observed in the 30 years of study as the tiny doted built-up areas category expands in all the years. The bother with the Kumasi Metropolitan (southern parts) is particularly seen to expanding as portrayed by the LULC maps. This development has a serious consequence on other critical LULC categories such as forests, arable land and water resources (Obeng-Gyasi, 2022; Bawa et al., 2022). The continuous and uncontrolled urbanization has serious effects on water supply systems as forests which protect rivers and streams (source of water to the Barekesses and Owabi Dams) are polluted or dry up (Ayesu et al., 2021).

Mining
Functional gold mining sites (legal and illegal) were seen in the study area during the field survey exercises. Environmental and land degradation from the extraction of natural resources and associated activities have been significant in Ghana and particularly worrying in the last decades (Nti, 2020). The adverse effect of mining activities on the environment, soil and human health is well recognized (Antwi-Agyei et al., 2019). Mining (gold prospecting and mining itself) is reckoned globally as a source of deforestation and land degradation is a potent threat to forest reserves, and ecosystem services played by forests and indigenes in surrounding communities (Siqueira-Gay et al., 2020). Mining operations in the study area are surface-based predominantly. These mining operations contribute extensively to the obliteration of natural vegetation and farming lands that produce cash crops and stable foods for local consumption. Additionally, mining activities pollute the water resources and watersheds, posing a danger to the drinking water sources for rural communities (Ogidi et al., 2022).

Agricultural Practices
Although there was a decreasing trend in agricultural activities in the study, some forest loss might be ascribed to farming activities. Unsustainable agricultural practices are widespread in the study area. The removal of the natural vegetation – the old-styled bush fallow method of farming surges annually in Ghana. Extended fallows needed for the regeneration of forests are impossible due to the increasing population. The economic needs for agrarian products have been exacerbated by the world market need for cash crops like cashew, cocoa, tobacco, coffee and oil palm (Jarzebski et al., 2020).

## Conclusions

Geospatial applications such as RS and GIS have demonstrated to be effective and economical for studying spatial and temporal LULC change in this study. The results demonstrate that the peri urban-rural districts of Greater Kumasi (study area) had undergone substantial LULC changes. The main thrust of the study includes (i) LULC map for the 30 years from 1990 to 2020, including Closed Forest, Open Forest, Agriculture, built up areas, and Water; (ii) there was a substantial loss of forest cover (open forest), built up areas increased significantly, agricultural land decreased significantly (iii) All the LULC types showed variations in extent over the different periods.

These findings may assist in explaining the effect of previous LULC strategies/practices and the various roles of several factors which include anthropogenic--socio-economic and environmental changes influencing the dynamics of the LULC changes. Insight into the drivers of LULC change might aid in future planning.

Further studies will concentrate on detailed documentation of the LULCC drivers and their impacts. Additionally, the cause of the fast LULC dynamics affects the natural environment and indigenous livelihoods and access to natural resources.

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Addo Koranteng, Isaac Adu-Poku, Bernard Fosu Frimpong,
Jack Nti Asamoah & Tomasz Zawiła-Niedźwiecki
Teledetekcja Środowiska
Polskie Towarzystwo Geograficzne
Oddział Teledetekcji i Geoinformatyki – Warszawa 2023