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Spatio-Temporal Analysis of the Pattern of Land use and Land Cover Changes among the Sub-Basins in the White Volta Basin

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Abstract

The White Volta Basin has witnessed a declining trend of vegetative cover due to intense human activities such as urbanization, deforestation, agricultural expansion, mining activities, and infrastructure development, which have significantly impaired the ability of the river basin to provide essential ecosystem services and livelihood support. Land use and land cover (LULC) changes in the White Volta Basin (WVB) were investigated using Landsat images of 1995, 2005, 2015, and 2023, and random forest (RF). Questionnaires were also employed to elicit views on the causes of LULC changes in the basin. The studies revealed that light savannah forest increased, with the highest rate observed in the Gambaga (117.80%), Kulpawn (47.58%), Middle White (39.81%), Nasia (37.48%), and Sissili (23.17%) sub-basins. Built-up areas also increased, with the Middle White basin showing the highest expansion rate at 13.21%, Kulpawn at 8.33%, Mole at 5.85%, Nabogo at 5.49%, Lower White at 4.67%, and Nasia at 3.975%. Cropland also increased with Gambaga (9.21%), Nasia (7.46%), Sissili (6.11%), Nabogo, and Mole, 5.75% and 5.655%, respectively, being the predominant sub-basins. The Kulpawn sub-basin was the most severely degraded, while the Gambaga sub-basin was the least degraded based on the LULC analysis. Agricultural activities, built-up, human population growth, mining, and fuelwood extraction were key drivers of the LULC in the sub-basins. The findings provide a comprehensive understanding of the extent of degradation across the various sub-basins and serve as a guiding document for the design of targeted interventions to address the impacts of land degradation, particularly in the most severely affected basins.

1. Introduction

Land use and Land Cover (LULC) changes is one of the leading causes of most environmental challenges across many landscapes [1–3]. The causes of these changes are multifaceted, but the key driving forces are largely anthropogenic [4, 5]. These factors are mostly influenced by consumption patterns, high human population growth, urban sprawl, industrialization, and socioeconomic and livelihood dynamics [6, 7]

Globally, LULC has been identified as a key driver of the decline in ecosystem services (ES), affecting food production, accelerating the occurrence of climate change, worsening poverty levels, and sometimes resulting in conflicts among communities [6, 8, 9]. This impact does not only lead to alteration and degradation, but also to the complete conversion of natural ecosystems. In many instances, it results in the disruption of critical ecosystem services and functions such as water purification, flood regulation, and soil retention [7, 10]. LULC changes also accelerate the frequency of natural hazards, such as floods, droughts, and wildfires [11, 12]

The degradation of land cover through deforestation, unsustainable agricultural practices, and urban expansion intensifies surface runoff and reduces groundwater recharge, which results in streamflow loss [13, 14]. Additionally, land degradation and excessive resource extraction significantly reduce the availability and quality of freshwater resources, increase sedimentation rates, as well as increase pollutant loads in rivers and streams, threatening aquatic habitats and water resources [15, 16]. Eventually, the livelihoods of rural people within the catchment are disproportionately affected [15, 18]. This often leads to a decline in agricultural productivity, as well as aggravating poverty among vulnerable communities. Studies by Frank et al [19] and Rai et al [20] highlighted the correlation between LULC and the value of ecosystem services. In many instances, high-value ecosystems such as wetlands and forests are converted to lower-value land uses such as degraded croplands or built-up areas, which leads to significant losses in ecosystem services and functions[21, 22]. In Africa, ecosystem asset values, including both services and natural resources, declined by 30%-40 % between 1992 and 2020 as a result of LUC changes [18, 23]. The magnitude of these impacts varies spatially and is largely determined by the spatial intensity of LULC changes and the socio-ecological context of the river basin [14, 23].

In Ghana, the cost of biodiversity loss through deforestation and land degradation is estimated at $520 million annually, representing 6.0% of the annual gross domestic product [14, 24, 25]. It is also projected that more than three million biological species will be extinct in the near future if the right abatement measures are not implemented to reduce the rate of deforestation and degradation [25, 26].

Over the last three decades, most river basins in Ghana have undergone serious land cover alterations due to varied land-use practices [29]. Anthropogenic factors (e.g., livelihood change, population growth, settlement patterns, and agricultural intensification), and natural factors such as seasonal variations and disasters have caused this transformation of vegetative covers [30]. Several LULC studies have been conducted in river basins in Ghana to explore the impacts of LULC changes and how they can be addressed sustainably [31]. The studies revealed that human activities in the Weija Reservoir have resulted in pervasive river catchment erosion, sedimentation, water pollution, increased turbidity, increased dissolved oxygen, and high nutrient loads. Frank et al[30] also highlighted increased runoff into the Densu Basin due to vegetation loss. The study concluded that the vegetative cover along the Densu River Basin will continue to degrade due to the increasing rate of urbanization and its associated activities, making the soil within the basin more vulnerable to erosion, with serious consequences on channel morphology and sedimentation.

The White Volta Basin (WVB) is an important river basin in Ghana that supports a wide range of socio-economic and ecosystem functions [32, 33]. However, increasing anthropogenic activities such as uncontrolled logging, artisanal mining, human settlement expansion, urbanization, rising livestock populations, and poor agricultural practices have significantly degraded the vegetative cover along the banks of this river system [34. It is estimated that between 1990 and 2020, the basin lost about 15–20% of its savannah forest cover, primarily due to logging, wildfires, and conversion to agricultural land [4, 35]. Agricultural land use within the basin increased by over 30%, with the Kulpawn, Sissili, and Nasia sub-basins witnessing the highest agricultural expansion rate [33, 37]. The population within major peri-urban towns in the basin, such as Wa, Walewale, Savelugu, Tamale, Yapei, and Bolgatanga, has increased by more than 40% over the past two decades, driving demand for housing and physical infrastructure [36, 38]. This rapid demographic and infrastructural growth have exerted pressure on local resources, especially sand, timber, and water, which are increasingly extracted from the river basin to meet urban development needs [34]. These extractive and land conversion activities have led to the degradation of riverbanks, destruction of wetland habitats and floodplains, and increased river pollution through sedimentation and chemical runoff [32, 38]. These anthropogenic activities threaten the ecological integrity and life-support systems of the WVB, with serious consequences for water availability, biodiversity, and ecosystem services and functions [35, 39].

Although some research has been conducted in the WVB, most of these studies were conducted in isolation without considering the impacts of LULC at the micro-basin level, and therefore, could not provide specific information on the land cover changes at the sub-basin level. Hence, their results lead to over generalization of the causes and effects. Also, most of these studies could not easily determine the specific interactions and relationships connecting the various sections of the river basin, especially the upstream, midstream, and downstream sections of the river. For instance, Tahidu [32] in the Nawuni section of the WVB examined the influence of LULC on water quality but did not explore the interrelationships across the entire basin, limiting the scope for a holistic assessment. Similarly, Nyadzi et al [33] assessed the impacts of LULC on hydro-climatic variables in the Nasia sub-basin but failed to link their findings to adjacent sub-basins, thereby contributing to a piecemeal understanding of the basin's dynamics. Furthermore, Nasare [34] focused narrowly on the effects of sand winning on vegetation cover in the Dallung catchment, without situating these effects within the broader context of the entire basin. While Osman et al [37] also looked at the effects of LULC on ecosystem services and functions in the Kulpawn basin, without considering the entire basin. These studies collectively demonstrated the over-concentration on the middle section of the WVB, neglecting the interconnectivity of the entire basin system. This fragmented approach risks producing uncoordinated, inefficient, and potentially misdirected management and policy interventions in the basin.

This study aimed to determine LULC change across the nine sub-basins of the WVB (Kulpawn, Sissili, Gambaga, Mole, Kpasenkpe, Nasia, Nabogo, Middle Volta, and Lower Volta) from 1995 to 2023. Studying the LULC dynamics of this timeframe allows for an understanding of how policy interventions, urbanization, agricultural expansion, infrastructure development, and other socio-economic factors have influenced land use patterns in the basin. Specifically, the study determined the pattern and magnitude of LULC changes across the sub-basins, identified the major causes of land cover transitions among the sub-basins, determined the level of degradation in the sub-basins, and offered vital information for biodiversity conservation and management.

2. Materials and Methods

2.1 Study Area

The WVB (Fig. 1) is located between 9°10' N-1°15'0 W with a total area of 107,417 $km^{2,}$ and a length of 885km. It is shared by three countries: Burkina Faso, Togo, and Ghana. In Ghana, the river basin is located at latitudes 8°50'N – 11°05'N and longitudes 0°06'E – 2°50'W and has a drainage area of about 50,000km [38]. The river flows through five administrative regions (Upper West, Upper East, North-East, Northern, and Savannah), traverses over 35 Districts, and shares boundaries with the Oti River Basin to the East, the Black Volta Basin to the West, and the South by the Main/Lower Volta sub-basins [40]

The basin is drained by tributaries of the White Volta and consists of 9 sub-basins (Sissili, Kulpawn, Mole, Kpasenkpe, Gambaga, Nasia, Nabogo, Middle, and Lower-Volta) that form the entire drainage system of the White Volta section of Ghana [35. The primary soil types in the basin are luvisols, regosols, vertisols, lithosols, planosols, cambisols, gleysols, and acrisols. Luvisols, regosols, and lithosols account for over half of the catchment. The major LULC types in the basin are agricultural lands, closed and open savannah, water bodies, and built-up areas [34, 38]

The most widespread vegetation in the basin is savannah woodlands, characterized by scattered and short trees, shrubs, and grasses. These plants are usually prone to fires and drought. The common indigenous trees in the area are the shea (*Vitellaria paradoxa*) and dawadawa (*Parkia biglobosa*), which have economic value and serve as important means of livelihood, especially for women [43–35]. The rainfall in the basin is unimodal, characterized by erratic patterns ranging from 600mm – 1000mm, and temperatures are usually high, averaging 34 ^{0}C. The maximum temperature could reach 42 ^{0}C and the minimum 16 ^{0}C [35, 45].

The basin is predominantly agrarian in nature, with activities such as crop farming, animal rearing, and fishing [46]. Other economic activities in the basin include artisanal mining, sand-winning, smock weaving, shea butter, and dawadawa processing enterprises. Additionally, charcoal and fuelwood extraction are important income-generating activities in the basin [45]. Despite the contributions of these activities to the socioeconomic advancement of the people in the area, the same operations have contributed to the destruction of vegetation and the loss of vegetative cover [33, 47]. According to the Ghana Statistical Service [36] majority of the population (60–70%) actively engages in agricultural and other associated agro-based enterprises.

2.2 Data Acquisition and Processing

2.2.1 Satellite Data

Landsat images (Table 1) covering the WVB were acquired from the United States Geological Survey (USGS) Earth Explorer website (www.earthexplorer.usgs.gov) for 1995, 2005, 2015, and 2023. The selection of images for any change detection assessment is expected to conform to the following criteria: (1) cloud coverage should be < 10% or cloud-free, and (2) the availability of selected satellite images should be in a long time series for at least 5 years or more between two images to maximize the separability and differentiate their different land-use classes [48, 49].

2.2.2 Pre-processing of Images

Pre-processing was done using the semi-automatic classification (SCP) plugin in QGIS. After pre-processing, the images were stacked using the composite bands function in ArcMap 10.6 and projected onto the WGS 84/UTM 30N coordinate reference system to ensure consistency with spatial analysis requirements. After projection, the satellite images were clipped to the study area using the study area's vector file and the clip function in ArcMap 10.6.

Table 1
Landsat satellite images used in the research

Satellite	Sensors	Spatial Resolution(m)	Year	Path/Row
Landsat 5	Thematic Mapper (TM)	30	1995	194/52
Landsat 7	Enhanced Thematic Mapper (ETM+)	30	2005	194/52
Landsat 7	Enhanced Thematic Mapper (ETM+)	30	2015	194/52
Landsat 8	Operational Land Images (OLI)	30	2023	195/54

2.2.3 Sample/Pixel Training

Coordinates obtained from Google Earth were used to train the land cover classes of the pre-processed Landsat image. An average of 200 coordinates was taken for each year (1995, 2005, 2015, and 2023). Ground truthing data were also collected through field surveys using GPS devices. About 300 coordinates were picked for the various land cover points across the basin. These coordinates were geocoded to verify the land cover conditions. Vegetation type, land use activities, degradation, and human influences were documented at each site. This information was used for training the classification model and to validate the accuracy of the LULC maps generated.

The various classes used for the land cover classification were Agricultural lands, Water, Built-up areas, dense savannah forest, and light savannah forest. These classes were identified as the major LULC in the WVB [33, 34, 38]. Table 2 describes the dominant land cover types in the study area.

Table 2
Land Cover Classification Scheme

No	Class	Description	Subclass
1	Dense Savannah Forest	Natural woody vegetation with a canopy cover of 35–65%, and a height above 5m	Woodlots, canopy woodlands, sacred groves.
2	Light savannah forest	Characterized by shrubs/ grasses with a cover of 10–35% and a height of 2.5- 5 m.	Shrubs, grasses
3	Water bodies	Area containing water	River, dams. Streams, reservoirs, and marshy areas
4	Built-up	Area covered by settlements, buildings, and infrastructure	Residential, commercial, industry, road network, rural and urban areas, and bare areas
5	Agricultural lands	The area under the cultivation of crops	Crops, lands, fallow lands, and degraded areas

2.2.4 LULC Classification and Change Detection

Random Forest (RF) machine learning algorithm using R software (R project 2021) was employed to classify the land use/cover types in the sub-basins. This technique was adopted because it has a faster processing time when handling large datasets and addresses data characteristics such as multicollinearity, high dimensionality, noisy data, outlier detection, and non-linear relationships. It is also very sensitive to minor changes and addresses the problems of overfitting [50]. Additionally, Random Forest (RF) is highly effective for processing geospatial data due to its ability to handle high-dimensional features, non-linear relationships, and multicollinearity, which are common challenges in LULC classification [51, 52]. It generates multiple decision trees and aggregates their outputs, improving accuracy and generalization without assuming specific data distributions [58]. It also enhances interpretability and aids dimensionality reduction.

In this study, RF enabled the reliable classification of multi-temporal Landsat imagery, supporting the accurate detection of land cover transitions across the WVB. Its scalability, noise tolerance, and robustness to missing and unbalanced data made it suitable for analyzing the diverse and complex landscape. Recent studies by Abdali et al [52] highlighted the performance of RF over other classifiers in land cover change analysis.

The spatial resolution of the images in the classification was 30m×30m for all the images. The classification and regression training function was used to build the model. The training samples were categorized into five (5) types: Agricultural lands, Built-up, Dense savannah forest, Light savannah Forest, and Water bodies

The caTools package in R with the sample split was used to split the data into a 70% training set and a 30% test set. Tuning of the data was performed by growing several trees (trees) in the forest and setting the number of variables randomly sampled at each stage [62]. Cross-validation was performed using K-fold cross-validation. After building the model, classification was executed on the pre-processed images. The confusion matrix, Overall Accuracy (OA), and the Kappa coefficient were generated to assess the accuracy of the classification.

Post-classification comparison method was utilized to detect changes in LULC. This resulted in LULC maps that present a complete array of changes over a period. A pattern of LULC changes over time was developed by calculating the total area covered by each class in the study area for each year [53, 54].

2.2.5 Accuracy Assessment

One of the key challenges in generating accurate LULC maps is ensuring a high level of classification accuracy and managing the significant processing time required [55]. These difficulties are commonly faced by scientists and practitioners working in the remote sensing field [54]. To address these challenges, the study applied the Kappa statistics and the Overall Accuracy (OA) metric to evaluate the reliability of the classified maps (Equations 1 and 2). Kappa is the

most widely used accuracy assessment measure because it provides robust results in many land cover change detection analyses. It reflects the actual agreement between the classified remotely sensed image and ground-based reference data [56].

$$\text{Overall Accuracy (OA)} = \frac{\text{Total number of correctly classified pixel (Diagonal)}}{\text{Number of total reference pixel}} \times 100 \quad \text{.....Eq. 1}$$

$$\text{Kappa Coefficient (Kappa)} = \frac{\text{Ts} \times \text{Tcs} - \Sigma\,(\text{Column total} \times \text{Row total})}{\text{Ts}^2 - \Sigma\,(\text{Column total} \times \text{Row total})} \times 100 \quad \text{..... Eq. 2}$$

TS = Total samples and TCS = Total corrected samples [15]. The accuracy of the classified LULC maps were assessed and validated using kappa statistics and overall accuracy (OA) metrics. This evaluation was conducted for the five LULC classes (agricultural lands, built-up areas, dense savannah forest, light savannah forest, and water bodies) for 1995, 2005, 2015, and 2023. The analysis covered all nine sub-basins of the WVB (Table 3).

2.2.6 Causes of LULC changes in the Basin

Qualitative and quantitative data collection methods were employed to thoroughly understand the causes and effects of land cover changes in the basin. These methods included household surveys, key informant interviews (KIIs), and focus group discussions (FGDs). The data collection process was guided by checklists and semi-structured questionnaires tailored to capture specific and broad perspectives on LULC changes.

Key informants who had in-depth knowledge of land management were purposively sampled. These included representatives from the District Assemblies, Environmental Protection Authority, Water Resources Commission, Department of Agriculture, Traditional and Religious Authorities, youth leaders and elders, representatives from NGOs, and community-based organizations. FGDs were also employed, with each group composed of 5–10 persons. The groups were formed based on shared characteristics (farmers, women, youth, etc.) to ensure focused and open dialogue, as well as facilitate interactive discussions and explore collective community experiences, perspectives, and strategies on LULC changes. Participants were also selected based on recommendations from local leaders and community-based organizations.

A total of 4000 households were identified, of which 10% (400) were considered the sample size and a confidence interval (CI) of 95%[15, 57]. About 70% of the households were male-dominated, and 30% female-dominated. The ages of the respondents for the survey were between 20–75 years. The questionnaire was administered to 400 respondents during the period of 2–30 May, 2024; of these, 350 were for individual household interviews, and 50 were key informant interviews (KIIs) conducted during the period of 14–21 May 2024, and focus group discussions (FGDs) were also held from 22–29 May 2024.

Simple random and purposive sampling techniques were used to select respondents for the household interviews, key informants, and focus group engagement. The responses gathered during the KIIs and FGDs sessions were used to triangulate the information provided during the household interviews to provide a comprehensive understanding of the perceptions of riparian communities on the forces behind LULC and its associated consequences in the basin. Data collected were statistically analyzed using Stata version 16 (simple linear regression model), and results presented in descriptive statistics format using tables and charts. The results of the causes of LULC were compared with the outcomes of the generated remote sensing maps and the application of GIS-based tools.

3. Results and Discussion

3.1 Classification Accuracy

The image classification yielded five classes for all years with an overall classification accuracy range of 75%-85% across all the sub-basins, indicating good agreement (Table 3). The Kappa Coefficient (Table 3) was also within the range of 0.65–0.80, which signifies good agreement [66]. These accuracy levels exceed or closely approach the widely accepted minimum thresholds (OA ≥ 80%, Kappa ≥ 0.65) for reliable LULC analysis [58, 68]. The classified maps were deemed sufficiently accurate for change detection and temporal comparison. However, the accuracy metrics were not only used to validate the classifications, but they also guided the selection and interpretation of subsequent land cover change analysis. For instance, post-classification comparison and LULC transition matrix methods were employed, both of which depend heavily on accurate classification to produce meaningful results.

From Table 3, the Nasia and Sissili sub-basins produced the highest classification accuracies throughout the study period, with Nasia achieving an OA of 82.9% and a Kappa coefficient of 0.71, while Sissili had values of 82.4% OA and a Kappa of 0.77. In contrast, the Gambaga sub-basin had the lowest accuracy metrics, with an OA of 74.5% and a Kappa of 0.66, indicating comparatively moderate agreement between the classified and reference data.

Agricultural land consistently showed high classification reliability, with Producer Accuracy (PA) and User Accuracy (UA) values being high across all the sub-basins (Table 3). This is a recognition that the classifier is very good at being able to identify and differentiate agricultural areas. Built-up areas also performed well, with PA and UA values generally above 78% in most sub-basins.

Water bodies, however, displayed greater variability. Notably, in the Gambaga basin, which witnessed a decline in classification accuracy for water bodies over time. Conversely, Kpasenkpe and Nasia sub-basins demonstrated improvements in water classification accuracy, indicating better differentiation in these areas. Additionally, dense and light Savannah classes, on the other hand, exhibited moderate variations in accuracy, likely due to spectral similarities between these vegetation types. Such overlaps can pose challenges to classification algorithms, leading to occasional misclassifications between the two classes.

The high classification accuracy values recorded across all the sub-basins indicated that the LULC maps generated were of high quality. These results provide a strong basis for the reliability of the data and justify their use in subsequent land cover change analyses and spatial decision-making.

Table 3
Kappa Coefficients and Overall Accuracy for the nine sub-basins of the White Volta Basin

Sub-basins		1995			2005			2015			2023		
	LULC	**PA (%)**	**UA (%)**	**Kappa**	**PA (%)**	**UA (%)**	**Kappa**	**PA (%)**	**UA (%)**	**Kappa**	**PA (%)**	**UA (%)**	**Kappa**
Gambaga	BLT	79.1	80.2	0.69	80.1	82.3	0.7	82.3	78.5	0.68	80.1	81.2	0.71
	WTR	82.1	80.1	0.72	73.2	74.3	0.72	70.1	67.2	0.68	66.5	73.1	0.68
	DF	79.2	81.2	0.71	70	73.3	0.71	69.5	66.8	0.67	70.1	68.2	0.82
	LF	72.1	70.1	0.7	75.1	72.1	0.72	72.1	71.5	0.71	74.6	71.3	0.82
	Agric	77.2	79.1	0.74	74.6	73.1	0.71	67.3	70	0.69	76.1	70.1	0.8
		OA = 78% kappa		**0.71**	**OA = 74.6%**	**Kappa**	**0.71**	**OA = 72.3%**	**Kappa**	**0.69**	**OA = 73.5%**	**Kappa**	**0.77**
Kpasenkpe	BLT	78.1	73.6	0.74	76.1	72.3	0.73	80	78	0.78	80.2	82.1	0.76
	WTR	71	71.2	0.7	75	75.2	0.74	78	80	0.79	81.2	80.4	0.8
	DF	74.1	74.4	0.74	78	76.1	0.76	71	70.1	0.71	78.2	78.6	0.73
	LF	76.1	74.1	0.75	80	78	0.79	72.1	70.1	0.71	80.1	80.1	0.75
	Agric	78	70.2	0.76	69	71	0.7	73.5	74.5	0.74	79.1	77.1	0.76
		OA = 75.5%	**Kappa**	**0.74**	**OA = 75.6%**	**Kappa**	**0.74**	**OA = 74.9%**	**Kappa**	**0.746**	**OA = 79.8%**	**Kappa**	**0.76**
Kulpawn	BLT	80.1	79.1	0.72	78	73.1	0.68	80	80.5	0.75	78.2	77.5	0.66
	WTR	79.4	80.1	0.7	70	70.2	0.64	79.3	76.6	0.66	77.3	80	0.7
	DF	79.3	78.6	0.74	72	71.2	0.67	81.1	78.4	0.72	80.1	78.3	0.73
	LF	81	80.1	0.78	73.1	72.5	0.68	80.4	80.1	0.76	79.4	80.1	0.75
	Agric	80.4	78.9	0.78	70.1	71.2	0.65	82.1	79.3	0.75	81.2	79.2	0.76
		OA = 80%	**Kappa =**	**0.74**	**OA = 72.6%**	**Kappa =**	**0.66**	**OA = 80.6%**	**Kappa =**	**0.728**	**OA = 79.2%**	**Kappa =**	**0.72**
Lower Volta	BLT	80	81.3	0.71	80.1	78.4	0.67	78.3	79.3	0.64	80	79.3	0.69
	WTR	78	80.1	0.67	79.4	77.4	0.64	70.6	78.3	0.66	81.2	80.3	0.7
	DF	77	78.2	0.64	80.3	79.5	0.71	80.3	79.1	0.68	79.4	79.4	0.67
	LF	82	81.2	0.7	79.1	80.2	0.71	78.4	74.4	0.69	78.5	78.9	0.66
	Agric	79	80.1	0.71	80.1	79.5	0.7	78.4	79.1	0.7	80.1	81.2	0.71
		OA = 79.2%	**Kappa**	**0.69**	**OA = 79.8%**	**Kappa**	**0.68**	**OA = 77.2%**	**Kappa**	**0.67**	**OA = 79.8%**	**Kappa**	**0.69**
Middle Volta	BLT	89.1	82.3	0.7	80.1	79.2	0.67	80	81.5	0.69	82.3	83.4	0.72
	WTR	74.2	79.5	0.64	82.3	81.2	0.71	81	80.3	0.7	82.1	80.5	0.69
	DF	81	80.1	0.67	83.2	80.1	0.72	79.4	80.1	0.66	81.3	82.1	0.71
	LF	79	78.6	0.63	79.5	80.1	0.71	80.5	79.4	0.67	79.6	81.2	0.67
	Agric	80.1	79.4	0.69	80.1	79.5	0.69	78.7	80.3	0.68	80.3	78.5	0.65
		OA = 80.8%	**Kappa**	**0.67**	**OA = 81%**	**Kappa**	**0.7**	**OA = 79.9%**	**Kappa**	**0.68**	**OA = 81.1%**	**Kappa**	**0.69**
Mole	BLT	79.1	80.2	0.7	81	82	0.7	81.4	83.1	0.72	81.2	84	0.71
	WTR	80	79.1	0.69	80.3	79.2	0.68	80.5	79.5	0.7	79.6	80.2	0.65
	DF	78.6	79.2	0.67	79.6	80.9	0.69	79.4	76.4	0.65	78.6	79.7	0.66
	LF	81	80.5	0.71	80.6	82.2	0.71	77.9	80.2	0.66	80.1	80.3	0.7
	Agric	79.6	81.1	0.7	81.4	83.1	0.71	82.3	79.7	0.69	81.4	83.4	0.71

BLT= Built-up, WTR = Water, Df = Dense Forest, Lf = Light Forest, Agric= Agriculture, OA=Overall accuracy, PA=Producer accuracy,

UA= User accuracy, Kappa =Kappa statistics

Sub-basins		1995			2005			2015			2023		
	LULC	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa
		OA = 79.7%	**Kappa**	**0.69**	**OA = 80.6%**	**Kappa**	**0.698**	**OA = 80.3%**	**Kappa**	**0.684**	**OA = 80.2%**	**Kappa**	**0.69**
Nabogo	BLT	78	77.3	0.63	78.8	80.3	0.67	80.2	79.9	0.67	81.3	84.3	0.71
	WTR	78.9	80.1	0.64	79.7	81.1	0.68	79.6	81.2	0.66	79.3	80	0.68
	DF	80.5	77.7	0.64	81.9	80.5	0.69	80.1	78.3	0.64	79.8	81.2	0.69
	LF	77.9	79.4	0.62	78.1	80.1	0.68	78	79	0.63	80.1	82.1	0.7
	Agric	80.1	78.9	0.65	77.5	79.2	0.65	81.4	83.3	0.69	82.1	82.1	0.7
		OA = 79.1%	**Kappa**	**0.64**	**OA = 79.2%**	**Kappa**	**0.674**	**OA = 79.9%**	**Kappa**	**0.66**	**OA = 80.5%**	**Kappa**	**0.69**
Nasia	BLT	81.2	80.1	0.67	82	80.1	0.69	82	80	0.68	80.9	81.4	0.71
	WTR	79.4	81.2	0.66	80	79.4	0.68	83.2	80.9	0.71	81.7	82.1	0.71
	DV	80.1	82.1	0.67	83	82.3	0.7	83.2	80.1	0.7	82.4	83.4	0.72
	LV	79.6	80.2	0.66	82.1	83.1	0.69	84.1	80.1	0.71	83.1	80.1	0.7
	Agric	80.1	82.2	0.68	81.4	79.3	0.67	82.3	83.3	0.72	81.5	82.3	0.71
		OA = 80.1%	**Kappa**	**0.67**	**OA = 81.7%**	**Kappa**	**0.69**	**OA = 82.9%**	**Kappa**	**0.704**	**OA = 81.9%**	**Kappa**	**0.71**
Sissili	BLT	82.1	80.1	0.68	80.1	82.1	0.67	82.1	81.1	0.7	81.1	82.1	0.7
	WTR	82	79.6	0.66	79.5	80.1	0.66	80.1	79.5	0.68	82.2	82.6	0.71
	DF	74.5	76.1	0.63	80.1	78.1	0.66	81.4	78.9	0.68	84.1	83.2	0.72
	LF	72.4	74.5	0.62	80.1	79.5	0.66	80.4	80.1	0.7	80.2	81.4	0.69
	Agric	77.6	78.3	0.64	81.2	80.5	0.67	82.1	80.2	0.7	84.4	80.2	0.72
		OA = 77.7%	**Kappa**	**0.65**	**OA = 80.2%**	**Kappa**	**0.66**	**OA = 81.2%**	**Kappa**	**0.69**	**OA = 82.4%**	**Kappa**	**0.70**

BLT= Built-up, WTR = Water, Df = Dense Forest, Lf = Light Forest, Agric= Agriculture, OA=Overall accuracy, PA=Producer accuracy,

UA= User accuracy, Kappa =Kappa statistics

3.2 Spatial Pattern and Distribution of LULC Classes

The pattern and distribution of LULC across the nine sub-basins of the WVB reveal notable heterogeneity and temporal dynamics over the study period (Fig. 2). The land use maps indicate that savannah vegetation remains the dominant land cover type across the sub-basins, particularly in Kulpawn, Sissili, and Nasia, which reflects the prevailing Guinea and Sudan savannah ecological zones. However, there has been an expansion of cropland and built-up areas across all sub-basins, suggesting increased anthropogenic pressure usually driven by population growth and agricultural intensification. This observation is consistent with the findings by Kumah et al[43] in the Nasia basin and Osman et al[37] in the Kulpawn basin. In the Kpasenkpe, Gambaga, and Nabogo basins, the distribution shows a more fragmented landscape, with natural vegetation increasingly being replaced by agricultural lands. This observation aligns with the findings of Nasare et al[34] in the Middle White and Nyadzi et al[33] in the Nasia sub-basins. This fragmentation is more pronounced between 2015 and 2023, indicating accelerated land transformation.

Furthermore, the Mole and Lower White sub-basins exhibited a transition from dense savannah forest to mixed land-use types, including cropland and bare surfaces, which may be attributed to deforestation, expansion in croplands, and land degradation. The Middle White sub-basin demonstrates a relatively balanced distribution of LULC classes, although a noticeable increase in built-up areas. This trend may be linked to urban expansion and infrastructural development, given its proximity to urban and peri-urban centres. However, water bodies remain relatively stable, though minor fluctuations may be observed, which reflects climatic variability and seasonal hydrological changes [58]. These spatial transformations have implications for hydrological processes, ecosystem services, and sustainable land management in the basin.

Table 4
Area coverage (km^2) and rate of LULC changes from 1995–2023 for the nine sub-basins of the WVB

LULC								
1995	Gambaga	Kpasenkpe	Sissili	Kulpawn	Middle White	Mole	Nasia	Nabogo
Agric	174.94(4.87%)	254.12(5.34%)	509(9.73%)	871(8.13%)	304.58(4.43%)	717.89(11.98%)	866.93(16.63%)	318.66(10.8
Built-up	2048.3(57.07)	2595.1(54.54)	2972.05(56.84)	3213(29.98)	3772.28(54.87)	3158.54(52.72)	3092.91(59.32)	1687.27(57.3
Dense	359.76(10.02)	567.25(11.92)	509.5(9.74)	1452.52(13.55)	668.22(9.72)	1217.14(20.31)	393.74(7.55)	160.21(5.45)
Light	814.26(22.69)	794.76(16.7)	679.2(12.9)	3471.4(32.39)	1781.01(25.9)	321.14(5.36)	489.65(9.39)	478.83(16.2
Water bodies	187.76(5.23)	521.31(10.96)	542.11(10.37)	1708.33(15.94)	349.28(5.08)	577.14(9.63)	370.95(7.11)	294.78(10.0
2005								
Agric	178.28(4.97%)	298.46(6.3)	539.36(10.32)	953(8.88)	338.42(4.91)	715.92(11.9)	1002.89(19.16)	358.63(12.1
Built-up	2077.38(57.9)	2623.93(55.15)	3147.26(60.19)	3140.12(29.27)	3771.6(54.72)	3122.21(51.93)	3259.8(62.29)	1711.22(58.(
Dense	409.54(11.41)	589.01(12.38)	535.12(10.23)	1365.23(12.72)	668.22(9.72)	1021.14(16.98)	400.72(7.66)	161.22(5.47)
Light	831.43(23.17)	785.1(16.5)	468.03(8.95)	3480.16(32.44)	1781.01(25.9)	360.18(5.98)	462.51(8.84)	529.94(17.9
Water bodies	92.53(2.58)	461.54(9.7)	539.58(10.32)	1791.12(16.69)	275.38(3.99)	792.53(13.18)	107.45(2.05)	185.81(6.31)
2015								
Agric	202.53(5.64%)	326.46(6.9)	610.96(11.68)	1035(9.66)	360.81(5.23)	730.67(12.15)	1071.78(20.4)	390.16(13.2
Built-up	2141.83(59.67)	2685.32(56.1)	3064.29(58.6)	3203.85(29.89)	3789.12(54.97)	3206.53(53.34)	3260.37(62.07)	1734.52(58.8
Dense	307.6(8.57)	598.51(8.8)	558.16(10.67)	1241.96(11.59)	630.94(9.15)	1084.25(18.04)	265.1(5.05)	170.35(5.78)
Light	821.21(22.88)	754.09(23.5)	429.8(8.22)	3480.16(32.44)	1876.11(27.11)	386.15(6.42)	482.9(9.19)	536.04(18.1
Water bodies	116.02(3.2)	393.11(6.6)	566.75(10.84)	1745.53(16.29)	187.33(2.72)	603.96(10.05)	172.88(3.29)	115.03(3.91)
2023								
Agric	187.18(5.20)	411.13(8.61)	626.16(11.97)	1003.23(9.3)	363.3(5.26)	807.03(13.31)	1015.2(19.22)	416.38(14.1
Built-up	2061.11(57.42)	2675.05(56)	3001.21(57.39)	3410.9(31.63)	3784.01(54.84)	3302.73(54.47)	3125.9(59.18)	1706.39(57.1
Dense	402.16(11.2)	653.37(13.68)	579.6(11.08)	1345.71(12.48)	595.37(8.64)	1278.09(21.08)	428.87(8.12)	216.01(7.32)
Light	857.63(23.89)	733(15.36)	417.8(7.99)	3491.7(32.58)	1960.5(28.44)	414.4(6.83)	515.87(9.77)	502.33(17.0
Water bodies	86.5(2.40)	303.76(6.36)	620.7(11.87)	1507.61(13.98)	177.26(2.57)	261.56(4.31)	195.87(3.71)	111.13(3.76)

3.3 Conversion Rate of LULC in the White Volta Basin

The WVB has experienced increased settlement and agricultural expansion from 1995 to 2023, causing the loss of dense savannah forest and an increase in light savannah forest (Table 5). It was also observed that dense and light savannah forests were being converted into built-up areas and agricultural lands. This modification was linked to an increase in human population growth and urbanization, especially in sub-basins located closer to the urban and peri-urban centres.

This observation aligns with Boakye et al [59] in the Pra basin and Nyadzi et al [33] in the WVB. They revealed that there was an increase in built-up areas with basins closer to the urban centres, with an average distance of 300m-500m. The conversion of various LULC into agricultural land classes may be linked to the agrarian nature of the basin since the majority of the riparian communities are engaged in agriculture and its related activities, therefore accounting for these observations [32, 36].

The study further revealed that the light savannah forest exhibited an increasing pattern, with the highest rate observed in the Gambaga (117.80%), Kulpawn (47.58%), Middle White (39.81%), Nasia (37.48%), and Sissili (23.17%) basins. Expansion in built-up areas also followed a similar trend, with the Middle White sub-basin recording the highest expansion rate in settlement patterns of 13.21%, Kulpawn 8.33%, Mole 5.85%, Nabogo 5.49%, Lower White 4.67%, and Nasia 3.975% (Table 5). The basin also experienced an increase in agricultural activities, resulting in the expansion of cropland, with the predominant sub-basins being Gambaga (9.21%), Nasia (7.46%), Sissili (6.11%), and the Nabogo and Mole values of 5.75% and 5.655% (Table 4). The high rate of conversion of LULC classes (Dense savannah forest, Light savannah forest, and Water bodies) into other LULC, especially croplands, across the various sub-basins may be attributed to the rural nature of the sub-basin, as most of the riparian community derives its

1995–2023 Sub-basins	LULC	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change
Gambaga	BLT	BLT 6.36	0.00	WTR 0.22	0.01	DV 0.68	0.02	LV 195.08	5.43	Agric 14.58	0.41
	WTR	0.54	0.02	25.63	0.71	7.00	0.20	14.32	0.41	26.13	0.73
	DF	0.06	0.00	1.92	0.05	27.42	0.76	20.05	0.56	56.95	1.59
	LF	25.62	0.71	4.59	0.13	200.91	5.60	4227.06	117.80	330.09	9.21
	Agric	80.55	2.44	0.68	0.00	68.42	1.91	608.85	16.95	76.39	2.13
Kpasenkpe	BLT	10.93	0.23	0.90	0.02	0.19	0.00	157.32	3.31	50.17	1.1 1
	WTR	0.19	0.00	10.56	0.22	1.07	0.02	3.31	0.07	13.18	0.28
	DF	0.75	0.02	0.20	0.00	4.31	0.10	4.82	0.10	21.82	0.46
	LF	50.39	1.11	11.99	0.25	39.39	0.83	392.00	8.24	134.70	2.83
	Agric	16.54	0.35	19.24	0.40	15.44	0.33	203.54	4.28	99.95	2.10
Kulpawn	BLT	891.24	8.33	0.03	2.34	1.12	0.01	413.63	3.84	415.17	3.81
	WTR	377.98	3.53	1.34	0.01	8.35	0.08	234.62	2.20	2.30	0.02
	DF	2230.48	20.83	0.87	0.01	312.77	2.92	3033.12	28.34	345.32	3.22
	LF	223.37	1.95	1.54	0.01	162.70	1.51	5087.39	47.53	83.47	0.78
	Agric	668.96	6.25	81.32	0.76	100.13	0.94	298.46	2.79	68.76	0.64
Lower white	BLT	219.89	4.67	28.75	0.61	5.44	0.12	49.62	1.05	4.73	0.10
	WTR	298.57	6.34	23.30	0.49	5.88	0.13	62.16	1.32	39.60	0.84
	DF	389.64	8.27	0.98	0.02	44.05	0.94	330.12	7.01	201.10	4.27
	LF	344.46	7.31	3.94	0.08	563.91	11.97	1146.96	24.35	52.78	1.12
	Agric	195.21	4.14	62.39	1.33	37.01	0.79	41.56	0.88	26.68	0.57
Middle white	BLT	910.47	13.21	0.45	0.01	5.56	0.08	141.64	2.06	100.00	1.45
	WTR	124.80	1.81	30.69	0.45	34.32	0.51	41.17	0.59	62.97	0.91
	DF	434.29	6.30	1.23	0.02	56.93	0.83	313.23	4.54	221.40	3.21
	LF	520.79	7.56	3.48	0.05	721.03	10.46	2744.22	39.81	181.85	2.64
	Agric	304.58	4.42	101.36	1.47	48.70	0.71	949.07	13.77	135.23	1.96
Mole	BLT	351.76	5.85	0.16	0.00	44.67	0.74	416.64	6.93	161.75	2.69
	WTR	0.03	5.16	0.19	0.00	37.33	0.62	39.88	0.66	3.75	0.06
	DF	234.98	3.91	0.26	0.00	127.98	2.13	240.25	3.99	339.94	5.65
	LF	339.25	5.64	0.11	0.00	27.38	0.46	378.03	6.29	135.10	2.25
	Agric	250.72	4.17	24.00	0.40	39.12	0.65	91.72	1.53	232.56	3.87
Nabogo	BLT	161.64	5.49	0.01	3.09	0.10	0.00	6.58	0.22	735.10	24.95
	WTR	0.12	0.00	1.20	0.04	5.65	0.19	35.54	1.21	77.85	2.64
	DV	71.37	1.18	0.03	0.00	6.74	0.23	51.50	1.75	63.60	2.16
	LV	14.84	0.50	0.21	0.01	49.75	1.69	275.17	9.34	169.30	5.75
	Agric	546.75	18.56	79.40	2.69	109.15	3.71	463.11	15.72	121.93	4.14
Nasia	BLT	207.93	3.97	0.01	1.22	0.09	0.00	20.76	0.40	277.70	5.31
	WTR	0.12	0.00	2.26	0.04	4.62	0.09	107.75	2.10	149.95	2.87
	DF	139.42	2.66	0.29	0.01	9.74	0.19	215.15	4.11	390.41	7.46
	LF	98.34	1.88	0.76	0.02	32.18	0.61	1961.52	37.48	162.72	3.11
	Agric	137.04	2.62	41.23	0.79	14.25	0.27	191.41	3.65	163.09	3.12

1995–2023 Sub-basins	LULC	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change	Area(km^2)	% change
Sissili	BLT	0.34	0.01	0.91	0.02	0.60	0.01	9.86	0.19	231.22	4.42
	WTR	0.11	0.00	0 53	0.01	1.61	0.03	97.09	1.86	6.91	0.13
	DF	0.03	6.64	0.01	2.10	12.49	0.24	81.57	1.56	75.19	1.44
	LF	11.74	0.23	1.57	0.03	0.85	0.02	1211.32	23.17	318.83	6.11
	Agric	205.19	3.92	70.19	1.34	153.85	2.94	114.77	2.20	300.84	5.75

livelihood from agriculture and its related activities [34, 38]. This activity was also considered the leading cause of land cover modification

Table 5: The Transition Matrix of LULC from 1995–2023 among the Sub-Basins of the WVB.Where; BLT=Built-up area, WTR=water bodies, DF=dense forest =light forest

3.4 Pattern of LULC changes among the nine Sub-Basins of the WVB.

The magnitude of degradation among the sub-basins was assessed (Fig. 3). The Kulpawn basin is considered the worst-impacted basin based on LULC analysis, with an annual percentage rate of change of 21.9% (1995–2023) compared to other sub-basins. This revelation may be driven by the high agricultural activities occurring in the basin due to the high rate of commercial agricultural activities in the area. Additionally, the sub-basin had some illegal gold mining activities in the catchment, which had attendant consequences on the river basin.

Most of the dense savannah forest has been converted into light savannah forest and bare land, particularly in the Kulpawn basin, at a rate of 28.34% (2230.48km^2 -3033.12km^2) as shown in Table 5. Additionally, the basin has experienced significant expansion of settlement patterns, making it the basin with the highest number of Metropolitan, Municipal, and District Assemblies[36, 43]. The Upper West region has eleven districts, with eight located in the sub-basin. This situation will naturally put pressure on the ecological resources in the sub-basin due to increased demand for infrastructure and associated socioeconomic needs, with cascading effects on the WVB.

The Nasia Basin (18.73%) was the second most severely affected basin (Fig. 3). This level of degradation could be linked to high agricultural activities, the expansion of settlements, and sand-winning activities. As shown in Table 5, more of the dense savannah forest is being converted into agricultural land and light savannah forest, from 139.42km^2-390.41km^2. These changes could be attributed to agriculture, deforestation, settlement expansion, and sand-winning activities, which agree with the findings by Nyadzi et al [33] in the Nasia sub-basin and Nasare et al [34] in the Middle White sub-basin.

The Mole sub-basin (14.44%) is the third most badly affected basin with agricultural activities, illegal mining, and expansion in built-up areas driving these changes. The Kpasenkpe sub-basin (12.14%) was the fourth most affected sub-basin, followed by the Lower White (10.56%), Sissili (9.32%), Middle White (6.93%), Nabogo (3.36%), and Gambaga (2.65%).

Largely, these changes observed at the individual sub-basin scale may be associated with an increase in croplands as dense savannah forest is converted into arable land. The activities of sand-winning, coupled with illegal mining activities, deforestation, and an increase in the commercial charcoal and firewood businesses in the area, could have contributed to these changes [35, 44]. Additionally, all these driving forces are propelled by high human population growth, with a multiplier effect on the dynamics of LULC in the basin [15]

3.4 Key Drivers of LULC Changes in the White Volta Basin

The driving forces behind the changes in LULC in the WVB were assessed across the nine sub-basins and identified as proximate and underlying factors responsible for the LULC transitions in the basin.

According to the catchment dwellers, the direct causes of LULC change among the riparian communities in the basin were agricultural activities, deforestation, extraction of fuelwood, mining, settlement expansion, bushfires, and overgrazing. The indirect driving forces were: human population growth, climate change, and poverty level (Table 6).

The respondents perceived agricultural activities as the main causes of LULC changes in the WVB, with a mean percentage of 17.81%, except in the Middle, Lower, and Mole sub-basins, which followed a different trend. Expansion in built-up areas was identified as the leading cause of LULC changes in the Middle White sub-basin, while artisanal small-scale mining was considered the major cause of LULC changes in the Lower White Volta basin. Fuelwood extraction dominated the Mole basin as a key driver of LULC changes. This may be attributed to the fact that communities within the sub-basin are predominantly rural, with agriculture serving as their primary economic activity [33, 46]. This activity results in the modification of the land, as most of the farming activities are carried out along the banks of the river. This observation is consistentwith the findings of Nsor et al [38] in the WVB. However, they diverge from that of Nasare et al [34], who concluded that sand-winning activities were the major drivers of LULC change in the middle section of the WVB.

Table 6
Inhabitants opinion on the causes of LULC in the White Volta Basin

LULC Driver/Causes										
Sub-Basin	Agric	Built-up	Mining	Fuelwood extraction	High population	Bushfires	Overgrazing	Deforestation	Climate change	Poverty level
Gambaga	80(20.0%)	53(13.25%)	25(6.25%)	19(4.75%)	42(10.50%)	38(9.50%)	27(6.75%)	40(10.00%)	63(15.70%)	13(3.25%)
Kpasenkpe	73(18.25)	46(11.50)	33(8.25)	54(13.50)	32(8.00)	41(10.25)	28(7.00)	35(8.75)	43(10.75)	15(3.75)
Kulpawn	78(19.50)	53(13.25)	41(10.25)	49(12.25)	51(12.75)	39(9.75)	26(6.50)	28(7.00)	22(5.50)	13(3.25)
Middle White	58(14.50)	74(18.50)	69(17.25)	28(7.00)	67(16.75)	23(5.75)	19(4.75)	17(4.25)	31(7.75)	14(3.50)
Lower White	67(16.75)	51(12.75)	70(17.50)	36(9.00)	42(10.50)	23(5.75)	28(7.00)	21(5.25)	45(11.25)	17(4.25)
Mole	52(13.00)	47(11.75)	54(13.50)	68(17.00)	53(13.25)	18(4.50)	15(3.75)	14(3.50)	59(14.75)	20(5.00)
Nabogo	78(19.50)	59(14.75)	29(7.25)	33(8.25)	52(13.00)	21(5.25)	29(7.25)	30(7.50)	41(10.25)	28(7.00)
Nasia	82(20.50)	66(16.50)	59(14.75)	31(7.75)	47(11.75)	18(4.50)	15(3.75)	26(6.50)	33(8.25)	23(5.75)
Sissili	73(18.25)	53(13.25)	60(15.00)	50(12.50)	40(10.00)	20(5.00)	17(4.25)	23(5.75)	42(10.50)	22(5.50)

Largely, expansion in built-up areas was the second leading cause of LULC in the WVB, with a mean percentage of 13.94%, as most rural communities are being transitioned into peri-urban centres due to their proximity to the district and regional capitals. Additionally, the creation of more districts and upgrades of the existing districts to municipal and metropolitan status are associated with infrastructure development, resulting in land clearing for these projects. These observations align with the findings by Kumah et al [43] who reported similar patterns of vegetation loss and land conversion. However, they contradict the conclusions of Tahiru et al [32] who identified cropland expansion as the primary driver of LULC change in the WVB.

High population growth and an increase in built-up areas were observed in the Middle White and Nasia sub-basins, which were responsible for the LULC changes in these basins. The increase in built-up areas will result in the clearing of land to pave the way for infrastructure development, converting grassland or forest into built-up areas [61, 62]. Mining activities such as sand and small-scale gold mining were identified by respondents as one of the causes, at the rate of 12.12%, of LULC changes. These activities result in extensive vegetation removal, which accelerates land cover changes. The extraction of these resources alters the natural landscape, often leaving it barren and susceptible to erosion, which leads to an increase in sediment levels in the river basin.

The respondents also reported that artisanal mining activities (i.e., gold and sand mining) were pervasive in the sub-basins, especially the Lower, Middle White, and Sissili sub-basins. These results are consistent with the findings of other authors [6, 16, 63].

Fuelwood extraction, climate change, bushfires, deforestation, and overgrazing were perceived by respondents as causes of land cover transition in the basin (10.22%, 10.50%, 6.69%, 6.50%, 5.64, and 4.58%). This assertion may be linked to the fact that the basin is considered an agrarian basin [36], where the majority of riparian communities are smallholder farmers who also depend on firewood and charcoal businesses as an additional source of income to supplement their farming activities, especially during the off-season. Some of the respondents also agreed that the felling of trees for timber, construction purposes, and other economic activities has serious negative ramifications on the vegetative cover of the area.

The Respondents agreed that high human population growth (11.83%) was one of the key underlying causes of LULC in the WVB. An increase in population will have a multiplier effect on the expansion of settlement and urbanization, changes in consumption patterns, high demand for energy, demand for construction materials, and lifestyle habits [64]. The majority of the population within the basin consists of rural communities with riparian households largely dependent on land resources for their livelihood support systems, with consequences on the trajectories of LULC dynamics in the area. This observation is consistent with the findings of [65] .

High poverty levels among riparian communities might have forced inhabitants to engage in unsustainable activities, which accelerated environmental degradation. Respondents also expressed their view that they may be tempted to engage in other unsustainable practices for their sustenance, such as charcoal production, fuel wood extraction, sand-winning, and other illegal mining activities, as a result of limited livelihood options for community members. As perceived by respondents, a poverty level of 4.58%, contributing to land cover degradation in the basin, suggests that even at relatively low levels of poverty, the impact on the environment can still be significant. Since some riparian communities engaged in the firewood business, charcoal burning, and unsustainable agricultural practices, group hunting, especially in the off-season, usually results in bushfires and other consequences, leading to serious transitions of the land cover in the basin. Respondents insist that these activities give them additional income and that families and individuals depend on these activities for their sustenance. They do not foresee these practices stopping soon unless deliberate interventions are implemented to create sustainable livelihood options for the riparian community. These findings are corroborated by the findings of Tengapoe et al [66], who reported that persistent dependence on riverine resources among riparian communities is likely to continue unless alternative and sustainable livelihood strategies are introduced.

3.5 Perceived Changes in LULC in the White Volta Basin

The views of respondents were assessed to determine the perceived changes in LULC over the last three decades in the WVB (Fig. 4) and the reasons behind those changes.

Interactions with respondents revealed that there was an increase in agricultural land of about 20% over the other classes of LULC in the area during the study period. This is consistent with the satellite images generated over that period and could be ascribed to the agrarian nature of the basin, as the majority of riparian households derive their livelihoods from agricultural activities. However, respondents also think government targeted policies and projects in the agricultural sector such as the Ghana Commercial Agricultural Project, the Rice Sector Support Project, the Savannah Zone Agricultural Improvement Productivity Project (SAPIP), the Savannah Investment Programme, and the Savannah Value Chain Development Project (SADEP), have led to the clearing of large tracts of lands for farming activities in the basin.

The findings also point to an increase in built-up areas (18%), which agrees with geospatial data generated for the same period. According to the respondents, a surge in the built-up areas could potentially be linked to population growth and the proximity of the basin to most of the district and regional capitals, which have seen most of the rural communities becoming peri-urban centres with high demand for infrastructure.

Light savannah forest areas in the basin continue to exhibit an increasing trend in land cover class (16%), and respondents noted that there has been a dramatic conversion of dense savannah forest to grasslands and shrubs over the last three decades, which was previously not the case. This finding may be attributed to the expansion of croplands and charcoal production activities and the felling of trees for firewood. Others also believed that the activities of illegal logging, especially rosewood businesses, have also contributed to the conversion of dense savannah forest into grasslands, which agrees with the findings of [39] and [40], who studied similar landscapes, and concluded that rampant harvesting of forest trees and unsustainable wood extraction have significantly accelerated the degradation of savannah woodlands, leading to extensive loss of tree cover and the expansion of grass-dominated landscapes across northern Ghana.

Respondents indicated that they have observed an increase in the size of water bodies (15%) over bare lands (13%), plantations (12%), and dense savannah vegetation (6%). The findings contradict the remote sensing data, which indicated a sharp decrease in the size of the river water across entire sections of the basin. This decline in water bodies, as revealed by the geospatial data (Table 4), aligns with similar studies by [34, 38] who concluded that the reduction in surface water extent in WVB was largely driven by agricultural expansion, deforestation, and prolonged dry spells associated with climate variability, which are the key drivers of LULC. These findings reinforce the effects of anthropogenic and climatic factors are jointly contributing to the shrinkage of water resources within the basin. Respondents also revealed that areas that were not usually covered by water are now inundated with water, especially in the rainy season, which is an indication of an increase in water bodies in their opinion. However, this perceived increase in water bodies may not be adequate but may be attributable to the annual spillage of the Bagri Dam from Burkina, coupled with the impacts of harsh climatic conditions [67]. Additionally, sand-winning and other anthropogenic activities have resulted in the removal of riparian vegetative cover along the river's banks, resulting in high siltation [34]. It is also believed that the high siltation rate in the river bodies may be an indication of low vegetative cover along the banks of the river, reducing the capacity of the river to hold the right volume of water [34, 38].

Increased bare land area is becoming a serious challenge, especially in areas where sand and mining activities are being conducted, as this impairs the water quality and quantity. Respondents indicated that not much has changed, with an increase in plantations over the years. However, there have been some interventions by the government in the study areas to increase the vegetative cover through the establishment of plantation schemes, which have not made a lot of impact, especially when the project ends. Some of these problems may be linked to sustainability issues, especially when they are communal.

This study further revealed that there has been a decreasing pattern of the savannah forest to other land use categories in the basin. This is likely to impair biodiversity and ecosystem services in the basin and its associated consequences on the water quality and quantity, as well as making the basin more vulnerable to the impacts of climate change. This finding is consistent with those reported by Tahiru et al [32] and Nyadzi et al [33], who also observed similar patterns of LULC changes in the basin.

3.6 Limitations and Future Direction

Despite the accuracy achieved in the LULC classification process, several sources of uncertainty may persist, which are likely to influence the reliability of the results and subsequent hydrological analysis. These uncertainties may arise from the nature of the satellite data, the classification models, and parameter assumptions in the modelling process.

Cloud contamination, atmospheric disturbances, and sensor noise are common issues in remote sensing, especially in tropical regions like WVB, where cloud cover is often prevalent during the rainy season. These factors can influence surface features and introduce misclassifications in certain land cover types, particularly water bodies, wetlands, and sparsely vegetated areas. Despite the use of cloud-masking algorithms or data compositing techniques, residual noise may still affect classification accuracy.

In supervised classification techniques, uncertainty may stem from ground data collected during field surveys not perfectly aligning with the satellite acquisition date, potentially introducing errors related to seasonal variations. For instance, dense savannah and light savannah forest may have overlapping spectral signatures, leading to misclassification. In addressing these limitations, recent studies advocated for the use of ensemble learning approaches implemented through Google Earth Engine (GEE). The Ensemble methods, such as Random Forest (RF), Gradient Boosted Trees, and Support Vector Machines (SVM), either individually or in combination, have shown improved robustness and classification accuracy, particularly when integrated with multi-temporal and multi-source datasets such as Sentinel-2, Landsat-8, and MODIS [50]. Several recent publications by Wang et al [51] and Abdali et al [52] have demonstrated the use of GEE-based platforms to analyze large-scale LULC classification, combine optical and radar imagery, incorporate ancillary data, and apply pixel-based uncertainty quantification.

Future studies in the WVB should consider adopting these ensemble-based approaches to improve classification accuracy, especially in the savannah ecological zone. Leveraging the computational efficiency and data availability in Google Earth Engine, coupled with ensemble machine learning methods,

would significantly enhance the scalability, accuracy, and reproducibility of LULC classifications in the savannah ecological zone of Ghana and other similar landscapes

4. Conclusion and Recommendation

An assessment of LULCCs across the nine sub-basins in the WVB from 1995 to 2023 revealed significant transformations with implications for the ecosystem and human wellbeing. Built-up areas showed an increased pattern across all the sub-basins, with the Middle White basin showing the highest expansion rate of 13.21%. Cropland also increased across all the sub-basins, with the increment primarily linked to the agrarian nature of the basin, and with the majority of the riparian community depending on the river basin for their livelihoods.

The key drivers of LULC in the basin were identified as agricultural activities, expansion in built-up areas, human population growth, artisanal mining, fuelwood extraction, and deforestation. The assessment of the magnitude of degradation among the sub-basins ranked the Kulpawn sub-basin as the most severely degraded basin (21.9%) and the Gambaga sub-basin as the least affected sub-basin (9.56%).

To ensure the sustainable management of the WVB and to provide immediate solutions to the hotspot basins identified, there must be targeted and concerted efforts by stakeholders (government, regulatory bodies, district assemblies, and individuals) to develop and implement integrated and comprehensive land management policies that integrate ecological considerations, sustainable agriculture practices, and urban planning to mitigate further LULC changes.

4.1 Policy and Management Implications

- These findings provide critical information for the management and policy formulation in the WVB, which are targeted at promoting ecological restoration interventions, such as reforestation, agroforestry, and riparian buffer zone protection. For the identified worst-degraded sub-basins (Kulpawn, Nasia, Lower White, and Kpasenkpe), agricultural activities identified as the major driver of degradation in the WVB can be mitigated through the promotion of sustainable land and water management (SLM) practices such as conservation agriculture, land-use planning, controlled burning, composting, and minimal tillage to address soil erosion challenges, preserve soil fertility, and enhance water conservation and retention.
- It is also imperative to integrate urban planning with green infrastructure that will promote sustainable development. This can be achieved through spatial planning and the enforcement of land-use regulations to prevent encroachment on ecologically sensitive areas in response to an increase in built-up areas in the basin.
- Additionally, the research highlights the need for inclusive governance frameworks that empower local communities to manage their natural resources. This promotes local environmental management and resilience among riparian communities.
- These findings provide a spatially explicit baseline for policymakers, the Water Resources Commission, White Volta River Authority, and other relevant stakeholders to design evidence-based interventions that reflect the unique challenges and the environmental conditions of each sub-basin. The application of these findings serves as a practical decision-support tool for promoting sustainable development, enhancing ecological resilience, and guiding integrated watershed management in the WVB and similar ecosystems facing land cover change pressures.

Declarations

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Data Availability

All data used in the study is available on request

Authors contribution

Zakari Osman: Conceptualization, Methodology, Investigation, Data curation, Writing, Formal analysis, Visualization. **Charles Gyamfi:** Methodology, Software, Data curation, Writing and reviews, editing, and supervision. **Boakye Ebenezer**: Methodology, data curation, writing and editing, Supervision, and visualization. **Ofosu Samuel:** Methodology, Software, Validation, writing, Supervision, Reviewing and Editing. **Bernard N. Baatuuwie:** Writing- Reviewing and Editing, Methodology, data curation

Ethics approval and consent to participate

The Humanities and Social Science Research Ethics Committee (HUSSREC) of KNUST granted ethical approval, and the study complied with the Declaration of Helsinki and institutional ethical guidelines. Participation was voluntary, and informed consent was obtained from all respondents. Participants were informed of the study's purpose, their right to withdraw at any time, and the measures in place to ensure confidentiality. No personal identifiers were collected, and all data were analyzed and reported in aggregate to maintain anonymity and protect privacy.

Consent for publication

Not applicable. This manuscript does not contain any person's identifiable data, images, or personal information.

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Competing interests

The authors declare no competing interests.

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Figures

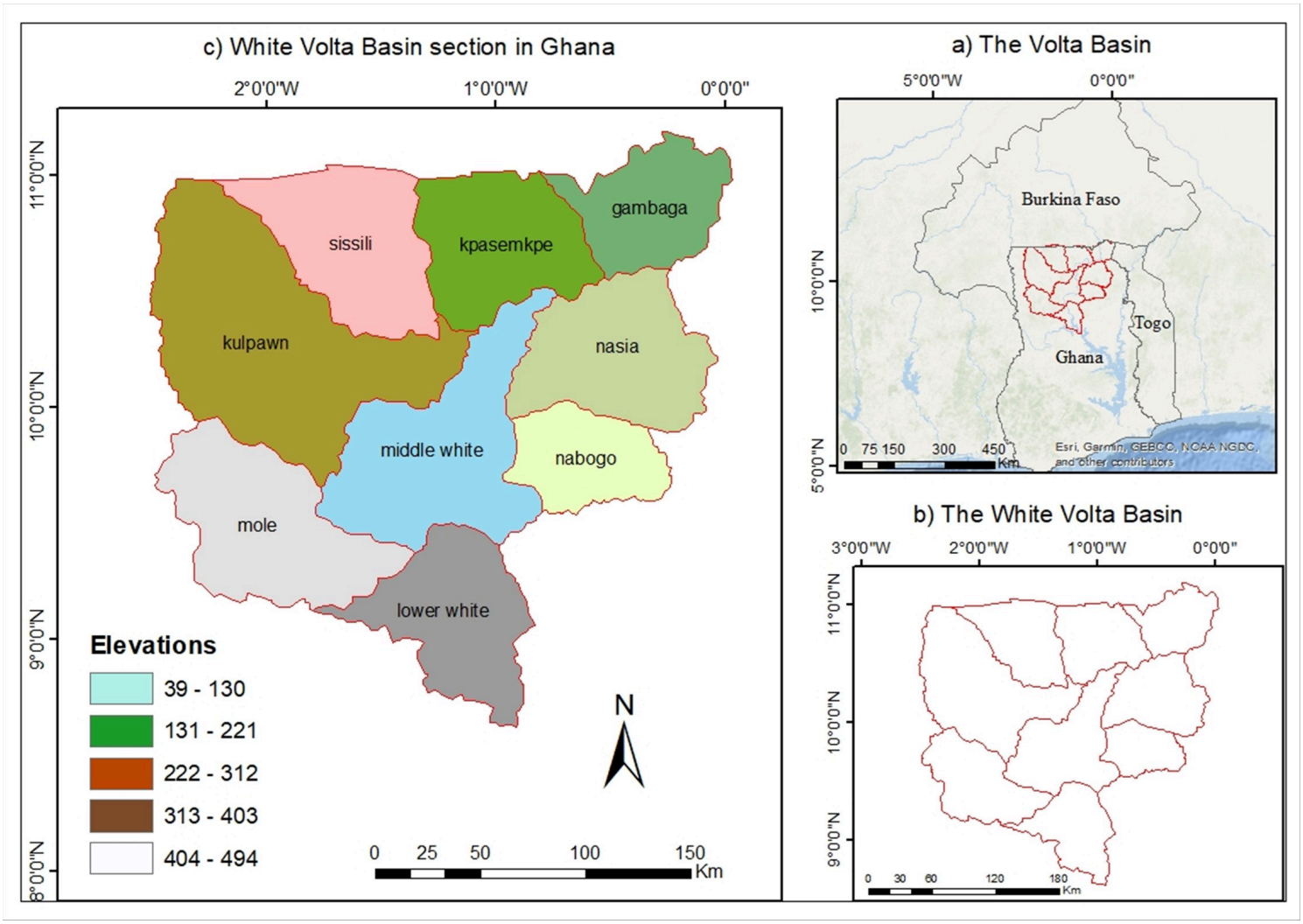


Figure 1

White Volta Basin depicting the nine sub-basins

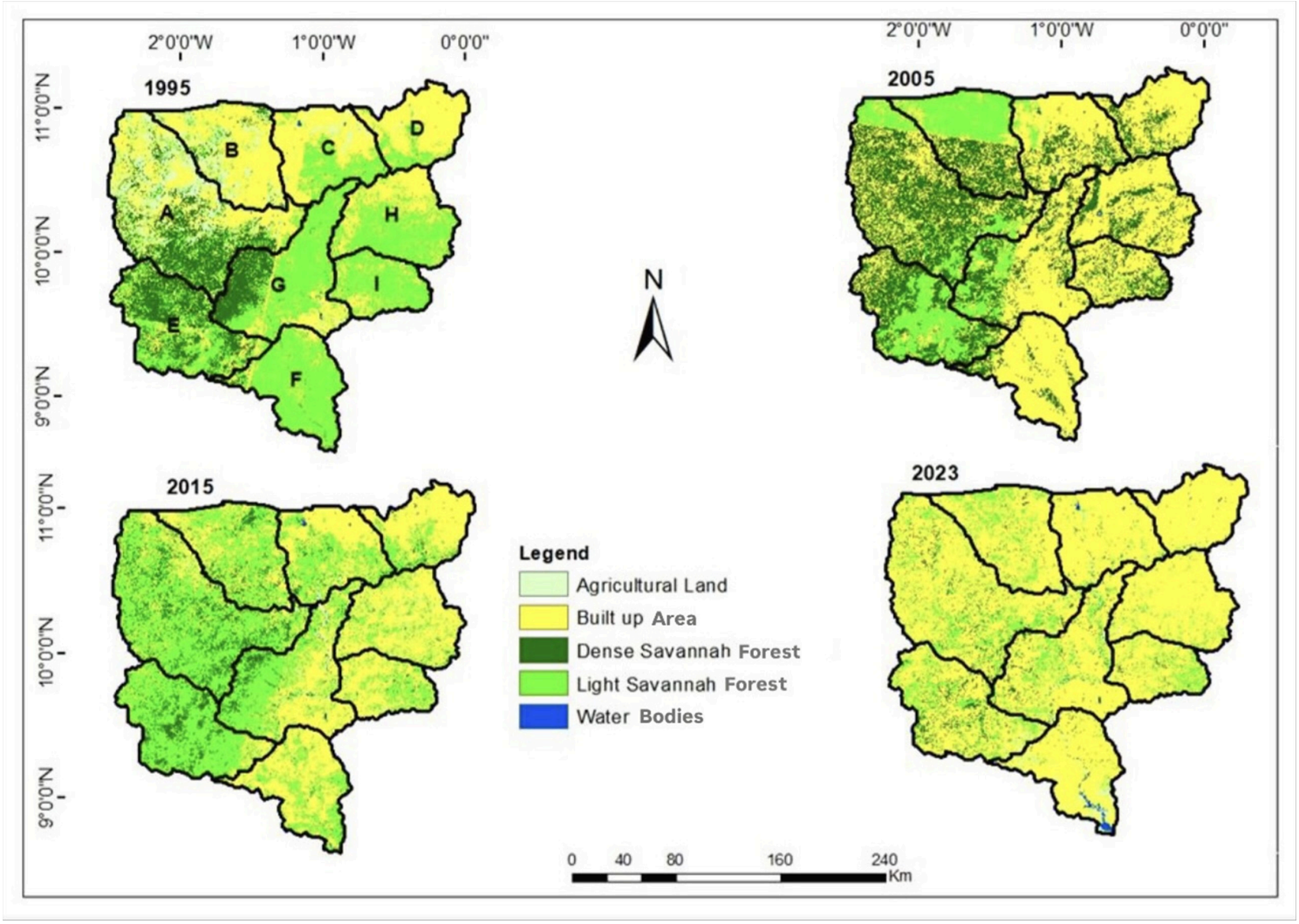


Figure 2

LULC maps for nine sub-basins within the WVB for 1995, 2005, 2015, and 2023. Where A) Kulpawn, B) Sissili, C) Kpasenkpe, D) Gambaga, E) Mole, F) Lower White, G) Middle White, H) Nasia, and I) Nabogo

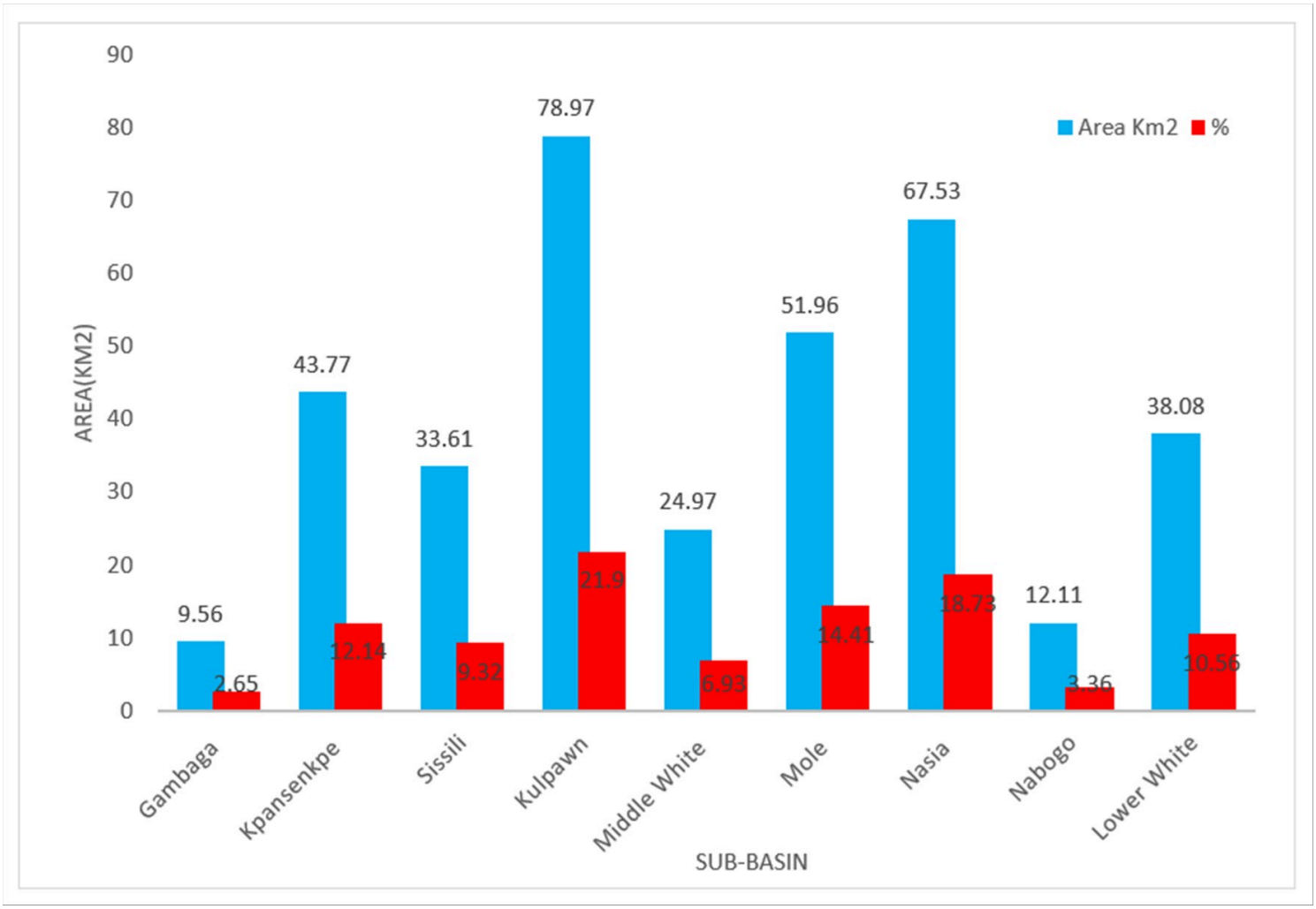


Figure 3

Area of sub-basins affected by LULCCs from 1995 to 2023

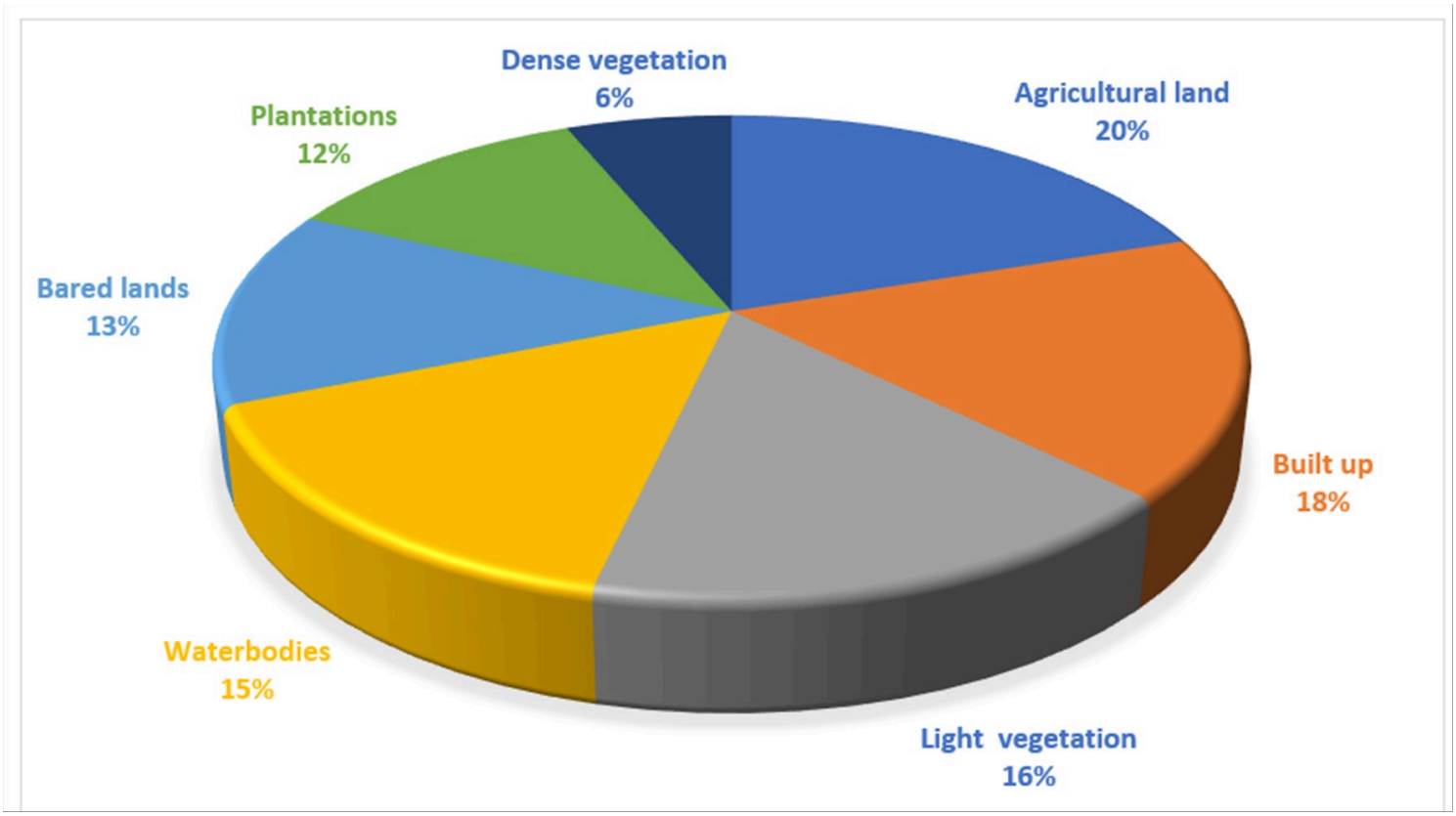


Figure 4

Respondents' views on the changes in LULC Classes in the WVB