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ASSESSING LAND COVER CHANGE IN LANGTANG – SOUTH LOCAL GOVERNMENT AREA, PLATEAU STATE, NIGERIA USING GIS AND REMOTE SENSING TOOLS: A CASE STUDY APPROACH.

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ABSTRACT

This study investigates land use and land cover changes LULC in Langtang South Local Government Area, Plateau State, Nigeria, over a 15-year period (2007–2022). Landsat 7 satellite imagery was sourced from the USGS EROS database for December 7, 2007 (Image ID: 200701207_02), and December 9, 2022 (Image ID: 20221209_02). The imagery was processed and analyzed using ArcGIS 10.3.1 software to examine spatial and temporal land cover change variations within the study area. Findings revealed notable LULC dynamics. Bare land increased significantly from 1.76% in 2007 to 7.05% in 2022, suggesting rising land degradation. Farmland, which dominated in 2007, declined substantially from 75.59% to 66.75%, indicating potential shifts in agricultural practices or land conversion. Settlement areas saw a modest rise, increasing from 0.16% to 0.57%, reflective of urban expansion. Vegetation cover experienced a positive change, growing from 22.27% to 25.13%, likely due to reforestation or conservation efforts. Water bodies also increased slightly from 0.21% to 0.51%, potentially influenced by improved rainfall or water management systems. The confusion matrix analysis revealed classification challenges, particularly between bare land and farmland, settlement and vegetation, and vegetation and water bodies, highlighting the need for advanced classification techniques to improve accuracy. To address the observed changes, the study suggests the implementation of sustainable land use policies, reforestation programs, and urban planning strategies to mitigate land degradation and promote environmental stability. Additionally, integrating local communities in land management decisions can foster long-term conservation goals and reduce the impacts of urbanization and agriculture on land cover.

Keywords: *Environment, GIS and remote sensing, Impact, Land cover change, Langtang-South Sustainable*

1. INTRODUCTION

A major global concern, land cover change has profound effects on both human livelihoods and the sustainability of the environment (Gebrehiwot et al., 2024). For instance, rapid urbanization, agricultural growth, and deforestation have fundamentally changed natural landscapes around the world, causing ecological disruption, biodiversity loss, and climate change (Singh, 2021; Hussain et al., 2024). Furthermore, demand on ecosystems has increased in recent decades and humans continue to depend on ecosystems for a variety of commodities and services that are necessary for their survival and well-being (Xu et al., 2024). Consequently, global ecosystems have severely degraded as a result, causing irreparable losses (Cabral et al., 2016; Zhang, Ren &

Peng, 2022). It has been estimated that, 62%of land areas worldwide have seen major land use change, with an increasing percentage of land being converted to croplands, urban areas, and built-up regions (Afuye et al., 2022; Mpanyaro et al., 2024; Afuye et al., 2024). Moreover, the GLC_FCS30D dataset highlights that globally, from 1985 to 2022, forest areas have decreased by about 2.5 million km², while cropland has increased by approximately 1.3 million km² (Zhao et al., 2024). Such disruptions which can vary in frequency and intensity, influencing different aspects of the environment and altering land use and land cover (LULC) change, which in turn affects deforestation, food security, and ecosystem service function (Ambarwulan et al., 2023).

Land cover refers to the physical characteristics of the earth's surface, captured in the distribution of vegetation, soil, water and other physical features of the earth whereas; land use is the way in which land has been used by humans and their habitat, usually with an emphasis on the role of land for economic activities (Akumu, Dennis, & Reddy, 2018; Liping et al., 2018;). However, land cover/land use are often used interchangeably (Akumu, Dennis & Reddy, 2018; Liping et al., 2018). As earlier stated, global land cover change is caused by a complicated web of interrelated variables, with human activity having the biggest impact (Admasu, Yeshitela & Argaw, 2023; Buthelezi et al., 2024). Urbanization, economic factors, environmental changes, and agricultural expansion are important drivers. For example, with considerable deforestation and wetland drainage taking place worldwide, agricultural conversion is a major contributor to changes in land cover (Renaud et al., 2021). For instance, around 7.6 million km² of land changed as a result of agricultural expansion between 1960 and 2019, especially in the Global South, which includes places like South America and Africa (She, 2022).

Changing land use patterns and increasing impervious surfaces, rapid urbanization contributes to land cover change, impacts local hydrology and ecosystems (Renaud et al., 2021). In emerging nations, where land conversion is fueled by population pressures, urban expansion is especially noticeable (Jabbour & Hunsberger, 2014). Moreover, significant changes are revealed by the global estimate of land cover change brought on by urbanization, especially between 1985 and 2015, with impervious surfaces increasing 32.91% in China's main cities (Ding et al., 2022). According to Liu et al. (2020), global urban land expanded by approximately 9,687 km² annually, four times faster than previous estimates. Land use and land cover change (LULCC) are also greatly influenced by environmental changes, such as changes in the climate, natural disasters, and soil degradation (Mook & Swanson, 2024). Climate change affects land cover and agricultural operations by changing temperature and precipitation patterns. Land degradation and changes in land use are caused by an increase in the frequency of extreme weather events, such as hurricanes and droughts (Mook & Swanson, 2024).

1.2 Literature Review

Studying land cover change using Geographic Information System (GIS) and remote sensing techniques have become more and more important for efficient resource management and urban planning (Raihan, 2023; Younes et al., 2024). Researchers may analyze both historical and present land cover data using GIS, which makes it simpler to identify trends and patterns across time (Aldea, Aldea & Perju, 2019; Puziene, 2024). This synthesis of data from many sources enables thorough assessments of land use and land cover changes, which is crucial for sustainable development and environmental protection (Ewane et al., 2023). Several GIS and remote sensing tools are used to monitor changes in land cover, which improves knowledge of land use dynamics. These applications offer insights on changes in the environment by using data from remote sensing and complex analytical methods. In order to categorize and track changes in land cover, remote sensing systems such as Landsat, Sentinel-2, MODIS, and ASTER amongst others, are essential (Dhillon et al., 2023; Rohith et al., 2023; Perez-Guerra et al., 2023; Aljanabi, Dedeoğlu & Şeker, 2024). Geographic Information Systems (GIS) tools are essential for classifying and tracking changes in land cover (Karandikar & Agrawal, 2023; Kumar, 2023; Kyle et al., 2024). Recent studies have made use of a variety of platforms, such as ArcGIS, QGIS, GRASS GIS, Google Earth Engine (GEE), and MapInfo amongst others (Chen, Yang, & Wu, 2023; Lemenkova, 2023; Sameer & Hamid, 2023; Tiwari, Pal & Kanchan, 2024). To improve mapping and analysis of land cover, these tools allow researchers to integrate remote sensing data with machine learning techniques, allowing them to produce precise and timely land cover classifications (Shanmugapriya et al., 2024; Shaik, Shaik, & Priya, 2024).

Socioeconomic factors such as population growth, uncontrolled land use, and economic expansion are the main causes of Africa's severe land cover problems (Sembosi, 2019; Olorunfemi, et al., 2022; Simon, Lyimo & Yamungu, 2023). Significant changes in land use have resulted from these dynamics, especially in metropolitan areas where built-up land has grown dramatically, frequently at the expense of agricultural land (Faye & Du, 2022). Around 75 million hectares of forest were lost between 1990 and 2010 as a result of agricultural development, making agriculture the main cause of land use change and responsible for 70–80% of Africa's total forest loss (Olorunfemi et al., 2022). Effective management is made more difficult by the intricacy of mapping land cover in areas such as the African savanna, where the available data is frequently limited and low resolution (Song et al., 2023). In Africa, GIS and remote sensing technologies are becoming indispensable instruments for evaluating changes in land use and land cover (LULC), greatly assisting policymakers in creating sustainable management plans. By making it easier to track the effects of urbanization on the environment, these technologies aid in making well-informed decisions (Damoah-Afari et al., 2023; Mashala et al., 2023; Cardenas-Ritzert et al., 2024).

Nigeria exemplifies a country grappling with significant land cover changes due to various human activities, including logging, agricultural expansion, and urbanization (Lawal, Buba, & Awe-Peter, 2024; Akinyemi & Speranza, 2024). These activities have particularly impacted forested and rural areas, leading to deforestation and environmental degradation. The consequences include loss of biodiversity, soil erosion, and changes in microclimatic conditions. Between 2000 and 2022, Nigeria's cropland virtually increased from 22% to 37%, which resulted in a significant drop in tree cover from 50% to 31% and wetland from 7% to 3.7% (Akinyemi & Speranza, 2024). Despite the urgent need for precise monitoring, comprehensive studies that use advanced GIS and remote sensing methods to track land cover change remain limited in Nigeria (Aliero et al., 2019; Wuyep et al., 2020). This study aims to apply these technologies to assess the extent and dynamics of land cover changes, focusing on Langtang Local Government Area (LGA) in Plateau State. The results will provide insights that can inform local and national land management practices and support efforts toward sustainable development.

2. MATERIALS AND METHODS

2.1 Description of the study area

Langtang South Local Government is one of the seventeen local government areas (LGAs) in Plateau State, Nigeria. It is located between Latitudes 8^0 20’ N and 9^0 40’ N; and between longitudes 9^0 30 and 10^0 10’ E. The administrative headquarters of this LGA is at Mabudi. Lashel

Timbol, Sabon Gida, Dadin Gowa, and Turaki are the four districts that make up Langtang South LGA (Iwuagwu, et al., 2023). Because of paucity of data on land cover change in Langtang South, the area was selected for the study. In 2006, the population of Langtang South was 105,173 (Federal Republic of Nigeria Official Gazette No. 2, Vol. 96, 2009). However, projected population for the area obtained from the national population commission (NPC) indicate the following: 2007 n=111,231, 2008 n= 117,637, 2023 n= 288, 186, and 2024 n= 304,785 (NPC Jos office, 2024).

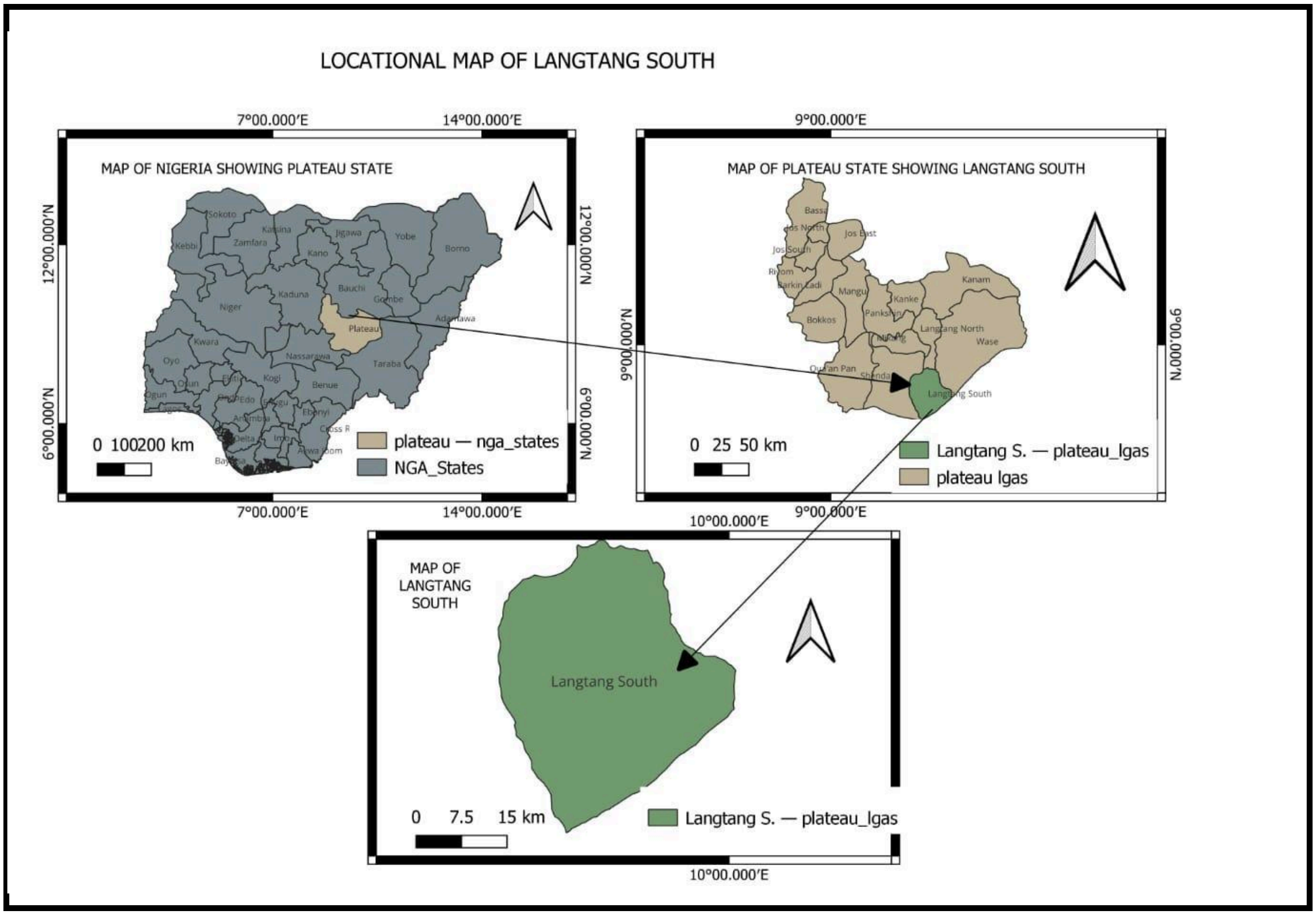

Figure 1: Map of Plateau State showing Langtang South local government area

The region has a tropical savanna climate with distinct dry and wet seasons. November through March is the dry season, and April through October is the wet season (Ali et al., 2022). The harmattan, which begins in October or November and lasts until roughly the middle of March, is a characteristic feature of the dry season. Rainfall peaks between July and September, with an annual total of 1000–1200 mm (Ali et al., 2022). Because of the high radiation income that is spread out quite equally throughout the year, the temperature in this area is high all year round (Ali et al., 2022). December and January often have the lowest temperatures, averaging 26°C, while April typically has the highest temperatures, with a maximum of 38°C (Badamasi et al., 2021). The main drainages in the region are the Wase and Shemankar rivers, as well as their dendritic-pattern tributaries, Pil-Gani, Bapkwai, Zamko, etc. (Ali et al., 2022). Due to human interference through land clearance and burning for farming, firewood, and grazing, the natural vegetation, which was composed of tall trees interspersed with tall grasses, has been replaced by a grassy savannah with sporadic bushes. (Ali et al., 2022). Though the ancient woodland vegetation (gallery forest) is still present along important waterways, this led to regrowth of vegetation at different levels. The majority of trees are deciduous, such as baobab, isoberlina, locust beans, and shea butter. (Ali et al., 2022). Since more than 80% of the population resides there, agricultural farming dominates the area's land use, followed by towns and livestock grazing. Maize, guinea corn, millet, rice, groundnuts, soy beans, yam, and hot and sweet peppers are the principal crops grown using primarily non-mechanized farming methods (Badamasi et al., 2021).

2.2 **Data acquisition**

In conducting research of this nature, various steps were undertaken to acquire the necessary data. Landsat 7 imagery was accessed from the USGS EROS website for two specific dates: December 7, 2007 (Image ID200701207_02) and December 09, 2022 (Image ID- 20221209_02). These images covered the same path and row (189/53), aligning with the study area. All acquired data were projected to a Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 32 north, ensuring consistency and accurate spatial analysis. Using ArcGIS 10.3.1 software. The study area, Langtang South LGA in Plateau State, was extracted from the Landsat imagery to focus specifically on this region for analysis.

2.3 Data processing

The following preprocessing steps were performed using ArcMap 10.3.1 software. All acquired data were projected to a Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 32 north, ensuring consistency and accurate spatial analysis. Using ArcGIS 10.3.1 software, the study area, Langtang South LGA in Plateau State, was extracted from the Landsat imagery to focus specifically on this region for analysis.

2.4 Image analysis and vegetation classification

To analyze the satellite images and classify vegetation cover accurately, the following steps were followed. Standard false-color **(FCC)** composites were created by applying appropriate band combinations to enhance the visualization of vegetation. The study area was extracted from the false-color composites using ArcGIS 10.3.1 software, focusing exclusively on Langtang South LGA for subsequent analysis. Supervised classification was performed using ArcMap 10.3.1 software by separating each band and using sampled data to identify and classify different land cover types such as bare land, vegetation, water bodies, and built-up areas.

2.5 Georeferencing and shapefile creation

In establishing a reference framework for the study area, the 1:250,000 scale topographic map was georeferenced using ArcMap 10.3.1 software, aligning the map with the appropriate spatial georeference system using dereferencing control points. Beside, based on the Geo-reference topographic map, a shape file was created to accurately demarcate the catchment area of Langtang South LGA, serving as a boundary for the study.

2.6 Data analysis and change detection

To analyze vegetation cover and detect changes over the 15-year period, the following approaches were employed. The Landsat images from 2007 and 2022 were visually compared to identify changes in vegetation cover, observing differences in vegetation patterns and conducting a qualitative analysis. Quantitative analysis techniques such as image differencing and vegetation indices (e.g., NDVI) were utilized in ArcMap 10.3.1 software to detect and measure changes in vegetation cover accurately.

3. RESULTS AND DISCUSSION

The research findings identified five types of land cover in the study area: settlements, bare land, vegetation, water bodies, and farmland (Figures 2, 3, 4, and 5). These findings highlight significant changes in land cover types in Langtang South over the study period, as shown in Table 1. Table 1 provides a detailed analysis of the percentage distribution of different land cover types in Langtang South for the years 2007 and 2022. The values indicate how the proportions of each land cover type have changed over time. For instance, from 1.76% in 2007 to 7.05% in 2022, the percentage of bare land increased significantly, indicating a major change in land cover that was probably caused by human activities. These findings agree with several other studies where bare land increased over time (Ying et al., 2017; Demattê et al., 2020; Tsheko, 2022). Numerous studies have shown that habitat degradation and the increase in bare land frequently result in a decline in the local flora and fauna (Ekka, et al., 2023; Edosa & Nagasa, 2024; Krištín, Hoi & Kaňuch, 2024). Furthermore, exposed land can lead to soil erosion and degradation, which can affect water retention and agricultural output (Guangyi, 2014). By decreasing carbon sequestration capacity and raising surface temperatures, bare land can worsen the effects of climate change (Capolupo et al., 2020). Increased bare land also has an impact on the ecosystem since the loss of vegetation changes the local hydrology, which may result in more flooding and less groundwater recharge (Kahlon, 2015).

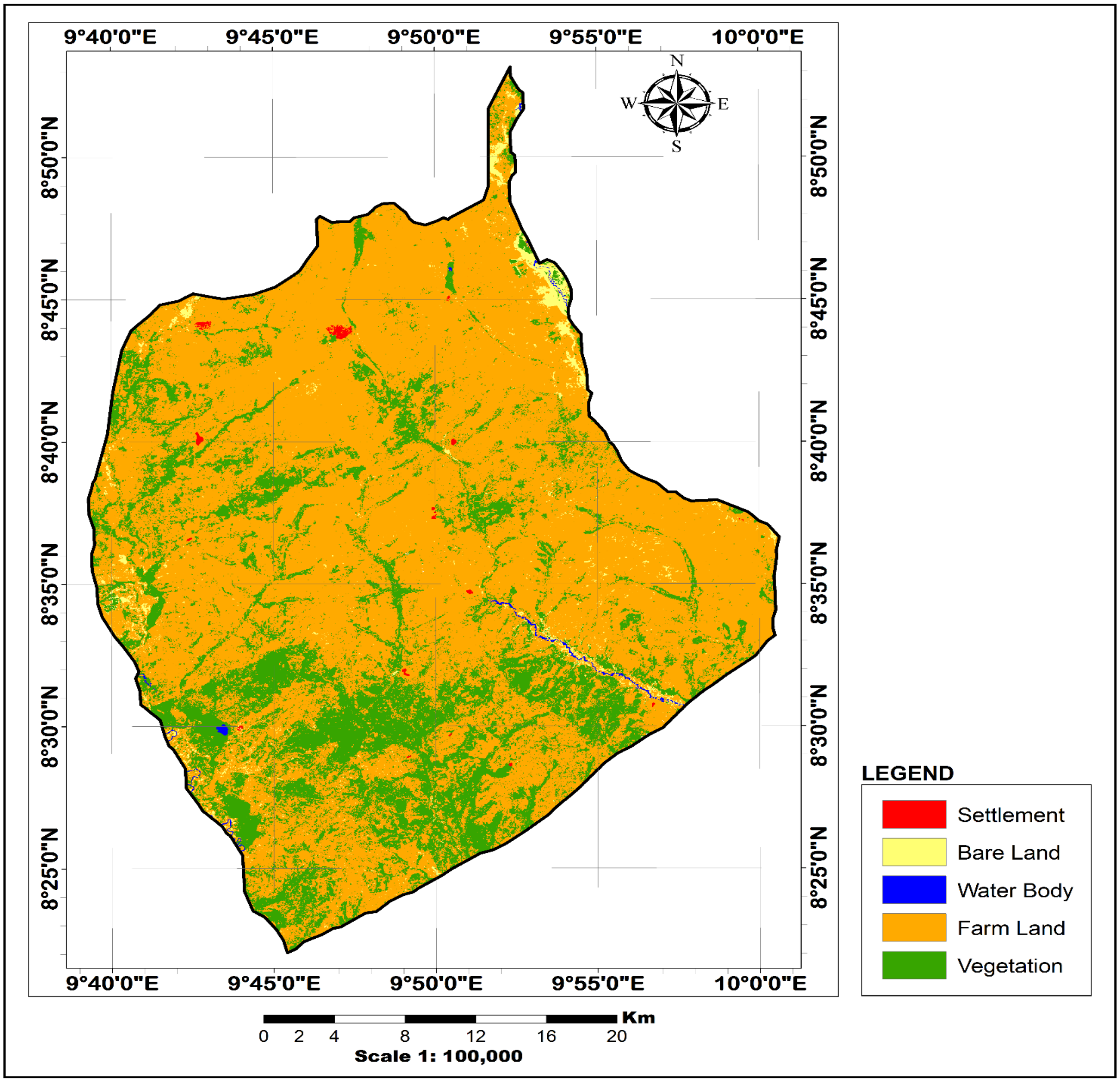

Figure 2: Supervised classification of the study area (December, 2007)

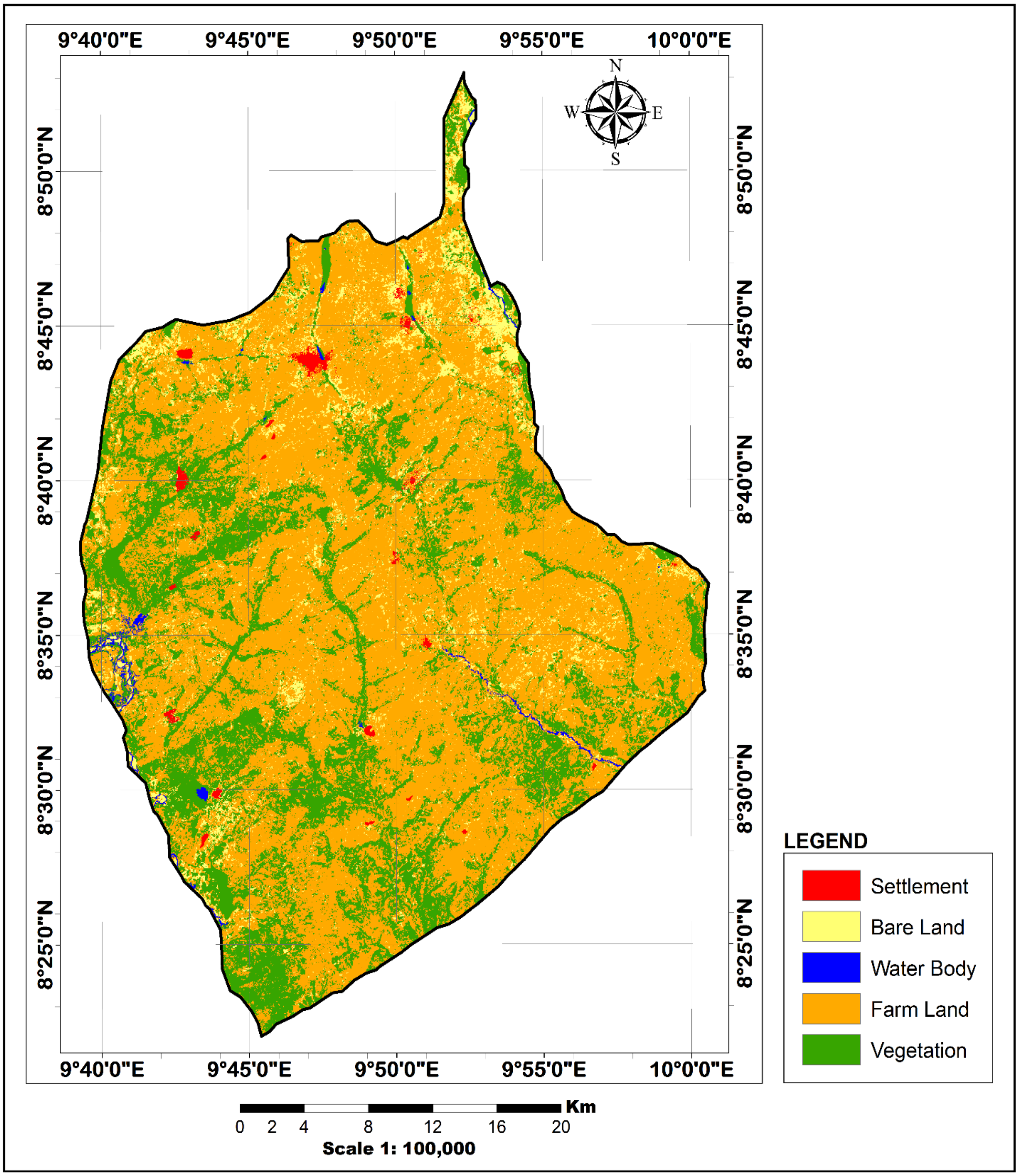

Figure 3: Supervised classification of the study area (November, 2022)

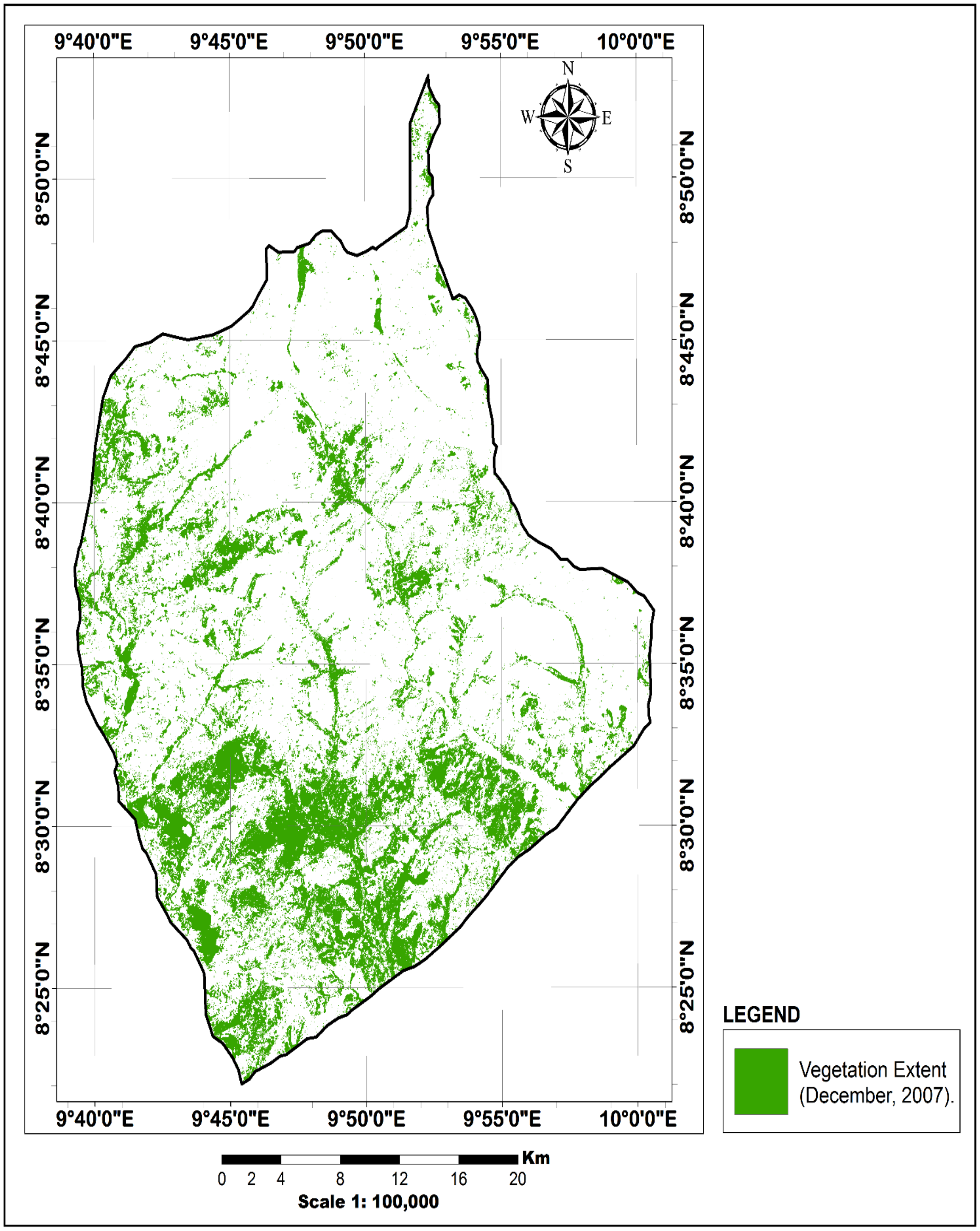

Figure 4: Vegetation extent of the study area (December, 2007)

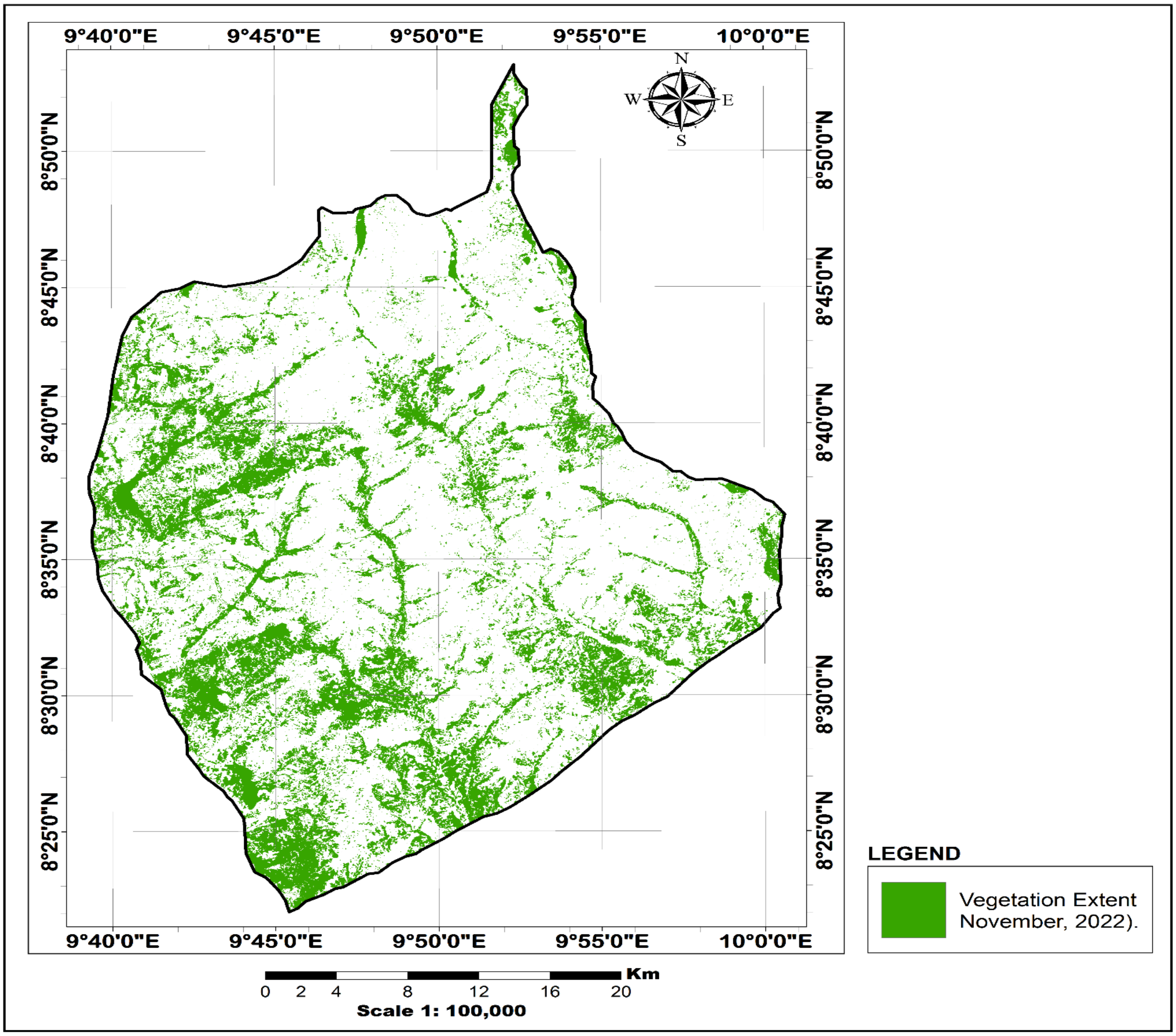

Figure 5: Vegetation extent of the study area (November, 2022)

A fundamental change in land use is shown by the notable decline in farmland from 75.59% in 2007 to 66.75% in 2022 (Table 1). This shift suggests that agricultural productivity may be under pressure, and that urbanization, industrialization, and other non-agricultural land uses may become more competitive (Raza et al., 2024). This may have a considerable impact on environmental sustainability and agricultural output. For example, studies have shown that land conversion in different regions might result in an average yield fall of 10%, which indicates that the loss of agricultural land can result in lower crop yields (Raza et al., 2024). Moreover, Food security becomes a critical issue when agricultural land shrinks, and sustainable land management techniques are required to lessen these impacts (Thawaba et al., 2017; Raza et al., 2024). Also, Farmland conversion to urban or industrial uses can lead to a rise in soil salinity and deterioration of soil quality, which can further affect agricultural productivity (Raza et al., 2024). The result of this study is similar to those obtained in several studies (Shifaw et al., 2019; Hussain et al., 2020).

In Table 1, the percentage of settlement areas has experienced a modest increase, from 0.16% in 2007 to 0.57% in 2022. This suggests a notable trend in urbanization and land use change, reflecting broader socio-economic dynamics. This modest rise indicates a shift towards more built environments, which can have significant implications for local ecosystems, resource management, and urban planning. Several studies with a similar result abound. For example, Ding et al. (2022) in their study on Land cover change in Shenzhen, China observed that, between 1979 and 2022, urban areas increased by 756.84 km2, showing significant urban sprawl and a commensurate decline in water bodies and vegetation. Another study In Jodhpur, India, by (Ram & Sheikh, 2023) revealed that urban land usage has proliferated as a result of swift urbanization, propelled by population increase and infrastructural demands, resulting in the transformation of agricultural land into developed regions. Slight increase in settlement areas represents a slow increase in the population or urbanization, reflecting increased human activities like housing, infrastructure development, and economic centers, which may lead to a decrease in the amount of natural or agricultural lands available (Schiavina et al., 2022). Growing populations are frequently associated with increased urbanization, which calls for more housing and services (Ram & Sheikh, 2023). By generating jobs and enhancing infrastructure, urban growth can boost regional economies (Abuelaish, 2018). This increase in settlements could also have an environmental implication. For instance, several studies have shown that habitat loss and decreased biodiversity might result from land conversion to settlements (Ettehadi & Kaya, 2017; Imaitor-Uku et al., 2021).

Vegetation cover increased significantly from 22.27% in 2007 to 25.13% in 2022 (Table 1, and Figure 5), indicating either successful reforestation or afforestation activities, natural vegetation recovery, or a decrease in anthropogenic pressures like deforestation. This is shown by the increase in vegetation cover which reflects broader patterns seen in several regions. Numerous studies that emphasize the importance of changes in vegetation cover throughout time corroborate this tendency. For example, vegetation Trend Analysis and Change Quantification based on Time Series Satellite data for Northeast India" (Nishant et al., 2022) used NDVI data to examine long-term vegetation changes and found nonlinear trends and positive anomalies in some areas. Moreover, research conducted in Mongolia, between 2006 and 2017, NDVI values increased in 89.03% of the studied region, indicating that vegetation was regenerating despite the difficulties caused by desertification (Ariya & Khurelbaatar, 2020). Due mostly to climate change, China has

seen a notable rise in vegetation cover over the past 20 years, with notable increases in NDVI across different vegetation zones (Xu et al., 2023). Once the vegetation cover increases historically, the impacts are far reaching. For example, Sapkota and Dahal. (2024) submitted that increased vegetation cover can improve habitat for a variety of species, fostering biodiversity and ecological resilience. Furthermore, better water retention and quality can result from increased vegetation's ability to improve soil quality and lessen erosion (Li & Gao, 2023). Additionally, significant increase in vegetation cover suggests favorable ecological changes, such as better environmental conditions, efficient management techniques, or successful restoration initiatives, all of which can boost the region's biodiversity and ecosystem services (Kushwaha et al., 2025).

Table 1: Changes in Land Cover Types in Langtang South Within the Study Period

S/No	CLASS	AREAL EXTENT (YEAR 2007)	PERCENTAGE DISTRIBUTION OF CLASS IN 2007	AREAL EXTENT (YEAR 2022)	PERCENTAGE DISTRIBUTION OF CLASS IN 2022
1	Bare Land	21.10	1.76	84.44	7.05
2	Farm Land	905.53	75.59	799.58	66.75
3	Settlement	1.97	0.16	6.80	0.57
4	Vegetation	266.83	22.27	301.01	25.13
5	Water Body	2.47	0.21	6.07	0.51
	TOTAL	**1197.90**	**100.00**	**1197.90**	**100.00**

The slight rise in water bodies from 0.21% in 2007 to 0.51% in 2022 (Table 1) raises the possibility of anthropogenic or environmental changes, such as better rainfall patterns, better management of water resources, or man-made interventions like reservoir development or dam building (Wojkowski et al 2022; Palazzoli, Montanari, & Ceola, 2023; Twisa, et al., 2023). Although it might potentially be a sign of floods or land-use conversion close to water sources, this shift could improve the amount of water available for domestic consumption, agriculture, and ecosystem services. These trends have been reported in a number of studies, underscoring the significance of water body monitoring for sustainable development. For example, the Lixiahe region in China showed a substantial increase in water bodies due to aquaculture, despite urbanization pressures (Jiang et al., 2024). Due in large part to aquaculture ponds, which made up 91.7% of the total water area in the Lixiahe region, water bodies increased from 459.3 km^2 in 1975 to 2373.1 km^2 in 2023 (Jiang et al., 2024). The area of Lake Hawassa grew from 91.9 km^2 in 1973 to 95.2 km^2 in 2011, while Lake Cheleleka completely vanished and became a mud-flat (Wondrade et al., 2014).

3.1 Confusion matrix for land cover classification

The confusion matrix (Table 2) represents the performance evaluation of the land cover classification algorithm. It compares the predicted land cover classes against the actual land cover classes within Langtang South. The confusion matrix provides a breakdown of the classification results for each land cover category.

Table 2: Confusion matrix for land cover classification

	BARE LAND	FARM LAND	SETTLEMENT	VEGETATION	WATER BODY	TOTAL
BARE LAND	8.03	8.91	0.13	3.26	0.76	21.08
FARM LAND	69.51	699.27	4.62	130.23	2.01	905.64
SETTLEMENT			1.91			1.91
VEGETATION	6.48	91.01	0.17	167.22	1.93	266.80
WATER BODY	0.40			0.23	1.83	2.46
TOTAL	**84.41**	**799.18**	**6.83**	**300.95**	**6.53**	**1197.90**

The confusion matrix (Table 2) above represents the performance evaluation of the land cover classification algorithm. It compares the predicted land cover classes against the actual land cover classes within Langtang South. The confusion matrix provides a breakdown of the classification results for each land cover category.

Out of the actual bare land pixels, 84.41% (Table 2) were correctly classified as bare land. However, there were misclassifications of 8.03% as farm land, 0.13% as settlement, 3.26% as vegetation, and 0.76% as water bodies. This suggests that while the classification is generally reliable, there are critical overlaps between land cover types that can lead to misinterpretation of land use changes (Christman, et al., 2015). These misclassifications indicate some confusion between bare land and other land cover types (Lowell, Reddy & Farmer, 2014). Among the actual farm land pixels, 699.27 were correctly classified as farm land, representing a high accuracy rate. This indicates that the classification model is effective in recognizing farmland as its correct land cover type. This performance is consistent with research showing the effectiveness of sophisticated categorization methods in mapping agricultural land usage (Hao, et al., 2024).

Despite the high accuracy, there are notable errors in classification. For instance, the 69.51% misclassification rate of farmland as bare land suggests confusion between these classes. This could occur due to seasonal variability, such as farmlands appearing barren after harvest, making them spectrally similar to bare land (Xue et al., 2024). The 130.23% misclassification rate as vegetation likely reflects overlap in spectral characteristics between farmlands with crops and natural vegetation. Cropped areas can mimic the spectral signature of vegetation, especially during growing seasons (Wanjura, 1984; Zhang et al., 2015). Misclassification of 4.62% as settlements and 2.01% as water bodies suggests that some areas of farmland share spectral features with settlements (e.g., agricultural structures) or are located near water sources, causing confusion. This pattern has been reported in similar studies (Awuah, 2018; Espinoza, Booth, & Viers, 2023). The provided misclassification results highlight the difficulty in accurately distinguishing settlement areas from other land cover types in a classification analysis (Awuah, 2018; Espinoza, Booth, & Viers, 2023): Only 1.91% of settlement (Table 2) pixels were correctly classified**,** indicating that the algorithm struggled to reliably identify settlements. The 8.91%

misclassification rate as bare land suggests overlap in the spectral characteristics between settlements and barren areas, possibly due to similar reflectance patterns in non-vegetated surfaces like roads or open spaces (Rasul et al., 2018). Advanced classification methods, such as Support Vector Machines (SVM) and Maximum Likelihood, have been employed to improve accuracy in distinguishing these land cover types (Nezhad et al., 2019).
There was Confusion with Farmland and Vegetation**:** The 0.17% classified as farmland and 3.26% as vegetation highlight challenges where small-scale settlements might include vegetation or agricultural activities, causing spectral confusion. Smallholder farms often utilize mixed cropping techniques, leading to overlapping spectral signatures that complicate classification efforts (Stratoulias et al., 2015). The 0.76% misclassified as water bodies could stem from settlements located near or adjacent to water bodies, leading to spectral mixing (Chatufale, Rege, & Bhatt, 2022). Out of the actual vegetation pixels, 167.22% were correctly classified as vegetation. However, there were misclassifications of 6.48% as bare land, 0.17% as farm land, 91.01% as settlement, and 1.93% as water bodies. These misclassifications suggest difficulties in accurately classifying vegetation cover, particularly distinguishing it from settlement areas. This outcome was observed in a similar study whereby significant misclassifications occurred; 91.01% of vegetation was mistakenly identified as settlements, suggesting that the spectral signatures of these classes may overlap (Pal et al., 2024).
Among the actual water body pixels, 1.83% were correctly classified as water bodies. However, there were misclassifications of 0.40% as bare land, 0.23% as settlement, and none as farm land. The misclassifications indicate challenges in accurately identifying water bodies and potential confusion with other land cover types. A study by (Pal et al., 2024), which investigates advanced techniques for extracting and classifying water bodies have raised a similar concern.
Overall, the confusion matrix highlights certain challenges and limitations in accurately classifying land cover types in Langtang South using the given classification algorithm. The misclassifications suggest confusion between certain land cover types, such as bare land and farm land, settlement and vegetation, and vegetation and water bodies. The difficulties in differentiating between land cover groups using remote sensing techniques are highlighted by similar studies that provide differing accuracy rates (Adam Elhag & Salih, 2013; Christman, et al., 2015).

4. CONCLUSION

The study concludes that significant changes in land use and land cover are occurring in Langtang South LGA. The expansion of bare land, coupled with the decline in farmland and modest increase in settlement areas, points to a growing urbanization trend and the pressure of human activities on land resources. While vegetation cover showed some improvement, it remains insufficient to mitigate the broader trends of land degradation and farmland loss. These modifications highlight the necessity of sustainable land management techniques and are consistent with larger patterns shown in related research conducted throughout Nigeria.

5. RECOMMENDATIONS

In order to address land cover changes and reduce their impacts, integrated land use management techniques that prioritize environmental conservation, agricultural intensification, and sustainable urban design are essential. The accuracy of land cover analysis can be increased and misclassifications can be decreased by utilizing ground-based data, higher-resolution imagery, and improved classification algorithms.

REFERENCES

Abuelaish, B. (2018). Urban land use change analysis and modeling: a case study of the Gaza Strip. *Geomatic Approaches for Modeling Land Change Scenarios*, 271-291.

Admasu, S., Yeshitela, K., & Argaw, M. (2023). Impact of land use land cover changes on ecosystem service values in the Dire and Legedadi watersheds, central highlands of Ethiopia: Implication for landscape management decision making. *Heliyon*, *9*(4), 1-14.

Adam, A. H. M., Elhag, A. M. H., & Salih, A. M. (2013). Accuracy assessment of land use & land cover classification (LU/LC), case study of Shomadi area, Renk County, Upper Nile State, South Sudan. *International Journal of Scientific and Research Publications*, *3*(5), 1712-1717.

Afuye, G. A., Kalumba, A. M., Ishola, K. A., & Orimoloye, I. R. (2022). Long-term dynamics and response to climate change of different vegetation types using GIMMS NDVI3g data over amathole district in South Africa. *Atmosphere*, *13*(4), 620-671.

Akinyemi, F. O., & Ifejika Speranza, C. (2024). Land transformation across agroecological zones reveals expanding cropland and settlement at the expense of tree-cover and wetland areas in Nigeria. *Geo-spatial Information Science*, 1-21.

Akumu, C. E., Dennis, S., & Reddy, C. (2018). Land cover land use mapping and change detection analysis using geographic information system and remote sensing. *International Journal of Human Capital in Urban Management, 3*: 167-178.

Aldea, A., Aldea, M., & Perju, S. (2019). GIS use of Land Use/Land Cover layers and historical data for water losses indices. In *E3S Web of Conferences*, 85, 1-5.

Aliero, M. M., Ismail, M. H., Alias, M. A., Ambursa, A. S., Muhammed, A., Umar, I., & Bunza, R. M. (2019, November). Spatiotemporal Assessment of Land Cover Change and Vegetation Degradation Using Remote Sensing in Kebbi State, Nigeria. In *Conference of the Arabian Journal of Geosciences* (pp. 347-350). Cham: Springer International Publishing.

Aljanabi, F., Dedeoğlu, M., & Şeker, C. (2024). Environmental monitoring of Land Use/Land Cover by integrating remote sensing and machine learning algorithms. *Journal of Engineering and Sustainable Development*, *28*(4), 455-466.

Ambarwulan, W., Yulianto, F., Widiatmaka, W., Rahadiati, A., Tarigan, S. D., Firmansyah, I., & Hasibuan, M. A. S. (2023). Modelling land use/land cover projection using different scenarios in the Cisadane Watershed, Indonesia: Implication on deforestation and food security. *The Egyptian Journal of Remote Sensing and Space Science*, *26*(2), 273-283.

Anne, Mook., Emily, Swanson. (2024). *Environmental Change.* The Blackwell Encyclopedia of Sociology.

Awuah, T. K. (2018). *Effects of spatial resolution, land-cover heterogeneity and different classification methods on accuracy of land-cover mapping*.Msc thesis, Swedish University of Agricultural Sciences.

Buthelezi, M. N. M., Lottering, R., Peerbhay, K., & Mutanga, O. (2024). Assessing the extent of land degradation in the eThekwini municipality using land cover change and soil organic carbon. *International Journal of Remote Sensing*, *45*(4), 1339-1367.

Cabral, P., Feger, C., Levrel, H., Chambolle, M., & Basque, D. (2016). Assessing the impact of land-cover changes on ecosystem services: A first step toward integrative planning in Bordeaux, France. *Ecosystem Services*, *22*, 318-327.

Chatufale, A. P., Rege, P. P., & Bhatt, A. (2022). Extraction of Waterbody Using Object-Based Image Analysis and XGBoost. In *Advanced Machine Intelligence and Signal Processing* (341-350). Singapore: Springer Nature Singapore.

Chen, H., Yang, L., & Wu, Q. (2023). Enhancing land cover mapping and monitoring: An interactive and explainable machine learning approach using Google Earth Engine. *Remote Sensing*, *15*(18), 4585-4598.

Christman, Z., Rogan, J., Eastman, J. R., & Turner, B. L. (2015). Quantifying uncertainty and confusion in land change analyses: A case study from central Mexico using MODIS data. *GIScience & Remote Sensing*, *52*(5), 543-570.

Capolupo, A., Monterisi, C., Saponaro, M., & Tarantino, E. (2020, August). Multi-temporal analysis of land cover changes using Landsat data through Google Earth Engine platform. In *Eighth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2020)* (11524, 447-458).

Demattê, J. A., Safanelli, J. L., Poppiel, R. R., Rizzo, R., Silvero, N. E. Q., Mendes, W. D. S., ... & Lisboa, C. J. D. S. (2020). Bare earth's surface spectra as a proxy for soil resource monitoring. *Scientific Reports*, *10*(1), 4461-4481.

Dhillon, M. S., Kübert-Flock, C., Dahms, T., Rummler, T., Arnault, J., Steffan-Dewenter, I., & Ullmann, T. (2023). Evaluation of MODIS, Landsat 8 and Sentinel-2 data for accurate crop yield predictions: A case study using STARFM NDVI in Bavaria, Germany. *Remote Sensing*, *15*(7), 1830-1840.

Ding, K., Huang, Y., Wang, C., Li, Q., Yang, C., Fang, X., ... & Dai, M. (2022). Time series analysis of land cover change using remotely sensed and multisource urban data based on machine learning: a case study of Shenzhen, China from 1979 to 2022. *Remote Sensing*, *14*(22), 5706-5718.

Ding, Q., Pan, T., Lin, T., & Zhang, C. (2022). Urban land-cover changes in major cities in China from 1990 to 2015. *International Journal of Environmental Research and Public Health*, *19*(23), 16079-16089.

Edosa, B. T., & Nagasa, M. D. (2024). Spatiotemporal assessment of land use, land cover change, driving forces, and consequences using geospatial techniques: The case of Naqamte city and hinterland, western Ethiopia. *Environmental Challenges*, *14*, 100830-100931.

Ekka, P., Patra, S., Upreti, M., Kumar, G., Kumar, A. & Saikia, P. (2023). Land Degradation and its impacts on biodiversity and Ecosystem services. *Land and Environmental Management Through Forestry*, 77–101.

Ekle A. E., Ibrahim H.B., John K.J., Emmanuel Y. Z., Ismaila M. A.,2 Pilika T.S.,Usman A.,Birma P.,Iorlaha V. A. (2022). Fertility evaluation of some soils in Mabudi Langtang South Local Government Area of Plateau State, Nigeria. *Adamawa State University Journal of Scientific Research, 10*(2), 22-27.

Espinoza, V., Booth, L. A., & Viers, J. H. (2023). Land Use Misclassification Results in Water Use, Economic Value, and GHG Emission Discrepancies in California's High-Intensity Agriculture Region. *Sustainability*, 15, 6829-6830.

Ettehadi Osgouei, P., & Kaya, S. (2017). Analysis of land cover/use changes using Landsat 5 TM data and indices. *Environmental monitoring and assessment*, *189*, 1-11.

Ewane, E. B., Deh-Nji, A., Mfonkwet, N. Y., & Nkembi, L. (2023). Agricultural expansion and land use land cover changes in the Mount Bamboutos landscape, Western Cameroon: implications for local land use planning and sustainable development. *International Journal of Environmental Studies*, *80*(1), 186-206.

Faye, B., Du, G., & Zhang, R. (2022). Efficiency analysis of land use and the degree of coupling link between population growth and global built-up area in the subregion of west Africa. *Land*, *11*(6), 847-861.

Federal Republic of Nigeria Official Gazette No. 2 Abuja — 2nd February, 2009 Vol. 96 (2009). Available online: https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://gazettes.africa/archive/ng/2009/ng-government-gazette-dated-2009-02-02-no-2.pdf&ved=2ahUKEwj5o625wY-KAxU-XEEAHeaaEH4QFnoECBgQAQ&usg=AOvVaw0q9U2ddLTdDt72AHqSLIcT. Access date: 5 December 2024.

Gebrehiwot, G. H., Bekitie, K. T., Yohannes, H., Anose, F. A., & Gebremichael, H. B. (2024). Time series land use/land cover mapping and change detection to support policies on sustainable environmental and economic management. *Environmental Systems Research*, *13*(1),1-13.

Gobry, J.J., Twisa, S.S., Ngassapa, F. & Kilulya, K.F. (2023). Impact of land-use/cover change on water quality in the Mindu Dam drainage, Tanzania. *Water Practice and Technology*, 18, 1086–1098.

Guangyin, H., Huijun, J., & Zhibao, D. (2014). Research of land-use and land-cover change (LUCC) in the source regions of the Yellow River. *Journal of Glaciology and Geocryology*, *36*(3), 573-581.

Hao, M., Dong, X., Jiang, D., Yu, X., Ding, F., & Zhuo, J. (2024). Land-use classification based on high-resolution remote sensing imagery and deep learning models. *Plos one*, *19*(4), e0300473.

Hasan, S., Shi, W., Zhu, X., & Abbas, S. (2020). Landscape urbanization and farmland reduction from 2010 to 2017 in South China. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 699-704.

Hussain, K., Mehmood, K., Anees, S. A., Ding, Z., Muhammad, S., Badshah, T., & Khan, W. R. (2024). Assessing forest fragmentation due to land use changes from 1992 to 2023: A spatio-temporal analysis using remote sensing data. *Heliyon*, *10*(14), 1-19.

Imaitor-Uku, E. E., Owei, O. B., Hart, L., & Ayotamuno, A. (2021). Impact of settlement growth on Yenagoa's urban environment. *European Journal of Environment and Earth Sciences*, *2*(1), 24-29.

Iwuagwu, T. E., Ibhafidon, A., Ononuju, A. H., Yohanna, W., Umar, I., Bongkur, P., & Ugwu, D. I. (2023). Knowledge of Risk Factors for Type 2 Diabetes Mellitus among Civil Servants in Langtang South Local Government Area, Plateau State, Nigeria. *Nigerian Journal of Health Promotion*, *16*(1), 63-74.

Jabbour, J., & Hunsberger, C. (2014). Visualizing relationships between drivers of environmental change and pressures on land-based ecosystems. *Natural Resources*, *5*(4), 147-160

Jiang, H., Ji, L., Yu, K., & Zhao, Y. (2024). Analysis of the Substantial Growth of Water Bodies during the Urbanization Process Using Landsat Imagery—A Case Study of the Lixiahe Region, China. *Remote Sensing*, *16*(4), 711.

Kahlon, S. (2015). Land use, land cover change and human–Environment interaction: the case of Lahaul valley. *International Journal of Geomatics and Geosciences*, *6*(2), 1568-1577.

Karandikar, A., & Agrawal, A. (2023). Performance analysis of change detection techniques for land use land cover. *International Journal of Electrical and Computer Engineering (IJECE)*, *13*(4), 4339-4346.

Khurelbaatar, T. & Ariya, B. (2022). Assessing human activities influences on the vegetation cover using trends of normalized difference vegetation index time series: Case study in Dornod Province. *International Trends*. *Interface Science and Technology*, 24–29.

Krištín, A., Hoi, H., & Kaňuch, P. (2024). Local population decline of the threatened Lesser Grey Shrike Lanius minor is linked to the modernisation of the rural landscape. *Bird Conservation International*, *34*, e18.

Kumar, S. (2023). Change Detection Analysis of Land Cover Features using Support Vector Machine Classifier. *International Journal of Next-Generation Computing*, *14*(2), 384.

Kushwaha, P., Nazir, A., Bansal, R., & Lone, F. R. (2025). Time series analysis of vegetation change using remote sensing, GIS and FB prophet. In *Next Generation Computing and Information Systems* (pp. 41-48). CRC Press.

Kyle, S., Devika, B. M., Priyadarshini, T. I., & Paul, S. (2024, June). Assessment of Land use Land Cover Changes in West Godavari District Using Gis. In *Journal of Physics: Conference Series* (2779, 1, 012097). IOP Publishing.

Lawal, J. O., Buba, F. N., & Awe-Peter, H. (2024). Assessment of the Impact of Land Use and Land Cover Change on the Surface Runoff of Hadejia River System, Kano, Nigeria. *International Journal of Latest Technology in Engineering, Management & Applied Science*, *13*(5), 130-141.

Lemenkova, P. (2023). A GRASS GIS scripting framework for monitoring changes in the ephemeral salt lakes of Chotts Melrhir and Merouane, Algeria. *Applied System Innovation*, *6*(4),1-25.

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PloS one*, *13*(7), 1-23.

Lowell, K., Reddy, S., & Farmer, E. (2014, July). Data and sampling issues associated with accuracy assessment of land cover change maps produced from multi-temporal image classification. In *2014 IEEE Geoscience and Remote Sensing Symposium* (4235-4238). IEEE.

Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023). A systematic review on advancements in remote sensing for assessing and monitoring land use and land cover changes impacts on surface water resources in semi-arid tropical environments. *Remote Sensing*, *15*(16),1-29.

Mpanyaro, Z., Kalumba, A. M., Zhou, L., & Afuye, G. A. (2024). Mapping and Assessing Riparian Vegetation Response to Drought along the Buffalo River Catchment in the Eastern Cape Province, South Africa. *Climate*, *12*(1), 1-22.

National Population Commission of Nigeria (NPC, Jos office), (2024). Projected population of Local government areas and districts in Plateau State, Nigeria.

Nezhad, M. M., Heydari, A., Fusilli, L., & Laneve, G. (2019, April). Land cover classification by using Sentinel-2 images: a case study in the City of Rome. In *Proceedings of the 4th World Congress on Civil, Structural, and Environmental Engineering (CSEE'19)*.

Nishant, N., Anilkumar, R., Chutia, D., Babu, E. R., & Raju, P. L. N. (2022). Vegetation Trend Analysis and Change Quantification Based on Time Series Satellite Data for Northeast India. In *Handbook of Himalayan Ecosystems and Sustainability,1* (203-223). CRC Press.

Olorunfemi, I. E., Olufayo, A. A., Fasinmirin, J. T., & Komolafe, A. A. (2022). Dynamics of land use land cover and its impact on carbon stocks in Sub-Saharan Africa: An overview. *Environment, Development and Sustainability*, *24*(1), 40-76.

.

Pal, A., Kumar, M., Suryavanshi, S., Kumar, N., Wesley, C. J., & Lal, D. Monitoring Land Use and Land Cover Change Through Earth Observation Datasets and Metric Analysis in the Barabanki District, Uttar Pradesh, India. *Current Journal of Applied Science and Technology*, *43*(9, 1-23.

.

Montanari, A., Palazzoli, I., & Ceola, S. (2023, May). Contribution of Anthropogenic and Climatic drivers to the Surface Water Extent Change in the Contiguous United States. In *EGU General Assembly Conference Abstracts* (pp. EGU-16278).

Perez-Guerra, J., Herrera-Ruiz, V., Gonzalez-Velez, J. C., Martinez-Vargas, J. D., & Torres-Madronero, M. C. (2023, August). Land Cover Classification Using Remote Sensing and Supervised Convolutional Neural Networks. In the Colombian *Conference on Computing* (pp. 13-24). Cham: Springer Nature Switzerland.

Puziene, R. (2024). Investigating Forest Cover Change Using Historical GIS Technologies: A Case Study with an Example of Jurbarkas District of the Republic of Lithuania. *Sustainability*, *16*(11), 4825-4839.

Raihan, A. (2023). A comprehensive review of the recent advancement in integrating deep learning with geographic information systems. *Research Briefs on Information and Communication Technology Evolution*, *9*, 98-115.

Ram, P. & Sheikh, M.M. (2023). Study and analysis of land use/land cover changes of jodhpur city and its impacts on economy and environment (1990–2022). *Journal of Global Resources*, 9, 86–95.

Rasul, A., Balzter, H., Ibrahim, G.R.F., Hameed, H.M., Wheeler, J., Adamu, B., Ibrahim, S. & Najmaddin, P.M. (2018). Applying built-up and bare-soil indices from Landsat 8 to cities in dry climates. *Land*, 7, 81-98.

Raza, A., Shahid, M. A., Safdar, M., Zaman, M., Sabir, R. M., Muzammal, H., & Ahmed, M. M. (2024). Impact of Land Use and Land Cover Change on Agricultural Production in District Bahawalnagar, Pakistan. *Environmental Sciences Proceedings*, *29*(1), 46-59.

Renaud, F. G., Sebesvari, Z., & Gain, A. K. (2021). Assessment of land/catchment use and degradation. In *Handbook of Water Resources Management: Discourses, Concepts and Examples* (pp. 471-487). Cham: Springer International Publishing.

Rohith, K., Vudatha, V.P.S.H.V., Rathna, T.K. & Lakshmi, G.J. (2023). *Remote Sensing- Based Vegetation Types Classification Using Landsat and Change Analysis Using Setinel-2a in Google EarthEngine*.

Sameer, M.K. & Hamid, A.M. (2023). Sameer, M. K., & Hamid, A. M. (2023). Remote Sensing and GIS Techniques in Monitoring Land Use Land Cover Change. *International Journal of Sustainable Construction Engineering and Technology*, *14*(1), 13-20.

Sapkota, L., & Dahal, R. P. (2024). Assessment of forest cover change, key drivers of change and perception of locals in Birendranagar Municipality, Surkhet District, Nepal. *Archives of Agriculture and Environmental Science*, *9*(2), 308-316.

Schiavina, M., Melchiorri, M., Corbane, C., Freire, S., & Batista e Silva, F. (2022). Built-up areas are expanding faster than population growth: regional patterns and trajectories in Europe. *Journal of land use science*, *17*(1), 591-608.

Sembosi, S. J. (2019). Implication of Socio-economic Factors on Land Use and Forest Cover Changes in and Around Magamba Nature Reserve in Tanzania: Perception of Local Stakeholders. *Advanced Journal of Social Science*, *5*(1), 108-117.

Shanmugapriya, N., Bostani, A., Nabavi, A., Sasikala, D., Elangovan, T. & Adilovna, K.S. (2024). Synergizing remote sensing, geospatial intelligence, applied nonlinear analysis, and AI for sustainable environmental monitoring. *Communications on Applied Nonlinear Analysis*, 31, 281–292

Shaik, A. S., Shaik, N., & Priya, D. C. K. (2024). Predictive Modeling in Remote Sensing Using Machine Learning Algorithms. *International Journal Current Science Research,*, *7*(06), 12-19.

Simon, O., Lyimo, J., & Yamungu, N. (2023). Influence of socioeconomic drivers on land use and cover changes using Remote sensing and GIS in Dar es Salaam, Tanzania. *Authorea Preprints*.

Singh, A. K. (2021). Landscape Fragmentation and Land Use and Land Cover Analysis of the Hinterland of Ranchi: A Case Study of Kanke Block, 2001 and 2019. *Urban India*, *41*(1), 166-184.

Song, L., Estes, A. B., & Estes, L. D. (2023). A super-ensemble approach to map land cover types with high resolution over data-sparse African savanna landscapes. *International Journal of Applied Earth Observation and Geoinformation*, *116*, 103152.

Stratoulias, D., De By, R. A., Zurita-Milla, R., Bijker, W., Tolpekin, V. A., Schulthess, U., & Ahmed, Z. U. (2015, October). The potential of very high spatial remote sensing in smallholder agriculture. In the 36th *Asian Conference on Remote Sensing, ACRS 2015: Fostering Resilient Growth in Asia* (pp. 1533-1539).

Sun, Q., & Li, J. (2024). A method for extracting small water bodies based on DEM and remote sensing images. *Scientific reports*, *14*(1), 760-791.

Thawaba, S., Abu-Madi, M., & Özerol, G. (2017). Effect of land-use/land-cover change on the future of rainfed agriculture in the Jenin Governorate, Palestine. *International Journal of Global Environmental Issues*, *16*(1-3), 176-189.

Tiwari, A. K., Pal, A., & Kanchan, R. (2024). Mapping and Monitoring of Land Use/Land Cover Transformation Using Geospatial Techniques in Varanasi City Development Region, India. *Nature Environment & Pollution Technology*, *23*(1), 365-379.

Tsheko, R. (2022). Non-seasonal Landsat based bare area gain detection in Botswana during 2002 to 2020 Period using Maximum Likelihood Classifier (MLC). *South African Journal of Geomatics*, *11*(1), 84-99.

Wanjura, D. F. (1984). Seasonal spectral characteristics of four crop canopy architectures. *Transactions of the ASAE*, *27*(6), 1734-1738.

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2022, May). Global land use transitions and their drivers during 1960-2019. In *EGU General Assembly Conference Abstracts* (pp. EGU22-9145).

Wojkowski, J., Wałęga, A., Radecki-Pawlik, A., Młyński, D., & Lepeška, T. (2022). The influence of land cover changes on landscape hydric potential and river flows: Upper Vistula, Western Carpathians. *Catena*, *210*, 105878.

Xu, X., Kong, W., Wang, L., Wang, T., Luo, P., & Cui, J. (2024). A novel and dynamic land use/cover change research framework based on an improved PLUS model and a fuzzy multiobjective programming model. *Ecological Informatics*, *80*, 1-15.

Xu, Y., Dai, Q. Y., Zou, B., Xu, M., & Feng, Y. X. (2023). Tracing climatic and human disturbance in diverse vegetation zones in China: Over 20 years of NDVI observations. *Ecological Indicators*, *156*, 1-12.

Xue, J., Zhang, X., Chen, S., Hu, B., Wang, N., & Shi, Z. (2024). Quantifying the agreement and accuracy characteristics of four satellite-based LULC products for cropland classification in China. *Journal of Integrative Agriculture*, *23*(1), 283-297.

Ying, Q., Hansen, M. C., Potapov, P. V., Tyukavina, A., Wang, L., Stehman, S. V., ... & Hancher, M. (2017). Global bare ground gain from 2000 to 2012 using Landsat imagery. *Remote sensing of environment*, *194*, 161-176.

Wuyep, S. Z., Daloeng, H. M., Isha, A. H., & Arin, H. B. (2020). Application of Remote Sensing and GIS to Detect Land Use and Land Cover Changes in Jos East, Plateau State, Nigeria. *Bokkos Journal of Science Rep*ort, *1*, 1-8.

Younes, A., Ahmad, A., Hanjagi, A. D., & Nair, A. M. (2023). Understanding Dynamics of Land Use & Land Cover Change Using GIS & Change Detection Techniques in Tartous, Syria. *European Journal of Geography*, *14*(3), 20-41.

Zhang, J., Wei, F., Sun, P., Pan, Y., Yuan, Z., & Yun, Y. (2015). A stratified temporal spectral mixture analysis model for mapping cropland distribution through MODIS time-series data. *Journal of Agricultural Science*, *7*(8), 95.

Zhang, X., Ren, W., & Peng, H. (2022). Urban land use change simulation and spatial responses of ecosystem service value under multiple scenarios: A case study of Wuhan, China. *Ecological Indicators*, *144*, 1-17.

Zhang, X., Zhao, T., Xu, H., Liu, W., Wang, J., Chen, X. & Liu, L. (2024). GLC_FCS30D: The first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method. *Earth System Science Data*, 16, 1353–1381.