Mapping and Predicting Land Use Land Cover Dynamics in the Sefwi Wiawso District, Ghana*

[1]F. O. Boateng and [1]M. S. Aduah
[1]University of Mines and Technology, Tarkwa, Ghana

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Abstract

Land use land cover changes can cause environmental problems; however, few studies have analysed land use land cover changes in Ghana's Sefwi Wiawso District. The Sefwi Wiawso District has been undergoing rapid expansion over the past decade, which, if not addressed, will have major environmental effects for the district. This study assessed land use land cover changes in Sefwi Wiawso District from 2010 to 2020 and predicted land use land cover changes for 2025 to highlight key shifts and opportunities for sustainable development and spatial planning. The study used Landsat satellite images for three years (2010, 2015, and 2020). The images were classified into four land use land cover classes, namely: closed forest, farmlands, barelands/settlement, and water bodies, using the maximum likelihood classification algorithm. The results obtained revealed closed forest declining from 37.9% in 2010 to 20.5% in 2020. Farmlands however, increased in 2015 but decreased in 2020. Barelands/Settlement showed a rapid increase from 5.7% in 2010 to 25.1% in 2020. To simulate future changes in LULC classes, an Artificial Neural Network - Cellular Automata model was used. The simulation showed that barelands/settlement may increase in 2025, but closed forest and farmlands could decrease. The result of this study can be useful for spatial planning as they can be used as a foundation for future land use and land cover analyses.

Keywords: Land Use Land Cover, Landsat, Maximum Likelihood Algorithm, Artificial Neural Network

1 Introduction

Satellite images have been used worldwide to map and monitor land cover/land use changes for several decades since the launch of the Landsat system. Land resources have been utilized to a greater level as a result of economic development, such as increased industrialization, urbanization and conversion of forest to agricultural land, resulting in land degradation (Ganasri *et al*., 2013). Despite the fact that urbanization only accounts for a small percentage of the Earth's land surface, it is thought to have had a considerable impact on the natural landscape, resulting in numerous changes in the environment and associated ecosystems at all scales. Models have been utilized to create quantitative links between land cover changes and their driving factors over the last three decades in order to gain a better understanding of the change processes and to simulate dynamic land cover/land use, which may be used to analyse the implications of future changes or different scenarios of changes (Aduah *et al*., 2018).

Despite the fact that various land use land cover mapping and modelling have been undertaken in West Africa, there is still a significant information gap in Ghana regarding land use land cover change processes, patterns, and driving forces at the local scale (Aduah *et al*., 2018). In Ghana, the formation of new regions and capital cities (Gyampo, 2018) necessitates the production of accurate land use land cover maps to aid spatial planning. The emergence of new regions intends to foster speedy growth in underdeveloped areas of the country. Since Sefwi Wiawso District capital, Sefwi Wiawso, became the regional capital of the Western North Region of Ghana, the district's land usage and land cover have changed rapidly over the past decade. A reliable and up-to-date land use land cover change data is therefore required to comprehend and assess the environmental repercussions of such changes (Giri *et al*., 2005). Few studies (Osei-Wusu *et al*., 2020) have looked into land use land cover analysis of the Sefwi Wiawso District. Osei-Wusu *et al*., (2020) studied the forest loss and predicted the susceptible area changes in the Sefwi Wiawso District. They concluded that forest reserve will reduce in size but farmland will increase in the future.

Application of artificial neural networks to predict land use land cover changes using satellite images has the potential to improve prediction accuracies and lead to accurate government decision making in spatial planning. The cellular automata (CA) approach and the Markov chain analysis with numerous modifications are two spatial models that have gained credibility and significant application in urban land change mapping and prediction (Attua and Fisher, 2010). According to Attua and Fisher (2010), Markov analysis relies on change information in the past to predict change in the future. Attua and Fisher (2010) considered the Markov Chain application to study successfully the past and future land cover changes of New Juaben Municipality, Ghana. The Markov modelling methodology is known for its ease of use and ability to forecast land-use change with minimal data

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(Attua and Fisher, 2010). However, the Markov modelling technique is less reliable since it ignores the driving factors that cause land use land cover changes. The CA-based model on the other hand, simulates the evolution of a system by utilizing local interactions (Attua and Fisher, 2010).

This study seeks to map and analyse the land use land cover dynamics in the Sefwi Wiawso District of the Western North Region of Ghana, as well as predict the land use land cover changes into the near future using a combination of CA and Artificial Neural Network (ANN)-based model.

2 Resources and Methods Used

2.1 Study Area

Between the latitudes of 6° 05' N and 6° 35' N, and the longitudes of 2° 45' W and 2° 20' W, the Sefwi Wiawso District is located in the Eastern section of the Western North Region of Ghana as shown Fig. 1. It shares a common boundary with Ahafo Region to the north, Juabeso, to the north-west, Bodi and Sefwi-Akontombra, to the west, Wassa Amenfi West, to the south, Sefwi Bibiani-Anhwiaso Bekwai District, to the east and Wassa Amenfi Central to the South-East. The district has an area of 1 010.62 km^2, approximately 10% of the land area of the Western North Region (Turkson and Appiah-Kubi, 2014). Sefwi Wiawso District has a population of 139 200 people, accounting for 5.9% of the region's total population. The Sefwi Wiawso District is located in the tropical rainforest climatic zone, with year-round temperatures ranging from 25 to 30 degrees Celsius and annual rainfall ranging from 1 524 to 1 780 millimetres. Rainfall peaks are in June-July and September-October, and they have double maximum features. Humidity is high, over 90% at night and 75% during the day (Turkson and Appiah-Kubi, 2014). The geology of the district is primarily of the Lower and Upper Birimian kinds, with the Lower Birimian formation to the east and north-eastern parts of the district. These are volcanic rocks formed by the solidification of molten elements (lava). Agriculture is the district's most important economic activity in terms of employment and revenue creation, with over 66% of the working population employed in this sector, which is the District's primary source of household income. Cocoa, palm trees, plantains, cocoyam, cassava, and maize are among the crops grown.

2.2 Materials

Landsat images were obtained from US Geological Survey Earth Explorer. Dates of Landsat images include 16th January, 2020, 23rd March, 2015 and 28th January, 2010. Landsat 7 and 8 were used in this study. Sensors include Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Aster GDEM was obtained from NASA Earth Data. Existing Ghana shapefiles were obtained from the internet. Software applications used include ESRI ArcGIS for the image pre-processing and classification, and QGIS for ANN modelling and CA predicting.

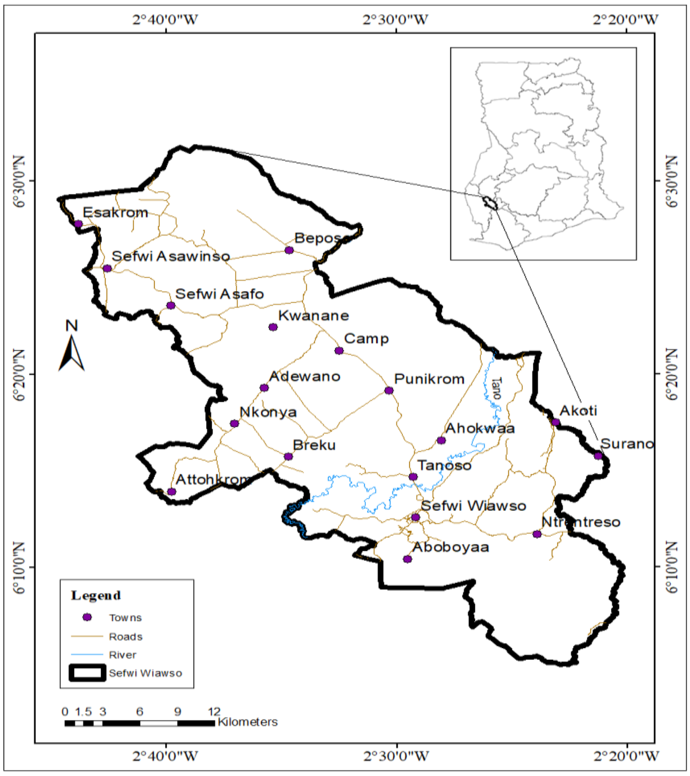

Fig. 1 Map of Sefwi Wiawso District

2.3 Methods

2.3.1 Satellite Image Pre-processing

The acquisition of three Landsat satellite images (2010, 2015, and 2020) from the USGS Earth Explorer was the first stage of this study. The satellite images with the least amount of land cloud cover were chosen and downloaded. NASA Earth data was also used to retrieve ASTER GDEM. Shapefiles of Ghana were also obtained from the University of Mines and Technology's Geomatic Engineering Department. The District of Sefwi Wiawso was extracted from the Ghana districts shapefile using ESRI ArcGIS, and the Landsat bands were clipped to the boundary. Radiometric and geometric corrections were carried out on the satellite images. With the raster calculator in Arc Toolbox, the surface radiance and reflectance bands were generated based on the parameters in their respective metadata. The radiance bands and the reflectance bands were computed using Equations (1) and (2).

$$L_\lambda = \frac{(LMAX_\lambda - LMIN_\lambda)}{(QCALMAX - QCALMIN)} \times (QCAL - QCALMIN) + LMIN_\lambda \quad (1)$$

where,

L_λ is Surface Radiance,
$LMAX_\lambda$ is Radiance Maximum Band,
$LMIN_\lambda$ is Radiance Minimum Band,
QCALMAX is Quantize Cal Maximum Band,
QCALMIN is Quantize Cal Minimum Band, and
QCAL is Raw Landsat Band.

$$\rho_\lambda = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos\theta_s} \quad (2)$$

where,
ρ_λ is Reflectance,
d^2 is Earth-Sun distance,
$ESUN_\lambda$ is ESUN values, and
$\cos\theta_s$ is Cos of Solar Zenith Angle (θ) in radiant.
Finally, composite bands were generated from the reflectance bands. Scanline errors are seen in Landsat 7 satellite images. Before pre-processing, the Landsat 7 image was adjusted for scanline defects using a Landsat toolbox.

2.3.2 Image Processing and Accuracy Assessment

On the composite images, supervised classifications were carried out. Ground truth points were collected randomly across the district and were used as training samples for the image classification. A supervised classification (Maximum Likelihood Classification) was used to classify the composite images into four LULC classes: closed forest, farmlands, barelands/settlement, and water bodies. The classified images were subjected to accuracy tests. The overall accuracies and kappa values of the categorised images were then calculated using the ground truth points and the confusion matrix.

Table 1 Land Use Land Cover Classes and Composition

LULC Classes	Detailed Composition
Closed Forest (CF)	Dense vegetation, canopy of trees
Farmlands (FL)	Grasses, bushes, farms, shrubs
Barelands/Settlement (BL/SM)	Urban residential, industrial, transportation, exposed lands
Water Bodies (WB)	Rivers, streams, wetlands

2.3.3 ANN Modelling and CA Prediction

Artificial neural networks (ANNs) are software representations of the human brain's neuronal structure. Artificial neural networks (ANNs) are designed to simplify and emulate the behaviour of the brain. They can be supervised or unsupervised during training. The network is trained in a supervised ANN by supplying matching input and output data samples, with the goal of having the ANN to generate a desired output for a given input. The goal of unsupervised learning in an ANN is to get the ANN to “understand” the structure of the input data on its own (Gurney, 1997). Pattern classification, clustering or categorization, function approximation, prediction or forecasting, optimization and control, are just a few of the areas where ANN can be used.

The multilayer perceptron is the most well-known and widely utilized neural network kind. Signals are typically transferred in one way inside the network: from input to output. There is no loop because each neuron's output has no effect on the neuron itself (Popescu *et al*., 2009).

Simple mathematical idealizations of natural systems are cellular automata. They are made up of a lattice of discrete identical sites, each of which takes on a finite set of values, such as integers. The values of the sites change in discrete time steps, following deterministic criteria that define each site's value in terms of the values of nearby sites. As a result, cellular automata can be thought of as discrete idealizations of partial differential equations, which are frequently employed to explain natural systems. Their discrete character also provides for a useful connection with digital computers: cellular automata can be thought of as rudimentary parallel processing machines (Wolfram, 1983).

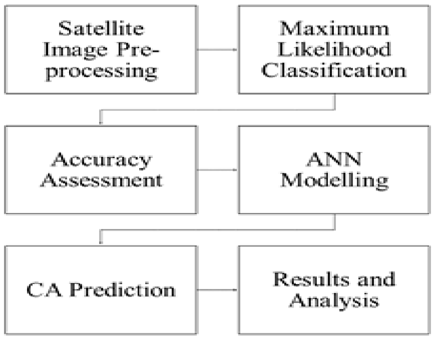

Fig. 2 Flowchart of Methods Used

3 Results and Discussion

3.1 Results

In this section, results obtained from the data processing are presented and discussed.

3.1.1 Land Use Land Cover Dynamics

Figs. 3 to 5 represent the 2010, 2015 and 2020 LULC Maps of the Sefwi Wiawso District respectively. The Kappa and overall accuracies of the LULC Maps were computed as shown in Tables 2, 3 and 4. The 2010 LULC Map produced an overall accuracy of 0.824 and a Kappa value of 0.739. The 2015 LULC Map also produced an overall accuracy of 0.809 and a Kappa value of 0.686. The 2020 LULC Map then produced an overall accuracy of 0.833 and a Kappa value of 0.749.

Table 2 2010 Confusion Matrix

Classes	Closed Forest	Farmlands	Barelands/ Settlement	Water Bodies	Total
Closed Forest	11	5	0	0	16
Farmlands	0	20	0	0	20
Barelands/ Settlement	0	4	6	0	10
Water Bodies	0	0	0	5	5
Total	11	29	6	5	51

Table 3 2015 Confusion Matrix

Classes	Closed Forest	Farmlands	Barelands/ Settlement	Water Bodies	Total
Closed Forest	7	7	0	0	14
Farmlands	1	32	0	0	33
Barelands/ Settlement	0	4	6	0	10
Water Bodies	0	1	0	9	10
Total	8	44	6	9	67

Table 4 2020 Confusion Matrix

Classes	Closed Forest	Farmlands	Barelands/ Settlement	Water Bodies	Total
Closed Forest	9	1	0	0	10
Farmland	0	27	0	0	27
Barelands/ Settlement	1	5	7	0	13
Water Bodies	1	1	1	0	10
Total	11	34	8	7	60

The LULC maps for the respective years are also shown in Figs. 3, 4 and 5.

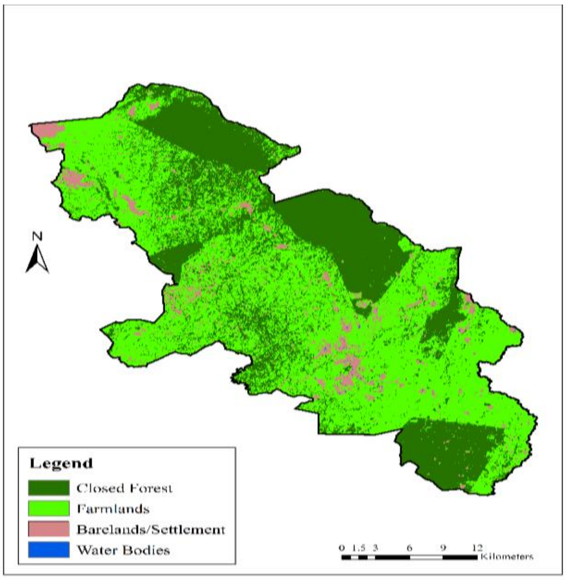

Fig. 3 2010 LULC Map of Sefwi Wiawso District

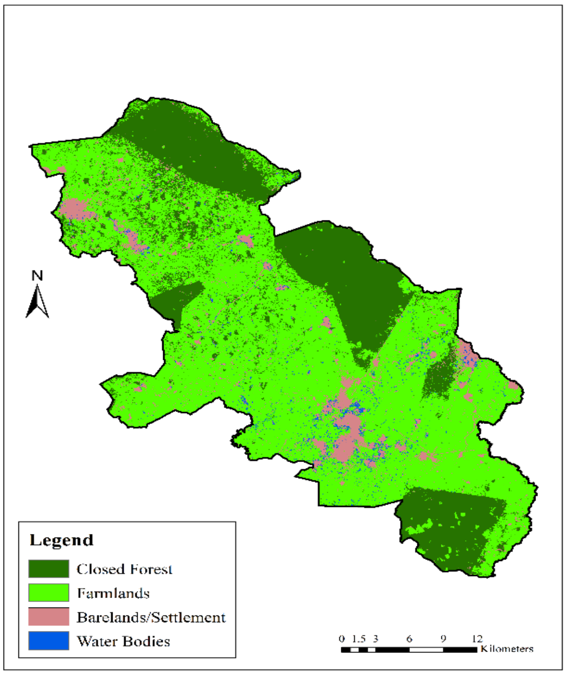

Fig. 4 2015 LULC Map of Sefwi Wiawso District

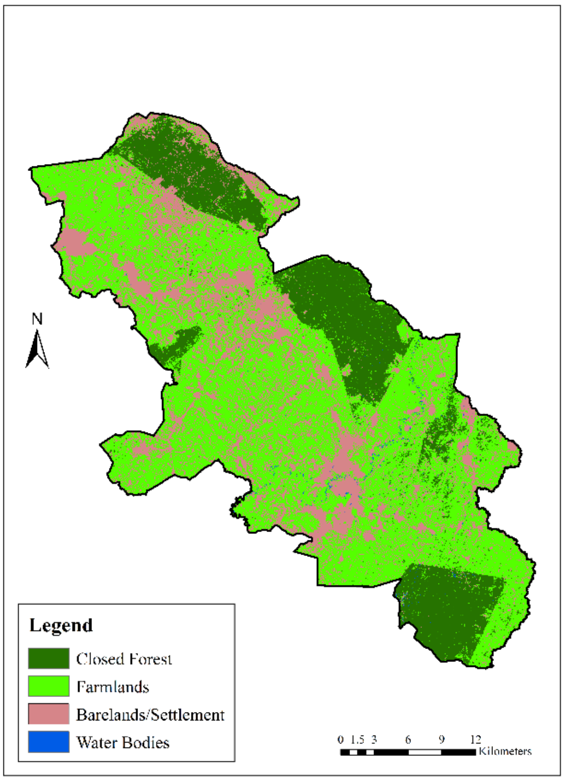

Fig. 5 2020 LULC Map of Sefwi Wiawso District

The Land Use Land Cover statistics and changes between the respective years are shown in Tables 5 and 6 respectively. A graph of the LULC changes from 2010 to 2020 is also shown in Fig. 6.

3.1.2 Prediction of Land Use Land Cover Changes

The LULC change map between 2015 and 2020 as well as its change statistics are shown in Fig. 7 and Table 7 respectively.

Also, the predicted 2025 LULC map as well as the change statistics between the 2020 and the predicted 2025 LULC maps are shown in Fig. 8 and Table 8 respectively.

Table 5 Land Use Land Cover Statistics

LULC Classes	2010		2015		2020	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Closed Forest	383.001	37.897	290.882	28.782	207.379	20.520
Farmlands	569.718	56.373	637.438	63.074	547.295	54.154
Barelands/ Settlement	57.259	5.666	68.307	6.759	253.293	25.063
Water Bodies	0.646	0.064	13.998	1.385	2.657	0.263
Total	1010.624	100.000	1010.624	100.000	1010.624	100.000

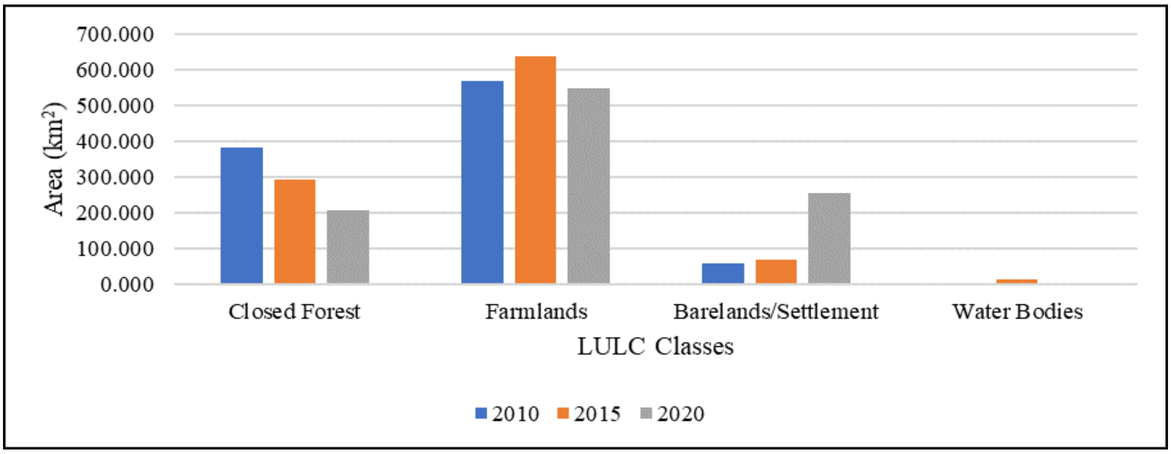

Fig. 6 Graph of LULC Changes from 2010 to 2020

Table 6 LULC Changes between the Years

LULC Classes	Between 2010 and 2015		Between 2015 and 2020	
	Area (km^2)	% change	Area (km^2)	% change
Closed Forest	-92.120	-24.052	-83.503	-28.707
Farmlands	67.720	11.887	-90.142	-14.141
Barelands/ Settlement	11.048	19.296	184.986	270.814
Water Bodies	13.352	2066.156	-11.341	-81.020

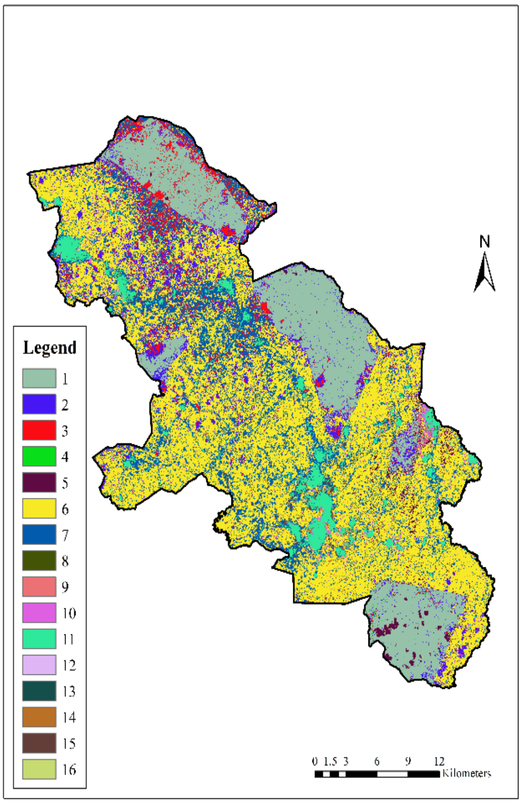

Fig. 7 LULC Change Map from 2015 to 2020

Table 7 Land Use Land Cover Change Statistics

Class	Land Use Land Cover	Area (km^2)
1	CF unchanged	192.826
2	CF to FL	63.706
3	CF to BL/SM	33.747
4	CF to WB	0.603
5	FL to CF	13.419
6	FL unchanged	460.985
7	FL to BL/SM	161.747
8	FL to WB	1.287
9	BL/SM to CF	0.946
10	BL/SM to Farmland	16.983
11	BL/SM unchanged	50.040
12	BL/SM to WB	0.338
13	WB to CF	0.188
14	WB to FL	5.622
15	WB to BL/SM	7.759
16	WB unchanged	0.428
	Total	1010.624

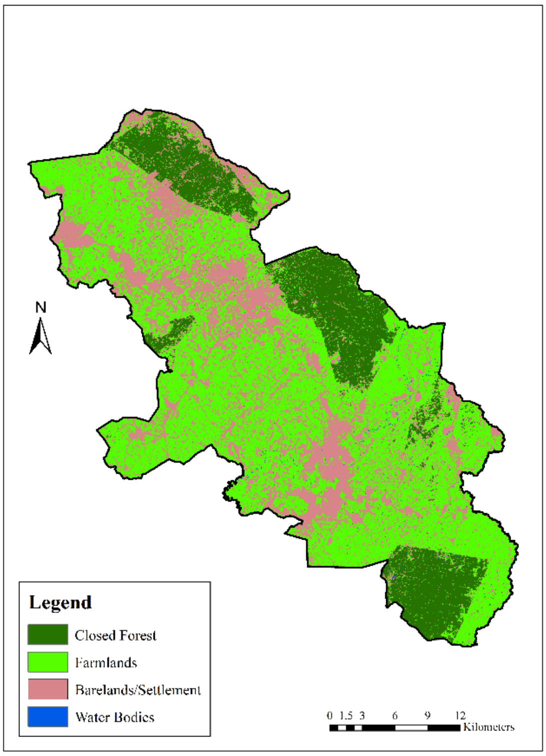

Fig. 8 Predicted 2025 LULC Map for Sefwi Wiawso District

Table 8 LULC Statistics between 2020 and Predicted 2025

	2020 LULC		Predicted 2025 LULC			
LULC Classes	**Area (km^2)**	**% of Area**	**Area (km^2)**	**% of Area**	**Area change (km^2)**	**% change**
Closed Forest	207.379	20.520	177.851	17.598	-29.528	-14.239
Farmlands	547.295	54.154	533.590	52.798	-13.705	-2.504
Barelands/ Settlement	253.293	25.063	297.464	29.434	44.171	17.439
Water Bodies	2.657	0.263	1.719	0.170	-0.938	-35.303
Total	1010.624	100.000	1010.624	100.000		

3.2 Discussion

Figs. 3 to 8 and Tables 2 to 8 above depict the results of the study. LULC maps for 2010, 2015, and 2020 are shown in Figs. 3, 4 and 5. In the study area, four LULC classifications were identified: closed forest, farmlands, barelands/settlement, and water bodies. For the classified images of 2010, 2015, and 2020, the overall accuracies were 82%, 81%, and 83% respectively. The kappa statistics for the LULC maps in 2010, 2015, and 2020 were 0.74, 0.69, and 0.75, respectively, indicating that the classified images and the referenced data were in good agreement.

Table 5 and Fig. 6 show that barelands/settlement covered 57.259 km^2 in 2010, accounting for just

5.7% of the study area, whereas closed forest and farmlands covered 383.001 km^2 and 569.718 km^2 respectively, accounting for 94.3% of the study area in 2010. From 2010 to 2015, LULC area changed gradually, as shown in Table 6, with barelands/settlement increasing by 11.048 km^2 (19.3%), farmlands increasing by 67.720 km^2 (11.9%), and closed forest decreasing by 92.120 km^2 (24.1%). Furthermore, between 2015 and 2020, barelands/settlement area increased by 184.986 km^2 (270.8%), whereas closed forest and agriculture areas reduced by 83.503 km^2 and 90.142 km^2 respectively.

The Ghana government's decision in 2017 to create new regions and capital cities in order to stimulate rapid growth in underdeveloped areas of the country (Gyampo, 2018) may have contributed to the increase in barelands/settlement. The inflow of individuals looking for land to build structures has been attributed to rising urbanisation and industrialisation. On the other hand, the area of water bodies increased and decreased dramatically throughout time. This is due to a lack of data, poor satellite resolutions, and low data accuracy.

The LULC change map between 2015 and 2020, as well as statistics, are shown in Fig. 7 and Table 7. The prediction model was trained using the change map. The Artificial Neural Network (Multilayer Perceptron) was trained to a validation kappa value of 0.49, which was satisfactory and effective in simulating the LULC of 2025. The predicted LULC map of 2025, as well as the change statistics between 2020 and the simulated 2025 LULC, are shown in Fig. 8 and Table 8. According to Table 8, barelands/settlement is anticipated to grow by 44.171 km^2 (17.4%). The area of farmlands is also predicted to shrink by 13.705 km^2 (2.5%).

4 Conclusion

In the Sefwi Wiawso District, analysis of remote sensing data revealed a large reduction in closed forest and a significant expansion of barelands/settlement during the last decade. Closed forest was at its peak in 2010, but it began to decline in 2015 and 2020. Farmland was expanded from 2010 to 2015. This shows that farmland increased at the expense of closed forest. At the expense of both closed forest and farmlands, barelands/settlement increased dramatically from 2010 to 2020. The 2025 LULC map anticipated barelands/settlement to increase, but farmland and closed forest to decline in area. If this LULC change trend continues, it will have environmental and economic ramifications, as well as a negative influence on local people's livelihoods.

Although the government is attempting to foster development in undeveloped areas of the country, the effects on agriculture should not be overlooked. The Environmental Protection Agency (EPA) should implement environmental by-laws and other rules governing land purchase, waste disposal, and agricultural practices to ensure effective land management in the study area. To increase the area of dense vegetation, a tree planting or re-afforestation program should be recommended.

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Authors

Frank Obeng Boateng is currently a Teaching Assistant at the Geomatic Engineering Department of the University of Mines and Technology (UMaT), Tarkwa. He graduated from UMaT and holds a BSc certificate in Geomatic Engineering.

Michael S. Aduah is a Senior Lecturer at the Department of Geomatic Engineering of the University of Mines and Technology, Tarkwa, Ghana. He holds BSc in Geodetic Engineering from the Kwame Nkrumah University of Science and Technology (KNUST), a double MSc degree in Geo-information Science and Earth Observation from University of Lund (Sweden) and ITC (The Netherlands) and a PhD in Hydrology from the University of KwaZulu Natal (UKZN), South Africa. He is a Professional Member of the Ghana Institution of Surveyors and a member of the International Association of Hydrological Science (IAHS). His research interests include the development of tools and techniques in Geo-information Science and Earth Observation for modelling the environment, land use change analyses and modelling, surface water hydrology and assessment of global change impacts.