Land use and land cover dynamics and the associated drivers in the Volta Delta, Ghana

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Abstract

Knowledge of the drivers of land use and land cover change (LULCC) is critical for explaining and managing change, yet, this has received a limited research focus. We analysed LULCC and associated drivers in the Volta Delta using geoinformation technologies and multinomial logistic regression based on 2002 and 2017 Landsat data. Explanatory factors considered were elevation, slope, population density, distance to road, distance to settlement, annual rainfall, and crop yield. Results showed 2.82% net gain in active croplands. Water and riverine vegetation experienced net increases of about 1.00% each. Grass savannah, mangrove, shrub savannah and thicket experienced net losses. Low-lying and highly accessible areas experienced intensified agricultural activity, whereas elevated terrains with sparse road networks retained more natural vegetation. These results highlight the strong influence of accessibility, geomorphology and human activity on land transformation in the Volta Delta. The study demonstrates that integrating multisource spatial data with statistical modeling provides an effective framework for quantifying and explaining LULCC dynamics. The findings have important implications for land-use policy, environmental monitoring and adaptive resource management. Strengthening participatory spatial planning, promoting climate-smart agriculture, and integrating elevation and flood risk mapping into policy frameworks are essential for balancing agricultural productivity with ecological conservation in deltaic landscapes.

Keywords: Land use and Land cover change (LULCC); Volta Delta; drivers of change, remote sensing; GIS; multinomial logit. regression, sustainable land management; Ghana

Introduction

Land use and land cover change (LULCC) remains one of the most visible manifestations of human influence on the Earth's surface and represents a major component of global environmental change (Lambin et al., 2003; Turner et al., 2007). LULCC operates at multiple spatial and temporal scales driven by a complex interplay of social, economic, institutional, technological and biophysical factors (Awotwi et al., 2018; Sonter et al., 2015). The study of LULCC therefore provides a lens through which the evolving relationship between society and nature can be understood. It also offers valuable insights for addressing pressing sustainability challenges such as deforestation, land degradation, biodiversity loss and climate change (Foley et al., 2005; Verburg et al., 2015).

Globally, the pace and magnitude of LUCC have accelerated markedly over the past century. Forests, wetlands and grasslands have been converted to cropland, settlements and infrastructure at unprecedented rates (Curtis et al., 2018). Empirical research shows that the drivers of these transformations are both *proximate* - direct, immediate activities that physically alter land cover - and *underlying* - referring to the broader structural forces that motivate or enable these activities (Geist and Lambin, 2002; Rudel, 2013). Proximate causes typically include agricultural expansion, logging, mining and urbanisation, while underlying drivers involve population

growth, policy frameworks, market forces, governance quality and technological change. These drivers interact non-linearly, producing dynamic landscape mosaics that reflect changing human-environment relations. Understanding these multilevel interactions remains central to predicting land-use trajectories and designing effective interventions (Lambin et al., 2001; Verburg et al., 2015).

Studies across the tropics reveal extensive deforestation and woodland degradation driven largely by agricultural expansion, fuelwood extraction and urban (Aleman et al., 2018; FAO, 2016). In Southeast Asia, oil palm and rubber cultivation have reshaped forest frontiers (Gibbs et al., 2010); in Latin America, cattle ranching and soy production dominate (Hansen et al., 2013); and in Sub-Saharan Africa, smallholder agriculture and charcoal production remain the principal drivers (Curtis et al., 2018; Achard et al., 2014). These transformations are often coupled with reforestation and afforestation in some regions, reflecting complex mosaics of land abandonment and recovery (Sloan and Sayer, 2015).

Across West Africa, rapid population growth, economic liberalisation, and infrastructural expansion have intensified land conversion pressures. Between 2000 and 2020, the sub-region recorded one of the highest rates of net forest loss globally (FAO, 2020). According to the Food and Agriculture Organisation (FAO, 2020), Ghana's forest cover declined by about 90, 600 ha between 2000 and 2010, but experienced a modest recovery of 4, 300 ha from 2010 to 2020. Drivers of change include agricultural expansion (particularly cocoa cultivation), mining, logging and increasing urbanisation. Simultaneously, urban areas have grown by nearly 60% in two decades, contributing to the loss of agricultural and wetland areas around major cities such as Accra, Kumasi and Tamale (Antwi et al., 2014; Addae and Oppelt, 2019).

Despite the extensive documentation of studies on LULCC patterns in Ghana and elsewhere in sub-Saharan Africa, persistent limitation remains: few studies quantitatively assess the relative contributions of specific drivers. Many analyses adopt qualitative approaches – interviews, descriptive statistics, or narrative accounts – that identify "drivers" in broad terms but do not measure their effect sizes or interactions (Acheampong et al., 2019; Deche et al., 2023). This gap highlights the need for context-specific studies that quantify how combinations of biophysical and socioeconomic variables drive observable land-use outcomes. Such analyses are essential for informing effective management and policy interventions, particularly in environmentally sensitive and socioeconomically dynamic landscapes such as the Volta Delta in Ghana. Quantitative assessments using statistical and spatial modelling approaches such as logistic regression, geographically weighted regression, or machine learning (e.g., random forests) provide stronger inferential power for understanding cause – effect relationships (Pontius and Millones, 2011; Chen et al., 2020). Such models also enable prediction of future land-use patterns and can inform scenario-based planning, yet remain underutilised in West African research contexts.

Furthermore, the contextual mix of drivers – the unique combination of biophysical, socioeconomic and institutional factors operating in a particular region – varies significantly across space. For instance, slope and elevation may restrict agricultural

expansion in upland areas, while rainfall variability can influence land abandonment or shifts in cropping systems (Li et al., 2016). Similarly, accessibility factors such as proximity to roads or markets can accelerate land conversion near urban centers (Overmars and Verburg, 2006). Recognising and quantifying these contextual variations are essential for developing targeted LULC management responses.

The Volta Delta, a low-lying, dynamic landscape is of immense ecological and socioeconomic significance: it supports agriculture, fisheries, tourism and urban development while providing critical ecosystem services such as flood regulation and carbon sequestration (Nitamoah-Baidu et al., 2017). However, it is also one of the most environmentally vulnerable regions in Ghana, threatened by sea-level rise, saline intrusion, shoreline erosion, and land degradation (Boateng et al., 2017). Over the past two decades, the Volta Delta has undergone rapid landscape transformation driven by multiple, overlapping pressures. The construction of the Akosombo and Kpong Dams has altered sediment flow and hydrological regimes, affecting agricultural productivity and land stability (Codjoe, 2007; Appeaning Addo et al., 2011). Coastal urbanization – particularly around Ada Foah and Sogakope – has expanded into wetlands and agricultural lands, while upstream deforestation has increased sedimentation and altered deltaic morphology (Ampim et al., 2021). These changes reflect complex interactions between natural processes (e.g., sea-level rise, rainfall variability and erosion) and human activities (e.g., urban expansion, sand mining and farming).

Although several studies have mapped LULCC patterns in Ghana's coastal zones (Antwi et al., 2014; Addae and Oppelt, 2019; Pabi and Adu-Asare, 2021), few have focused specifically on the Volta Delta as a coupled socio-ecological system. Existing research tends to emphasize descriptive mapping rather than causal quantification. Consequently, there remains limited empirical evidence on (i) the dominant land-use transitions within the delta, (ii) the relative importance of biophysical versus socioeconomic drivers and (iii) the spatial heterogeneity of these processes. Addressing these gaps is critical for informed policy formulation, especially as Ghana pursues its Nationally Determined Contributions (NDCs) and Sustainable Development Goals (SDGs) relating to land, climate and biodiversity.

This paper aims to analyse the spatiotemporal dynamics of LULCC in the Volta Delta between 2002 and 2017 and to quantify the contributions of selected natural and anthropogenic drivers. The study integrates remote sensing and geospatial analysis with statistical modeling to identify which factors most strongly influence land-use transitions. Specifically, the research tests the hypothesis that, collectively or in different combinations, topographic variables (elevation, slope), climatic variables (rainfall), and socioeconomic factors (population density, proximity to roads and settlements, crop yield) explain substantial variation in observed LULCC outcomes. The study's design enables both descriptive mapping and inferential modeling, offering a more rigorous basis for understanding how landscape processes unfold in deltaic environments. First, by quantifying driver contributions, it contributes to broader debates in land change science about the balance between human and environmental causation in landscape transformation. Second, the

results can guide spatial planning and resource governance, particularly in identifying zones of high conversion risk or areas suitable for ecological restoration. Third, insights on driver interactions can inform climate adaptation strategies, as LULCC patterns influence vulnerability to flooding, erosion and food security.

Methodology

The Study area

The Volta Delta in Ghana, is 4,562km² in size and is bounded by longitudes 0°40' E and 1°10' E and Latitudes 5°25' N and 6°20'N (Fig 1). The 5-meter contour above sea level served as the operationally defined boundary of the delta (Addo et al., 2018). The Delta is characterized by a mosaic of geomorphic and ecological zones, including flood plains, wetlands, lagoons, mangrove stands, agricultural lands and built-up areas. Vegetation of the delta is mostly grassland with some shrubs and isolated trees distributed across the coastal savannah zone. The climate is tropical savannah, with bimodal rainfall patterns (March-June and September-November) and annual precipitation ranging from 783 to 836 mm. Mean annual temperatures vary between 23ºC and 32ºC (Ayamga et al., 2021). The delta is drained by the Volta River, the Keta Lagoon and the Songor Lagoon. The hydrological regime is heavily influenced by the Akosombo and Kpong Dams, which regulate sediment and water discharge to the deltaic plains (Codjoe et al., 2017). The population density exceeded 200 persons per km² in in some coastal communities (Ghana Statistical Service, 2012). Farming, fishing, fish processing, salt mining, sand mining, crafts and other trading activities comprise the livelihood (Lazar et al., 2015). The production of fundamental food staples including cassava, yam, cocoyam, plantains, and maize is mostly reliant on rainfall in the study area. Additionally, on the dry coastal plains, vegetable cultivation is mostly done using irrigation water, primarily from wells and includes planting onions, shallots,

Fig. 1 Location of the Study area

cabbages, tomatoes, okra, and pepper (Codjoe et al., 2017; Porter et al., 1997). The area was selected as a case study because it exemplifies a rapidly transforming socio-ecological system where multiple interacting drivers – natural and anthropogenic – contribute to land-use transitions. The region also represents an ideal laboratory for studying deltaic vulnerability and adaptive land-use processes under climate stress.

Methods

Research design

The study adopted a quantitative research approach, combining remote sensing and GIS-based land-use change detection with statistical modelling to identify and quantify the relative influence of key drivers of LULCC between 2002 and 2017. The explanatory research design adopted emphasised the feedback linkages between human activities and biophysical processes. This integrative approach allowed a comprehensive understanding of landscape dynamics. The overall workflow (Figure 2, schematic representation) follows the following steps:

1. Data acquisition and pre-processing;
2. LULC classification and accuracy assessment;
3. Change detection and transition matrix analysis;
4. Selection and preparation of potential driving factors;
5. Statistical modelling of drivers

Data collection and pre-processing

Two multispectral Landsat satellite images (Table 1), were downloaded from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/) for the dates of April 2017 and May 2002. Dates and
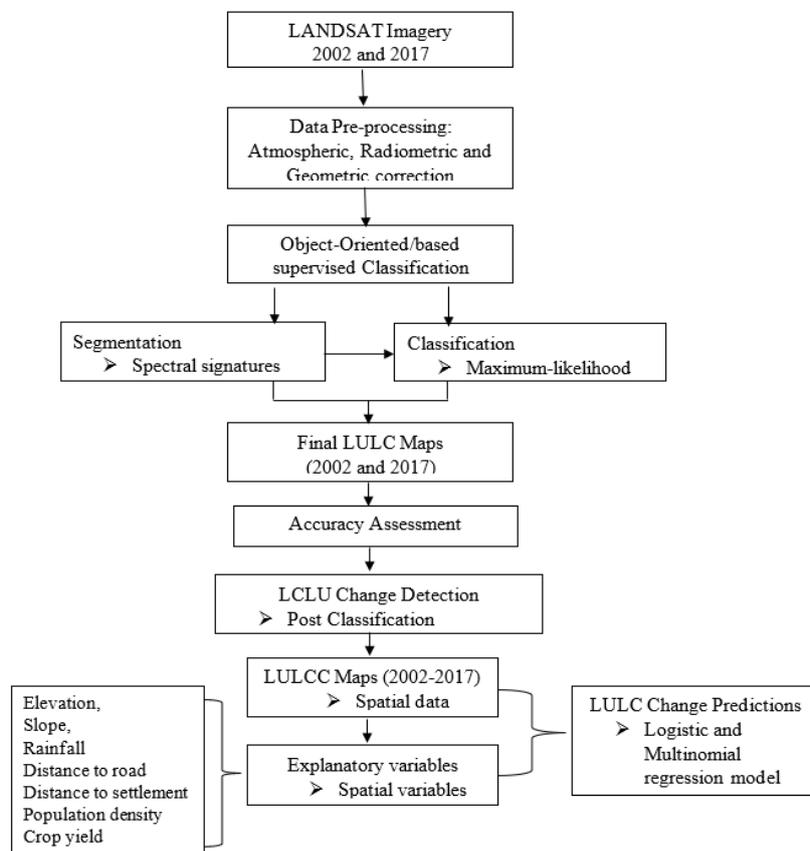

Fig. 2 Flowchart of methodology used for this study

image quality were considered in selecting the Landsat satellite images. The pre-processing included geographic, radiometric, and atmospheric adjustment. A vector boundary layer from the study region was then used to sub-set the area of interest.

Land use and land cover classification, accuracy assessment and change detection
Segmentation was used to create training and signature files based on spectrally homogenous segments of known land use and cover types in satellite imagery using IDRISI TerrSet software. Google Earth, GPS locations, prior knowledge of the research region served as the ground-referenced data for developing the classification scheme. The classification was done using a supervised Maximum Likelihood Classifier (MLC) algorithm. The MLC algorithm solves the issue of overlap in spectral value frequency distributions and takes into account changes that may exist within spectral categories (Campbell and Wynne, 2011). A total of nine (9) land use and land cover classes (Table 2) were adopted for the classification scheme.

Confusion matrices and kappa statistic were used to evaluate the classification accuracy.

TABLE 1
Data sources: satellite imagery, ancillary and socioeconomic data

Data	Path/row	Resolution	Source
Landsat 7 images (ETM+)	193/056	30 m	earthexplorer.usgs.gov
	192/056		
Landsat 8 images (ETM+)	193/056	30 m	earthexplorer.usgs.gov
	192/056		
Digital elevation model (DEM)		30 m	
Slope (^{o})			USGS
Distance to road (m)			
Distance to settlement (m)			Rasterized (m)
Rainfall (mm)		1km	Ghana meteorological agency
Population density (people/km^2)		District-level	Ghana statistical service (2010)
Crop Yield (ha)		District-level	MoFA statistics research and information directorate (SRID)

TABLE 2
LULC classification scheme used for the study

LULC Types	Description
Water (W)	Including rivers, lakes, lagoons, reservoirs, salt pans
Riverine Vegetation (RV)	Including waterweeds tall grasses and riparian vegetation
Shrub Savannah and Thicket (SSandT)	Small to medium-sized woody plant, bushes/scrubland,
Grass Savannah (GS)	Grass cover with isolated shrubs. Short plants with long, narrow leaves growing wild or cultivated.
Active Crop Land (ACL)	Areas utilized for agricultural activities, cropland, and fallow lands, etc.
Built-up and Bareland (B-UandB)	Include settlements, open spaces, roads, bare/exposed surfaces, and sand beaches
Cloud Cover (CC)	Cloud
Wetland and Marsh Land (WandML)	Include wetlands with or without vegetation and marshlands
Mangrove (M)	Mangrove dominated lands

The number of correctly identified samples in each class was divided by the corresponding reference totals to determine the producer's accuracy, and the number of correctly identified samples in each class was divided by the classified totals to determine the user's accuracy (Hyandye, 2015). By dividing the entire number of correctly identified land use classes by the total quantity of reference data, the overall classification accuracy was calculated. The following formula was used to determine kappa statistics, commonly referred to as the K_{hat} - Coefficient of Agreement:

$$\widehat{K} = \frac{N \sum_{i=1}^{k} X_{ii} - \sum_{i=1}^{k}(X_{i+} \times X_{+i})}{N^2 - \sum_{i=1}^{k}(X_{i+} \times X_{+i})}$$

where N is the total number of observations in the entire error matrix, k is the number of rows, xii is the number of observations correctly classified for a specific category (summarized in the matrix's diagonal), and x_{i+} and x_{+i} are the marginal totals for row and column *i* related to the category.

To estimate the amount, direction, and mechanism of change between 2002 and 2017, the post-classification technique was used. The method compares classified maps according to the extent of land cover using cross-tabulation and spatial overly procedures (Estoque and Murayama, 2011). A net change per category was computed by taking the previous landcover areas, adding the gains, and then subtracting the losses in the category. This was done in order to undertake a quantitative assessment of change by graphing gains and losses by landcover category.

Modeling agent contributions to land use and land cover change

Table 1 shows the potential LULCC drivers and data sources for the modelling. The drivers are population density, terrain (elevation and slope), distance factors (from road and settlements), rainfall, and crop yield shown in Table 1 above. The LULCC outcome image were reclassified into five (5) classes (Table 3). The reclassification was based on significant net changes observed in the study area and changes of biological or ecological significance (see Table 5). Point data of the drivers were interpolated using kriging technique and gridded. Point database was generated for randomly selected vectors for all the predictor variables and LULCC image. These constituted the database for the multinomial statistical analysis. Test was carried out to verify if the data met the assumptions for use in the regression modelling. For the multicollinearity test, Pearson's correlation was used. Only one of the correlation coefficient was high (r>0.6) and this was excluded in the logistic regression model to prevent co-linearity. To confirm this, an analysis was carried out to determine the

TABLE 3
List of dependent factors used in the multinomial logistic regression model

Selected dependent factors	Abbreviation
Shrub/grassland to Shrub/grassland	SG – SG
Shrub/grassland to Build up areas	SG – BU
Shrub/grassland to Active cropland	SG – AC
Shrub/grassland to Water	SG – W
Shrub/grassland to Wetland*	SG – WL
Active cropland to Active cropland	AC – AC
Active cropland to shrub/grassland	AC – SG
Active cropland to build up	AC – BU
Active cropland to Water	AC – W
Active cropland to Wetland*	AC – WL

* used as the reference category in multinomial logistic regression

Variance Inflation Factor (VIF) and tolerance (I/VIF) for the degree of collinearity among the spatial predictor variables. A rule of thumb of VIF less than 10 was used to select predictors for the multinomial regression modelling (Addinsoft, 2019; Field, 2009). Logistic regression analysis was first performed to determine the probabilistic influence of the covariates on the outcomes of LULCC in the study area. From the suite of potential predictors, the configuration with the lowest Akaike Information Criterion (AIC) score and AIC difference greater than 2 (AIC > 2) was used to select the best model. This allowed spatial visualisation of dominant local drivers. The drivers (predictors) and the reclassified LULCC as outcome (dependent) variable were then used in a multinomial logistic regression analysis (Table 3). The changed images contained more than two (2) categories of LULCC classes, hence, the choice of multinomial logistic model. This analysis was carried out for changes involving shrub/grassland and active cropland. Multinomial logistic regression is widely used to identify significant causal factors of LULCC (Kamwi et al., 2018; Kim et al., 2014). In the logit model, the magnitude of the likely change in LULC resulting from a change of one unit in the independent variable was translated from the exponents (eβ) of the individual regression coefficients of the independent variables (odds ratios). After adjusting for other model parameters, the odds ratio shows the change in the likelihood of falling into one of the outcome's categories when a predictor's value rises by one unit (Kamwi et al., 2018; Kim et al., 2014). Active cropland changes to wetland and shrub/grass savannah change to wetland classes were used as the reference category. A null hypothesis of all predictors simultaneously having no effect on determining changes in the dependent variables with respect to the reference category was analysed. The hypothesis was tested at 0.05 significant level. All the regression models were performed using SPSS 21.0.

Results

Classification and accuracy assessment
The overall classification accuracy for 2002 and 2017 images were 84% and 93% respectively. The recorded Kappa statistics were 0.81 and 0.91 (Table 4). The area of LULC classification in hectares (ha) and the percentage coverage for 2002 and 2017 are

TABLE 4
Classification accuracy verification values

| LULC Classes	2002		2017	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Water	99.68	98.53	96.80	99.50
Riverine Vegetation	74.47	96.14	63.17	64.35
Shrub and Thicket	74.29	94.41	96.43	97.59
Grass Savannah	93.33	74.41	89.00	99.84
Active crop land	78.85	88.27	94.05	85.15
Built-up and Bare	75.88	64.46	89.70	92.98
Cloud	100.00	100.00	100.00	99.25
Wetland and Marshy	88.21	78.88	94.54	90.26
Mangrove	95.80	51.57	96.14	71.15
Overall Accuracy (%)	83.95		92.60	
Kappa Coefficient	0.8136		0.9111	
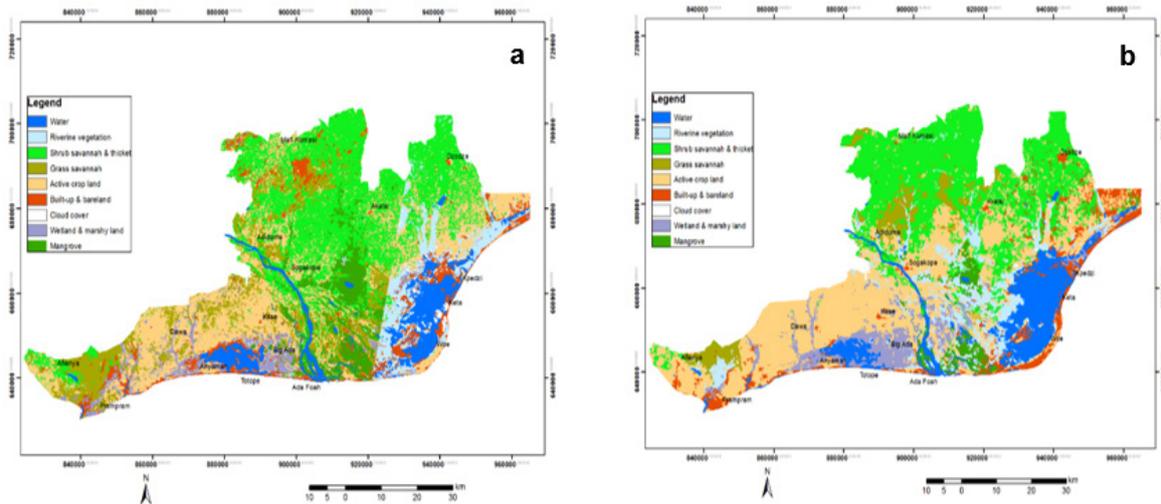
Fig. 3 Classified LULC for the Volta Delta. (a) LULC classification of 2002. (b) LULC classification of 2017
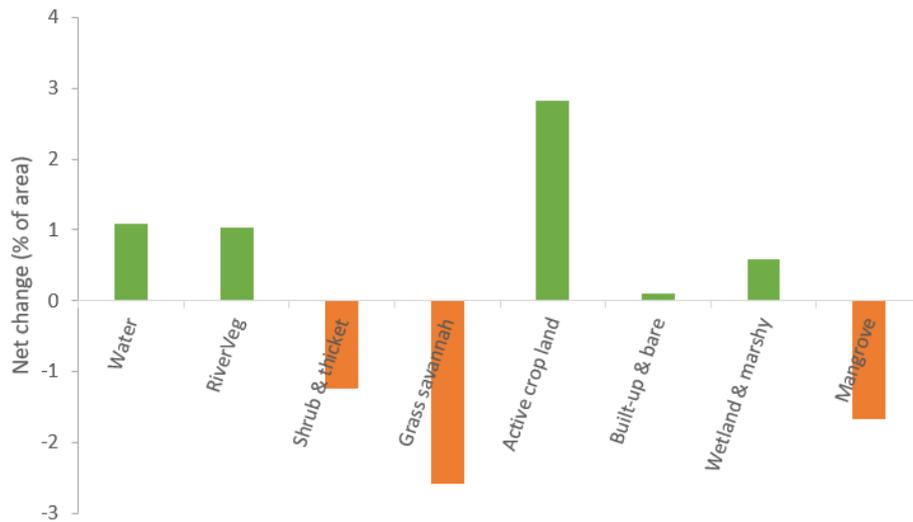

Fig. 4 Net land use and land cover change between 2002 and 2017 (% of area)

displayed in Table 5, Figures 3 and 4. In 2002, about 29.0% of the land was covered by shrub savannah and thicket, with active cropland (26.0%) and grass savannah (12%) following closely behind. About 7.0% of the area was made up of waterbody, built-up and bare lands, riverine vegetation and mangrove each. Also, 5.0% of the total area was made of wetlands and marshy areas. For the 2017 LULC, however, active croplands were predominant. While active cropland increased by 7%, shrub savannah andthicket decreased by 3%. Waterbody and riverine vegetation increased by 2.7% and 2.6% respectively. Mangrove and grass savannah decreased by 4.2% and 6.5%,

respectively. Wetlands and marshy areas saw a marginal increase of roughly 1.5% in 2017.

Land use land cover change

Table 5 shows the types of LULC change and transfers that took place between 2002 and 2017. A total of 1818.7 hectares of water bodies were transformed primarily into marshes and wetland. The majority of the riverine vegetation was converted into wetland and marshland (1616.0 ha) and active cropland (6824.0 ha). A total of 32363.5 hectares of shrub savannah and 19648.4 hectares of thicket and grass savannah were converted into active cropland. There were more conversions from

TABLE 5
Land use and land cover changes and area transfer matrix 2002-2017 (ha)

	LULC category	2002 LULC									Total	Proportion of area (%)
		Water	Riverine Vegetation	Shrub and Thicket	Grass Savannah	Active cropland	Built-up and Bare	Cloud	Wetland and Marshy	Mangrove		
2017 LULC	Water	**30743.2**	5464.0	326.8	113.2	192.7	6157.9	1249.7	1190.2	1208.6	46646.2	10.2
	Riverine Veg.	620.6	**7199.5**	11606.0	7196.0	4116.3	2445.8	154.9	585.9	8203.3	42128.5	9.2
	Shrub and Thicket	51.2	3998.7	**69203.5**	11864.4	20685.7	4354.7	123.4	226.0	6339.0	116846.6	25.6
	Grass Savannah	0.7	161.2	9700.0	**7483.4**	4071.3	1273.1	0.0	219.3	1173.3	24082.5	5.3
	Active crop land	232.1	6824.2	32363.5	19648.4	**72979.7**	5182.0	296.4	9229.8	3776.5	150532.5	33.0
	Built-up and Bare	381.9	3930.1	4467.4	1823.0	11421.6	**8441.4**	365.9	3025.4	480.3	34337.1	7.5
	Cloud	14.6	279.6	249.2	25.4	288.4	72.4	**13.5**	6.4	21.9	971.3	0.2
	Wetland and Marshy	1818.7	1616.2	2038.8	5553.4	4262.9	4985.2	42.3	**8714.1**	848.3	29879.9	6.5
	Mangrove	381.2	767.6	1177.5	126.3	56.3	191.4	11.9	7.8	**8177.5**	10897.5	2.4
	Total 2002	34244.3	30241.1	131132.7	53833.4	118075.0	33104.0	2257.9	23204.9	30228.8	**456322.0**	
	Proportion of area (%)	7.5	6.6	28.7	11.8	25.9	7.3	0.5	5.1	6.6		
2002-2017	Gains	15903	34929	47643	16599	77553	25896	958	21166	2720		
	Losses	-3501	-23042	-61929	-46350	-45095	-24663	-2244	-14491	-22051		
	Net change (% of area)	1.08	1.03	-1.24	-2.59	2.82	0.11	-0.11	0.58	-1.68		

Note: Figures in bold (diagonal) are the LULC persistence (no change) while the figures in the column represent the status transferring out nature of the preliminary LULC state. Similarly, figures in the same row are increases or transferring in nature of the final LULC.
Percent Area = (# Pixels changed for a class / total area of the land cover map) *100

wetland and marshland to active cropland than persistence. Furthermore, 11864.4 ha of grass savannah and 20685.7 ha of active cropland were significantly transformed into shrub savannah and thicket, respectively. Although a significant amount of active cropland area persisted (72979.7 ha), about 11421.6 ha was converted to built-up and bare land. A larger percentage of mangrove was converted into riverine vegetation (8203.3 ha), while roughly 6158 ha of built-up and bare land were turned into water.

A net land cover change, either gain or loss of a particular class was influenced by changes in other land cover categories (Table 5 and Fig 4). The net gain on active crop areas was approximately 2.82%. Likewise, there was a net increase of about 1% for both riverine vegetation and water. Nonetheless, grass savannah, mangrove, and shrub savannah and thicket suffered significant net losses (-2.59%, -1.68%, and -1.24%, respectively).

Modeling land use and land cover change determinants

The result of correlation among the covariates is shown in Appendix A. Distance to road and distance to settlement showed a positive correlation (r=0.332). Population density and annual crop yield were highly correlated (r=0.659). Annual rainfall, elevation, and annual crop also showed a positive correlation (r>3.25). However, weak correlations were found between distance to settlement and the other spatial factors examined. Multicollinearity was not an issue when estimating the predictor coefficients under the multinomial regression model, as indicated by the VIF values, which ranged from 1 to 2.12 (with a corresponding tolerance level greater

than 0.1).

Table 6 shows the summary of the best logistic regression models (overall results is in Appendix B). The results show that the probability of active cropland change is associated with slope, annual crop yield, annual rainfall, and elevation. These factors, except for slope, influenced the probability of wetland change. Also, the probability of shrub/grassland change is a function of road distance, population density, slope, and elevation. The most influential and significant explanatory variables selected for the probability of built-up changes are road distance, slope, annual

rainfall, and elevation.

Table 7 shows the summary results of the statistical significant (p<0.05) effects of the variables on the LULCC and odd ratios (overall results is in Appendix C). The odds ratio value of less than one (1) in this table shows less likelihood of a change in LULC occurring as a result of a unit change in the independent variable. Compared to the reference dependent category, the change is more likely to occur when the odds ratio value is greater than 1. For changes in shrub/grassland to other land use category, an increase distance to road, annual crop yield and elevation were found to

TABLE 6

Coefficients estimates of logistic regression best model to determine the probability of LULCC in the Volta Delta

Variable	AC	SG	WL	BU
DistRoad		-0.00023*		0.001343***
PopDens		2.76e-03		
DistSettl				
SlopeDelta	-0.19034*	-9.30e-02		0.187897
CropYield	0.000308		-0.00468**	
Annlrain	0.005085***		0.009579*	-0.00738***
Dem_delta	0.004861*	-1.51e-02***	0.075206***	-0.01216*
AIC score	442.04	717.02	717.02	105.29

*** 0.001, **0.01, * 0.05 significance level

TABLE 7

Factors of LULCC using multinomial logistic regression (2002~2017)

LULCC Class	Explanatory Variable	Odds Ratio (e^β)	P-value	95% Confidence Interval	
				Lower Bound	Upper Bound
SG-AC	DistRoad	0.999	0.001	0.999	1
	CropYield	1.001	0.042	1	1.002
	DEM	1.033	0	1.021	1.044
SG-BU	CropYield	1.002	0.02	1	1.003
	DEM	1.038	0	1.025	1.052
SG-SG	CropYield	1.002	0.008	1	1.003
	DEM	1.041	0	1.029	1.052
SG-W	DEM	1.015	0.009	1.004	1.027
AC-AC	DistRoad	0.999	0.003	0.998	1
	DEM	1.033	0.027	1.004	1.064
AC-BU	DistRoad	0.998	0	0.997	0.999
	Annlrain	1.009	0.049	1	1.019
AC-SG	DistRoad	0.999	0.014	0.998	1
	DEM	1.045	0.004	1.014	1.076
AC-W	DEM	1.035	0.044	1.001	1.069

Reference categories: SG – WL and AC - WL

significantly increase the likelihood of shrub/grassland change to active cropland (OR = 0.999), compared to the reference category (active cropland to wetland) assuming other explanatory variables are held constant. Similarly, an increase in annual crop yield and decrease in elevation significantly influenced the conversion of shrub/grassland to build up and shrub/grass to shrub/grass (OR >1.000). Elevation was found to be a significant determinant of shrub/grassland change to water (OR = 1.015) compared to the reference category.

For active cropland change determinants, distance to road and elevation were found to increase the likelihood of active cropland change to active cropland (OR = 0.999 and 1.033 respectively) compared to the reference category (active cropland to wetland). Similarly, the distance to road and elevation were found to have a significant effect on active cropland change to shrub/grass. Also, distance to road and annual rainfall were found to have a significant effect on active cropland change to built-up areas (OR = 0.999 and 1.009 respectively). An increase in elevation was found to have a significant effect on active cropland change to water (OR = 1.035) compared to the reference category. The odds ratio associated with population density, distance to settlement and slope do not show the significant likelihood of the observed LULCC in both active cropland and shrub/grassland (P>0.05) (see Appendix C). Less attention is paid to the effects of these independent variables in this paper.

Discussion

The classification accuracy of the satellite imagery used in this study was satisfactory, as indicated by the Kappa coefficient exceeding 0.80 (i.e. >80%), representing a strong agreement between the classified outputs and the ground reference data. This level of accuracy aligns with established benchmarks from earlier remote sensing applications in land use and land cover (LULC) studies, which typically range between 60% to 90% using Landsat imagery (Ellis and Baerenklau, 2010; Kamwi et al., 2018; Congalton and Green, 2019). The high accuracy reinforces the robustness of the classified maps and the reliability of the derived LULC transitions in the Volta Delta between 2002 to 2017 (Table 5).

The temporal comparison of LULC categories clearly reveals that the Volta Delta landscape is dynamic, undergoing significant transformations over time. These transformations are attributable to both natural processes and anthropogenic activities. Consistent with previous findings (Liping et al., 2018a; Pabi, 2007), the transitions observed in this study demonstrate a non-linear and complex process where LULC categories interconvert in multiple directions. Notably, the conversion from Shrub/thicket to grassland and cropland was more extensive than the reverse process, indicating progressive agricultural encroachment. This trend reflects a broader regional pattern in West Africa, where intensified smallholder agriculture continues to drive the expansion of cultivated areas at the expense of natural vegetation (Curtis et al., 2018; Rudel, 2013; van Vliet et al., 2016). Of particular concern is the significant conversion of wetland areas into cropland (Table 5). Wetlands in the Volta Delta provides critical ecological services, including flood regulation, sediment trapping and biodiversity support (Beuel et al., 2016; Junk et al., 2013). Their degradation, therefore, compromises ecological stability and resilience in the deltaic ecosystem. Similar

findings have been reported in other tropical deltaic systems where agricultural expansion and population pressures have led to the loss of wetland integrity (Sloan and Sayer, 2015; Gumbricht et al., 2017). This underscores the urgent need for integrated land-use planning and ecosystem-based management approaches to balance livelihood needs and ecological preservation (Mensah et al., 2023).

The logistic regression modelling results (Table 6) highlights the significant influence of geomorphologic factors – particularly slope and elevation – on the dynamics of LULC in the Volta Delta. These factors, acts as natural barriers to change by limiting human accessibility and land conversion potential. Areas with low elevation and gentle slope in the Volta Delta are more susceptible to LULC transitions due to their accessibility and suitability for cultivation and settlement. This finding corroborates the results of Ellis and Baerenklau (2010) and Kamwi et al. (2018), who demonstrated that topographic parameters substantially determine spatial patterns of land conversion, particularly in marginal agricultural zones. Similarly, proximity factors such as distances to roads and population density increased the odds of transitions involving shrub/grassland, built up and bare land, indicating that accessibility remains a crucial determinant of LULC dynamics (Msofe et al., 2019; van Asselen and Verburg, 2012).

The multinomial logistic regression model (Table 7) revealed that distance to roads and annual crop yield were among the most influential drivers of conversion between shrub/grassland and cropland. Reduced travel distance to roads lowers transportation costs and increases market access, thereby incentivising agricultural expansion (Ouedraogo et al., 2010). In the Volta Delta, where agriculture is the predominant livelihood activity, increased crop production often necessitates land conversion from natural vegetation to cropland. This is consistent with national development policies that prioritise agricultural modernisation and rural employment (MOFA, 2018; Ofori et al., 2016). However, while these interventions improve livelihoods, they inadvertently exacerbate LULC pressures, emphasizing the need for policy coherence that integrates agricultural productivity goals with sustainable land management frameworks (FAO, 2022; Lambin and Meyfroidt, 2011).

Interestingly, population density, distance to settlement and slope were statistically insignificant in explaining certain LULC transitions in the multinomial model. This could partly be due to the spatial resolution of the demographic data used. Aggregating population data at broader administration scales may obscure localised variations that more precisely correlate with land change dynamics (Turner et al., 2007; Weng 2002). Moreover, omitted variables which were unavailable for the study – such as soil fertility, land tenure, or access to irrigation – may provide better explanatory power in predicting LULCC patterns in the Volta Delta. The exclusion of these variables underscores the challenges in developing comprehensive models that capture the full complexity of LULCC processes (Verburg et al., 2019).

Despite these limitations, the study provides critical insights into the interplay between physical geography, accessibility and agricultural expansion in shaping the spatial and temporal evolution of the Volta Delta landscape. Understanding of the LULCC phenomenon that involves intricate processes like those investigated in this study is crucial for predicting future land-use trajectories and for informing policy interventions aimed at sustainable land and resource management.

Further studies could enhance explanatory accuracy by integrating socio-economic survey data, climate projections, and high-resolution geospatial datasets to model dynamic feedbacks between human activities and environmental change.

Ultimately, the findings reaffirm that LULCC in the Volta Delta is a product of intertwined biophysical and socio-economic processes. To achieve sustainable land-use outcomes, integrated management strategies that consider both environmental thresholds and human development needs are indispensable. Such approaches are vital for achieving national goals related to food security, biodiversity conservation and climate resilience.

Conclusion

This study examined LULCC in the Volta Delta between 2002 and 2017, and the associated drivers of change focusing on the biophysical and socio-economic drivers that shaped these transformations. The findings revealed distinct change trajectories characterized primarily by the expansion of agricultural lands at the expense of natural vegetation - particularly grasslands, mangroves, shrubs and thickets. These transformations highlight the increasing dominance of agricultural activities and settlement expansion as key drivers of LULCC in the deltaic environment. Anthropogenic pressures, interacting with geomorphological and climatic factors emerged as principal forces shaping land transformation. Specifically, elevation, proximity to roads, annual rainfall, and crop yield significantly influenced the spatial distribution of land cover changes. High elevated terrain with a sparse road networks and low agricultural activities retained natural vegetation, whereas low-lying, easily accessible areas with extensive road networks experienced intensified agricultural

conversion. This underscores an urgent need for coherent, multi-sectoral land-use policies that balances food production with ecological conservation. Spatial planning, therefore, must integrate slope, elevation and proximity data to guide decisions on agricultural expansion, urbanisation and conservation zoning. In particular, low-lying and flood-prone areas, should be prioritized for wetland restoration, conservation and ecosystem-based adaptation projects rather than intensive cultivation or infrastructure development. Enhancing the capacity of local governments and traditional authorities to engage in participatory land-use planning will improve enforcement and sustainability. These actions should align with Ghana's national climate adaptation strategies and the sustainable Development Goals (SDGs 2, 13 and 15) ensuring that development in the Volta Delta enhances food security, environmental resilience and sustainable livelihoods.

The integration of remote sensing, GIS techniques and multisource spatial data proved effective in quantifying and modeling the complex patterns of LULCC. This methodological approach enhances the reliability of spatial analysis and provides a solid foundation for predictive modeling of future land-use dynamics. Future studies should build upon the current analysis by incorporating finer-scale socio-economic, biophysical and institutional variables to better capture the complexity of LULCC processes in the Volta Delta.

Author Contributions

Conceptualization, design of study and writing—original draft preparation, J.A; methodology, formal analysis, writing-review and editing, O.P. and J. A. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

Data Availability Statement

Satellite data used for the study were obtained from earth explorer.usgs.gov, while the food production data was reported by Ghana's Ministry of Food and Agriculture.

Conflicts of Interest

The authors declare no conflict of interest.

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APPENDIX A

Correlation matrix for explanatory variables

Variables	DistRoad (m)	Popdens (Km²)	Dist_to_setl (m)	SlopeDelta (°)	Annlcrop (Y/ha)	Annlrain (mm)	Dem_deltaU (m)
DistRoad	**1.000**						
Popdens	-0.086	**1.000**					
Dist_setl	0.332	-0.045	**1.000**				
SlopeDelta	-0.049	0.200	-0.008	**1.000**			
Annlcrop	-0.170	0.659	-0.069	0.314	**1.000**		
Annlrain	-0.091	0.268	-0.119	0.111	0.327	**1.000**	
Dem_deltaU	0.095	0.209	0.137	0.401	0.367	0.253	**1.000**

APPENDIX B

Comparison of logistic regression models of LULC changes in the Volta Delta, Ghana. The models are shown, in order of decreasing rank, with the model log-likelihood (LL), a number of estimated parameters (K), Akaike's Information Criterion (AIC), AIC difference (Δi), and AIC weight (wi).

	Rank	Variables	LL	K	AIC	Δi	wi
AC	1	Dem_DeltaU, SlopeDelta, CropYield, Annlrain	-215.93	5	442.04	0.00	0.79
	2	DistRoad, PopDens, DistSettl, SlopeDelta, CropYield, Annlrain, Dem_DeltaU	-214.11	8	444.64	2.60	0.21
	3	Dem_eltaU, SlopeDelta, Popdens, CropYield	-225.86	5	461.89	19.85	0.00
	4	Dem_DeltaU, SlopeDelta	-228.85	3	463.77	21.73	0.00
	5	CropYield	-234.96	2	473.95	31.91	0.00
	6	CropYield , DistRoad, DistSettl	-233.11	4	474.34	32.30	0.00
	7	CropYield, DistRoad	-234.70	3	475.47	33.43	0.00
	8	Null	-237.08	1	476.17	34.13	0.00
SG	1	Dem_DeltaU, DistRoad, Popdens, SlopeDelta	-353.46	5	717.02	0.00	0.78
	2	DistRoad, DistSettl, SlopeDelta, CropYield, Annlrain, Dem_DeltaU	-353.08	7	720.35	3.33	0.15
	3	Dem_DeltaU, SlopeDelta	-358.29	3	722.62	5.60	0.05
	4	Dem_eltaU, SlopeDelta, Annlrain	-357.86	4	723.78	6.76	0.03
	5	CropYield, DistRoad	-397.27	3	800.58	83.56	0.00
	6	CropYield , DistRoad, DistSettl	-397.26	4	802.60	85.58	0.00
	7	CropYield	-410.79	2	825.60	108.58	0.00
	8	Null	-418.01	1	838.03	121.01	0.00
WL	1	Dem_DeltaU, CropYield, Annlrain	-33.60	4	75.73	0.00	0.69
	2	CropYield, Annlrain, Dem_DeltaU, Popdens	-33.58	5	77.97	2.24	0.23
	3	Dem_DeltaU, CropYield	-37.54	3	81.39	5.67	0.04
	4	DistRoad, PopDens, DistSettl, CropYield, Annlrain, Dem_DeltaU	-33.46	7	82.47	6.75	0.02
	5	Dem_DeltaU, Annlrain	-38.37	3	83.06	7.33	0.02
	6	Null	-52.93	1	107.90	32.17	0.00
	7	CropYield, DistRoad	-51.26	3	108.83	33.10	0.00
	8	CropYield, DistRoad, DistSettl	-50.31	4	109.16	33.43	0.00
BU	1	Dem_DeltaU, SlopeDelta, DistRoad, Annlrain	-47.39	5	105.29	0.00	0.78
	2	DistRoad, PopDens, DistSettl, SlopeDelta, CropYield, Annlrain, Dem_DeltaU	-45.39	8	108.05	2.76	0.20
	3	CropYield , DistRoad, DistSettl	-52.28	4	112.90	7.61	0.02
	4	CropYield, DistRoad, Popdens	-54.64	4	117.62	12.32	0.00
	5	Dem_eltaU, SlopeDelta, Annlrain	-58.84	4	126.03	20.73	0.00
	6	CropYield, Popdens	-67.02	3	140.24	34.95	0.00
	7	Dem_DeltaU	-72.90	2	149.90	44.61	0.00
	8	Null	-74.01	1	150.05	44.76	0.00

APPENDIX C
Factors affecting the LULC class/conversions

LULCC Class	Explanatory Variable	Odds Ratio (e^β)	P-value	95% Confidence Interval	
				Lower Bound	Upper Bound
SG-AC	DistRoad	0.999	0.001	0.999	1.000
	Popdens	1.007	0.412	0.990	1.024
	Dist_to_setl	1.000	0.061	1.000	1.000
	SlopeDelta	0.958	0.764	0.723	1.269
	Anncrop	1.001	0.042	1.000	1.002
	Annlrain	0.996	0.184	0.990	1.002
	Dem_deltaU	1.033	0.000	1.021	1.044
SG-BU	DistRoad	1.000	0.318	0.999	1.000
	Popdens	1.005	0.605	0.986	1.025
	Dist_to_setl	1.000	0.740	1.000	1.000
	SlopeDelta	0.887	0.483	0.633	1.241
	Anncrop	1.002	0.020	1.000	1.003
	Annlrain	0.998	0.662	0.991	1.006
	Dem_deltaU	1.038	0.000	1.025	1.052
SG-SG	DistRoad	1.000	0.709	1.000	1.000
	Popdens	0.997	0.740	0.980	1.014
	Dist_to setl	1.000	0.227	1.000	1.000
	SlopeDelta	0.969	0.821	0.739	1.272
	Anncrop	1.002	0.008	1.000	1.003
	Annlrain	0.999	0.763	0.993	1.005
	Dem_deltaU	1.041	0.000	1.029	1.052
SG-W	DistRoad	1.000	0.720	1.000	1.000
	Popdens	1.007	0.449	0.989	1.024
	Dist_to_setl	1.000	0.146	1.000	1.000
	SlopeDelta	0.928	0.632	0.685	1.258
	Anncrop	1.000	0.494	0.999	1.002
	Annlrain	1.001	0.803	0.995	1.007
	Dem_deltaU	1.015	0.009	1.004	1.027
AC-AC	DistRoad	0.999	0.003	0.998	1.000
	Popdens	1.011	0.562	0.975	1.048
	Dist_to_setl	1.000	0.612	0.999	1.000
	SlopeDelta	0.869	0.716	0.408	1.851
	Anncrop	0.999	0.666	0.997	1.002
	Annlrain	1.003	0.581	0.993	1.012
	Dem_deltaU	1.033	0.027	1.004	1.064
AC-BU	DistRoad	0.998	0.000	0.997	0.999
	popdens	1.009	0.652	0.971	1.048
	Dist_to_setl	1.000	0.500	0.999	1.000
	SlopeDelta	0.535	0.138	0.234	1.223
	Anncrop	1.001	0.573	0.998	1.003
	Annlrain	1.009	0.049	1.000	1.019
	Dem_deltaU	1.026	0.105	0.995	1.058

APPENDIX C *count.*
Factors affecting the LULC class/conversions

LULCC Class	Explanatory Variable	Odds Ratio (e$^\beta$)	P-value	95% Confidence Interval	
				Lower Bound	Upper Bound
AC-SG	DistRoad	0.999	0.014	0.998	1.000
	popdens	1.003	0.885	0.966	1.041
	Dist_to_setl	1.000	0.437	0.999	1.000
	SlopeDelta	0.800	0.571	0.369	1.734
	anncrop	1.000	0.947	0.998	1.002
	Annlrain	1.007	0.165	0.997	1.016
	Dem_deltaU	1.045	0.004	1.014	1.076
AC-W	DistRoad	0.999	0.082	0.997	1.000
	Popdens	0.969	0.490	0.885	1.060
	Dist_to_settl	1.000	0.329	0.999	1.000
	SlopeDelta	1.297	0.582	0.513	3.280
	anncrop	0.999	0.587	0.996	1.002
	Annlrain	1.003	0.665	0.991	1.015
	Dem_deltaU	1.035	0.044	1.001	1.069

LULCC Class	Explanatory Variable	Odds Ratio (e$^\beta$)	P-value	95% Confidence Interval	
				Lower Bound	Upper Bound