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ASSESSMENT OF THE EFFECTS OF KIDNAPPING INCIDENCE ON LAND USE AND LAND COVER ALONG KADUNA-ABUJA EXPRESSWAY

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Abstract

This research examines the effects of kidnapping on land use and land cover (LULC) along the Kaduna-Abuja expressway, utilizing data from multiple sources. The study employs satellite imagery, including Landsat-7 (ETM) from 2012, Landsat-8 (OLI) from 2017 and 2022, as well as a 2015 Digital Elevation Model (DEM). Additionally, data on reported kidnapping incidences obtained from the Kaduna State Police Command were integrated into the analyses using ArcGIS software. The Post-Classification Comparison Method (PCM) was employed to construct a change matrix, enabling the exploration of temporal variations and dynamics in LULC within the study area. The findings reveal significant trends in land cover changes over the decade. In 2012, the landscape was predominantly characterized by agricultural lands and vegetation cover, which together accounted for over 72% of the total land cover. This distribution is attributed to the widespread abandonment of farmsteads along the expressway due to the threat of kidnapping. By 2017, the dominance of bare ground, agricultural lands, and vegetation cover persisted, representing over 87% of the observed changes. A noteworthy decline in built-up areas, approximately 14.3%, during this period led to a slowdown in urban expansion. In 2023, vegetation cover and bare land remained the dominant land cover types. However, there was a significant decline in both built-up areas and agricultural parcels, leading to a 6.4% reduction from 2012 to 2022. This reduction is linked to the increasing prevalence of kidnapping, which has further influenced land cover dynamics by increasing bare ground and vegetation coverage. The study underscores the necessity for systematic, biannual, comprehensive, and continuously updated assessments of LULC changes in the study area as a crucial means for establishing a foundation for informed decision-making and supporting sustainable development initiatives in the area.

***Keywords**: Image, Kidnapping, Land Cover, Satellite and Vegetation Cover.*

Introduction

Land use and land cover (LULC) play a pivotal role in the strategic planning and management of a myriad of activities, constituting fundamental components in the modeling and comprehension of Earth as a complex system (Dires and Temesgen, 2020). The utilization of land stands as one of the most critical natural resources, serving as the underpinning for all human endeavors. Throughout the annals of history, human interventions have consistently reshaped the landscape to meet various sustenance and essential needs. In the contemporary epoch, the unprecedented rates, extents, and intensities of changes in land use and land cover (LULCC) have led to substantial modifications in ecosystems and environmental processes at local, regional, and global scales- a phenomenon hitherto unparalleled in history (Wang, Li, Tao, and Du, 2022).

Kidnapping, a global phenomenon interwoven into human activities, exerts varying impacts on countries with diverse prevalence rates and motives. It manifests in manifold forms and exhibits disparate frequencies across regions. As underscored by Ibrahim, Andrew, Dashit, Audu, and Vakpa, (2020), kidnapping remains a salient issue on a global scale, particularly prominent in countries such as Mexico, Nigeria, Venezuela, and the Philippines. The causative factors behind kidnapping are intricate and multifaceted, influenced by socio-economic, political, and personal elements, thereby carrying severe consequences for victims, their families, and society at large (Aubrey, 2015). The relationship between kidnapping incidence and modifications in land use and land cover is marked by a nuanced interplay of social, economic, and environmental factors (Wang, Li, Tao, and Du, 2022). The rapid advancement of urbanization frequently initiates the swift expansion of informal settlements, leading to the marginalization of specific communities and significantly increasing the vulnerability of these areas to criminal activities, notably kidnapping. This susceptibility is driven by insufficient infrastructure, security, and social services, which kidnappers exploit by specifically targeting individuals within these vulnerable neighborhoods.

Similarly, economic transformations within a region often align with changes in land use, where the transition from agricultural to industrial or commercial land use may give rise to economic disparities, contributing to social unrest and criminal activities, including kidnapping (Ibrahim *et al*., 2020). Economic instability and disparities in wealth distribution create conditions favorable for criminal enterprises. Changes in land use that exacerbate these economic disparities may unintentionally contribute to an escalation in kidnapping incidence. Also, alterations in land cover, such as deforestation and resource exploitation, can lead to environmental degradation, triggering conflicts over remaining valuable assets and further destabilizing regions. Criminal groups strategically employ kidnapping as a tactic in these conflicts, capitalizing on the ensuing chaos and insecurity (Aubrey, 2015). Additionally, environmental degradation has the potential to displace local populations, pushing them into poverty and rendering them susceptible to criminal exploitation.

In areas characterized by diverse land uses and covers, such as borderlands, the dynamics of kidnapping incidence are intricately influenced by geopolitical factors. Changes in land use along borders, whether driven by economic interests or geopolitical tensions, can create security vacuums, facilitating criminal activities. Kidnappers exploit the porous nature of these areas, where jurisdictional complexities and weak governance contribute to an environment conducive to their operations (Wang *et al.*, 2022).

Recognizing the correlation between kidnapping incidents and changes in land use and land cover is imperative for the development of effective prevention and mitigation strategies. Integrated approaches that comprehensively address social, economic, and environmental aspects are essential. Also, strengthening urban planning, promoting sustainable development, addressing economic disparities, and implementing robust environmental conservation measures collectively contribute to the reduction of vulnerability in areas prone to kidnapping incidents.

In light of the circumstances outlined above, this research is conducted to assess the effects of kidnapping incidents on land use and land cover along the Kaduna-Abuja Expressway. The analysis aims to scrutinize the trends and rate of changes in order to mitigate the consequences and promote the overall well-being and development of communities situated along this crucial transportation corridor.

Materials and Method

The Study Area

The Kaduna-Abuja Expressway is located between Longitudes 7º 20' 23'' E and 7º 20' 24'' E of the Greenwich Meridian and between Latitudes 09º 20' 13'' N and 10º 30' 13'' N of the Equator. It spans approximately 190 kilometers, extending from Abuja Junction in Kaduna State to Zuba Junction in Abuja FCT. The route features a minimum elevation of about 493 meters, an average elevation of 550 meters, and a maximum elevation of 653 meters. It traverses three Local Government Areas

(LGAs) in Kaduna State-Chikun, Kachia, and Kagarko-and also extends into Niger State, including Tafa and Zuba Junction, as illustrated in Figure 1.

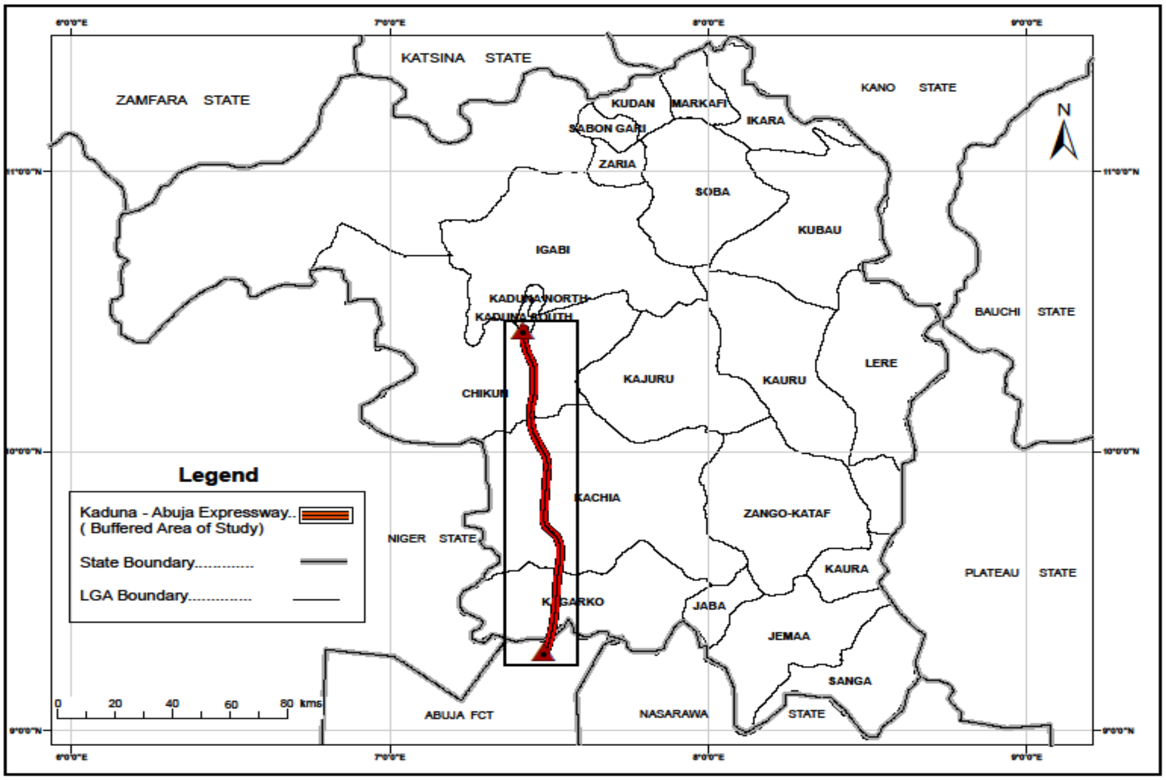

Figure 1: Kaduna-Abuja Expressway
Source: Adapted from the Administrative Map of Kaduna State (2024)

Data Type and Sources

The data utilized in this study encompasses secondary data sources, which include several key datasets. These datasets comprise Landsat satellite imagery at 30-meter resolution: Landsat 8 (OLI) Collection Level 2, Step 2, providing surface and temperature reflectance images; Landsat 7 (ETM) Collection Level 2, Step 1; a Digital Elevation Model (DEM); and Police Crime Reports, obtained from their respective sources as detailed in Table 1. Table 2 outlines the characteristics of the satellite imagery employed in this research.

Table 1: Data Type and Sources

S/No	Data Type	Date Acquired	Resolution Scale	Source	Purpose
1.	Landsat 7 (ETM)	2012	30m	USGS	NDVI, Reclassification, Explanatory data sets
2.	Landsat 8 (OLI)	2017, 2022	30m	USGS	Data Analysis NDVI, Reclassification and
3.	STRM	2015	30m (Void filled)	USGS	Hypsometric Details
4.	Police crime data	2022		KDSPC	Data Analysis

Sources: United State Geological Service (USGS) Database, (2024), Kaduna State Police Command Kaduna (2023)

Table 2: Satellite Data Characteristics

S/No	Data Type	LS Product Identifier	Path/Row	Grid Cell size Reflectance	Cloud Cover (%)	SR (m)	Bands	Date Acquired by Satellite
1.	Landsat 8 (TM)	189052_20220212_TI	0618/051	30.00	< 10	30	Visible (B 4,5)	1/3/ 2012
2.	Landsat 8 (OLI)	189053_20220217_TI	189/052	30.00	< 10	30	Visible (B 4,5)	1/3/ 2017
		189053_20220222_TI	189/053	30.00	<10	30	Visible (B 4,5)	1/3/ 2022
3.		14218,11465		2015		30	-	2015

Source: United State Geological Service (USGS) Database, (2024)

Processing of Kidnapping Data

The spatial analysis utilized kidnapping data from 2012 to 2022, which was derived from records of reported kidnapping cases documented by the Kaduna State Police Command. Raw counts of kidnapping incidents aggregated across spatial units can potentially yield misleading results in spatial analysis. To address this issue, incidence counts were normalized into percentages, using the total number of individuals at risk as the denominator. Specifically, the rates were computed per 100 individuals at risk in each settlement traversed by the road within Local Government Areas (L.G.A.). This approach, recommended by Olaore in 2017, improves the realism and precision of the analytical results concerning the incidents. The formula used for this conversion is as follows**:**

$$\text{Crime rate} = \frac{\text{Number of kidnapping committed}}{\text{Population of Settlement}} \times 100 \quad \ldots\ldots [1]$$

The data, which included location coordinates, was initially downloaded in Excel (.csv) format. It was then converted to a database (.dbf) file format for compatibility with ArcMap. Following this conversion, the data was transformed into a shape file by projecting the coordinates into a specific projected coordinate system as point features. A targeted subset of crime incidents was subsequently extracted through spatial queries and further refined (masked) to match the study area's boundary. This process ensured that only kidnapping incidents within the defined area were retained. By focusing on this subset, the analysis aimed to accurately reflect the kidnapping rates within the designated spatial unit, thereby ensuring the results effectively represent the characteristics of the study area.

Processing of the Satellite Data

The Landsat Satellite Images acquired from the United State Geological Service (USGS) were downloaded through the gateway https://earthexplorer.usgs.gov website. The downloaded datasets were imported into the ERDAS Imagine raster-based remote sensing software where it was processed into a Normalized Difference Vegetation Index (NDVI) dataset.

The Digital Elevation Model (DEM) of 30m spatial resolution was also sourced from the United State Geological Service (USGS) through the gateway address. The image provided the platform for the extraction of hypsometric (relief/height) information which was used for terrain analysis. The Band 4 and Band 5 of the 2012, 2017 and 2022 Landsat image were extracted along the study area which aided in the analysis while the Digital Elevation Model (DEM) of the same set of years aided in extraction of the nature of the terrain in percentages.

Vegetation Cover

To ascertain the magnitude of vegetation cover change in each of the local government area, the study utilized the concept of Normalized Difference Vegetation Index (NDVI), using band 4 and band 5 of the Landsat image.

The model used in estimating NDVI was; NIR - PAR / NIR + PAR ------------------------- [2]

This formula yields a value that ranges from -1 (usually water) to +1 (strongest vegetative growth).

Where; NDVI - Normalized Difference Vegetation Index, NIR - Near Infrared band imagery, PAR-Photosynthetic Active Radiation band imagery.

In this study, the Red band imagery was adopted as the PAR.

Thus, the formula; NDVI = NIR - Red / NIR + Red --------------------------- [3]

Thus, R band 5 and R band 4 are the land surface reflectance in the near infra-red and the visible bands respectively; the raster calculator option of the spatial analysis tool in ArcGIS software was utilized for the NDVI calculation.

Terrain Analysis

A 30m resolution Digital Elevation Model (DEM) was used to determine the magnitude in elevation, utilizing the slope function of the surface tool in the spatial analysis tools of ArcGIS Software. The percentage rise in slope was utilized to determine mountainous area, area with steep valley and flat or relatively flat terrain.

The relief configurations are investigated in this study as they affect the vulnerability of the physical and economic environment such as agriculture, settlement, road network among others. It also constitutes a pool or push factor which further buttresses the economic factor. Relief in the study area are vast, rugged and hazardous interspersed by diverse forested landscapes, some of which are dotted by wetlands, rocks and caves which serves as safe haven for hoodlums and criminals (Olapeju and Peter, 2021). Apart from being separated from each other, they are equally far separated from the center of governance at the local and state levels. Most importantly, they are grossly under-policed to the point that makes them conducive for all forms of jungle criminality especially those perpetrated by kidnappers.

Land Use/Land Cover Classification Scheme

In this study, Landsat 7 (ETM) dataset was used to derive the land use/land cover map of 2012. Since the Landsat (OLI) series was released for download after the year 2013. A false color composite combination of bands 5 and 4 for Landsat 8 (OLI) was used; hence areas of interest were selected using the ANDERSON classification scheme. The following classified scheme was derived using the supervised classification algorithm namely: built-up-areas, water body, agricultural lands, vegetation cover, and bare ground/rock outcrop as described in Table 3.

Table 3: Land Use/Land Cover Categories

S/N	Land use/Landover	Categories
1.	Agricultural lands	Irrigated agricultural area and agricultural fallow land,
2.	Built-up areas	Settlements and roads,
3.	Water body	Areas covered by perennial river and ponds
4.	Thick vegetation	Undergrowth, foliage, forest, flora, shrubbery, plants.
5.	Bare Lands and Out crops	Areas devoid of vegetation, e.g., sediments, Landslide zones, degraded forest area etc.

Source: Researcher's Work, (2024)

Analysis of Kidnapping Data

Several spatial analytical techniques were employed in this study. These includes the areal spatial autocorrelation techniques (Global and Local Moran's *I* and Getis Ord) which assisted in identifying the clustered locations and the spatio-temporal distribution of kidnapping rates in the study area and the Inverse Distance Weighed (IDW) which assisted in the creation of a continuous smooth raster image.

Analysis of Satellite Data

Landsat satellite images which include Landsat (ETM) and Operational Land Imager (OLI) that are geometrically corrected were acquired in collection level 2 steps 2 from the United States Geological Survey (USGS). To properly compare the NDVI differences, all images were acquired in the month of March in order to discern the different kinds of vegetation in their stable stage. In addition, the time gap between the satellite images was more than 16 days, due to cloud cover or technically damaged scenes.

The method for the analysis of the LULC change is the Post-Classification Comparison Method (PCM) as adopted by Ejaro and Abdullahi (2013). Post classification comparison analysis reveals the change between two epochs. Change data was generated from the analysis and from the change statistics, the rate of change (percentage) was computed. The spatial and temporal changes were then examined. Classification Accuracy Assessment average score of 96% was achieved using the error matrices method. Verification was carried out in order to generate additional data to test the quality or accuracy of the classification. This was done by creating a confusion matrix, in which classification results are compared to the additional ground verification information in order to test the quality or accuracy of the satellite image classification. The output of the Land use/ land cover change data obtained from each epoch is presented in colour composite maps and tables.

Accuracy Assessment

In this study, field verification was conducted using a handheld Garmin S76 Global Positioning Systems (GPS) device, digital camera and a field note. A total of 150 field points coordinates were generated using the GPS device. Observations of land use land cover characteristics and human imprints were made and recorded. According to Jensen, 2012 the ideal number of checkpoints required to be tested in the land use classification map is determined from the binomial probability given in the equation below:

$N = 4 (p) (q \sim e) / e^2$ …………………………………………………. (4)

Where: N = is the number of points required,

p = is the expected percent accuracy

q~ = the difference between 100 and

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e = is the maximum allowable error

For an expected 96% accuracy and allowable error of 5%, the minimum number of points required is 144. This shows that the number of checkpoint (150) established on the field is higher than the number of checkpoints required. The coordinates were imported into ArcGIS environment as ground trothing points overlaid on a maximum resolution google earth image which served as a base for assessing accuracy. The error matrix was calculated and derived from a compares of reference map pixels to the classified map pixels organized as a two-dimensional matrix. From the error matrix, the overall accuracy and the Kappa Coefficient were determined.

Results and Discussions

The results and discussion on the analysis of the effects of kidnapping on land use/land cover changes are presented in this section. The analyzed parameters were classified into water body, bare lands, built- up areas, agricultural lands and vegetation cover. Table 4 presents the error Matrix and Accuracy Assessment of the Image Classification for the year 2012.

Table 4: Error Matrix and Accuracy Assessment of the Image Classification for the Year 2012

S/N	Parameters (2012)	Water body	Vegetation	Agricultural Lands	Built-up Lands	Tools	User's Accuracy (%)	Kappa Statistics
1.	Water body	4	0	0	0	4	100.00	1
2.	Vegetation	1	48	1	1	50	96.00	0.94
3.	Agricultural Lands	0	0	48	0	48	100.00	1
4.	Built-up Lands	0	0	0	48	48	100.00	1
6.	Total	5	48	48	49	150		
7.	Producer's Accuracy (%)	100.00	100.00	100.00	97.96			
8.	Overall Accuracy	0.98						
9.	Overall Kappa Statistics	0.98						

Source: Researcher's Work (2024)

Base on result in Table 4, the overall classification accuracy of 0.9867 and overall Kappa statistics of 0.9805 for the 2012 image classification was determined. Vegetation area has a user's accuracy of 96% because two of its reference cells were classified as cells for water-body and built-up land. Agricultural lands, water-body and built-up lands recorded 100% user's accuracy because all reference cells for the classes were classified as same.

Table 5: Error Matrix and Accuracy Assessment of the Image Classification for the Year 2017

S/N	Parameters (2017)	Water body	Vegetat ion	Agricultural Lands	Built-up Lands	Tools	User's Accuracy (%)	Kappa Statistics
1.	Water body	4	0	0	0	4	100.00	1
2.	Vegetation	0	49	1	0	50	98.00	0.97
3.	Agricultural Lands	0	0	44	6	50	88.00	0.82
4.	Built-up Lands	0	0	0	46	46	100.00	1
6.	Total	4	49	45	52	150		
7.	Producer's Accuracy (%)	100.00	100.00	97.78	88.46			
8.	Overall Accuracy	0.95						
9.	Overall Kappa Statistics	0.93						

Source: Researcher's Work (2024)

Based on result presented in Table 5, the overall classification accuracy of 0.9533 and overall Kappa statistics of 0.9318 for the 2014 image classification was determined. Vegetation area has a user's accuracy of 98% because one of its reference cells was classified as cell for Agricultural Land. Agricultural lands have the user's accuracy of 88% because six of its reference cells were classified as cells for built-up lands. Water body and built-up lands recorded 100% user's accuracy because all reference cells for the classes were classified.

Table 6: Error Matrix and Accuracy Assessment of the Image Classification for the Year 2022

S/N	Parameters (2012)	Water body	Vegetation	Agricultural Lands	Built-up Lands	Tools	User's Accuracy (%)	Kappa Statistics
1	Water body	2	0	0	0	4	100.00	1
2	Vegetation	2	33	4	0	39	84.62	0.80
3	Agricultural Lands	0	0	16	6	18	88.89	0.87
4.	Built-up Lands	0	0	0	91	91	100.00	1
6.	Total	4	33	20	93	150		
7.	Producer's Accuracy (%)	100.00	100.00	80.00	97.85			
8.	Overall Accuracy	0.94						
9.	Overall Kappa Statistics	0.90						

Source: Researcher's Work (2024)

Based on result presented in Table 6, the overall classification accuracy of 0.9467 and overall Kappa statistics of 0.9031 for the 2019 image classification was determine. Vegetation area has a user's accuracy of 84.62% because four of its reference cells were classified as cells for agricultural land and two were classified as water body as shown in Table 6, Agricultural land has a user's accuracy of 88.89% because two of its reference cells were classified as cells for built-uplands. Water-body and built-up lands recorded 100% user's accuracy because all reference cells for the classes were classified as same.

Land Use/Land Cover changes along Kaduna-Abuja Expressway

The land use/land cover changes along Kaduna-Abuja expressway for the year 2012 is presented in Figure 2 and Table 7.

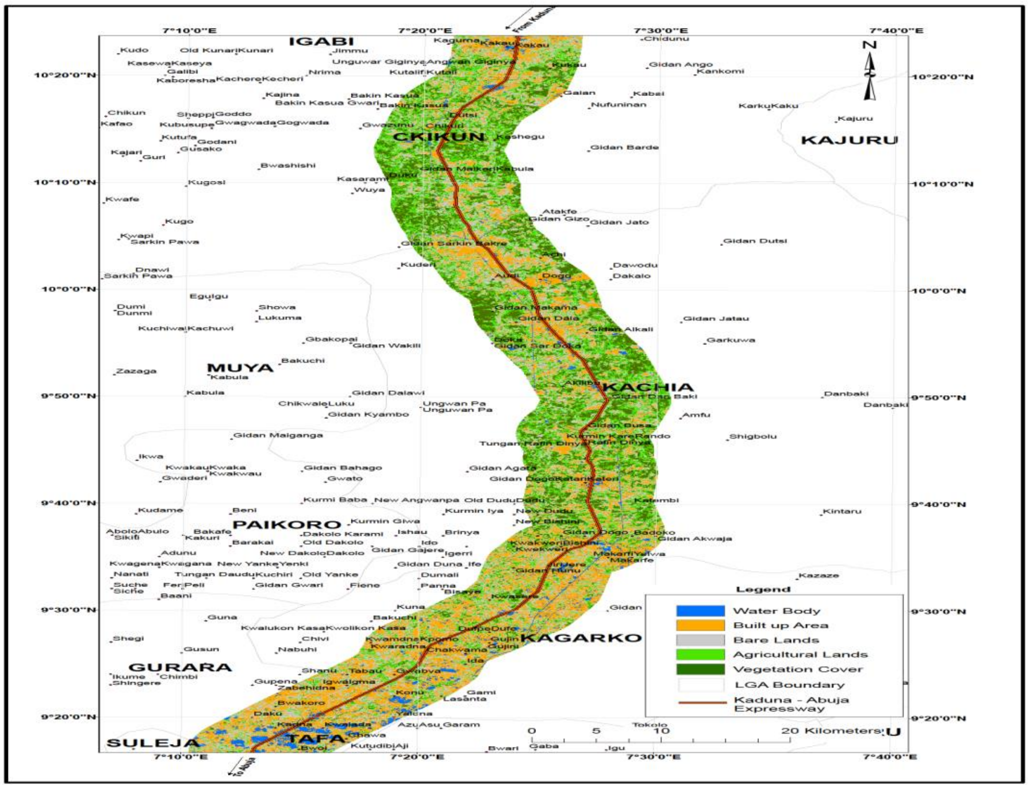

Figure 2: Land Use/Land Cover Changes along Kaduna-Abuja Expressway in 2012
Source: Author's Analysis from the 2012 NDVI of the Study Area, (2024)

Table 7: Land Use/Land Cover Changes along Kaduna-Abuja Expressway for the Year 2012

Land Cover	Area Cover (km^2)	Percentage (%)
Water body	0.121	0.0002
Built-up-Areas	11211.0	27.101
Bare-ground/Outcrop	10122.1	24.469
Agricultural Lands	10002.21	24.179
Vegetation Cover	10031.10	24.249
Total	**41366.53**	**100**

Source: Author's Analysis, (2024)

Based on the findings presented in Table 7, it is evident that built-up areas comprised 27.10% of the overall land use. The bare ground, agricultural lands, and vegetation collectively represented more than 72% of the total land cover, with the remaining 2.9% attributed to water bodies. This indicates that a substantial majority (exceeding 72%) of land cover alterations in 2012 can be principally ascribed to changes in agricultural lands, vegetation cover, and bare lands.

The elevated incidence of kidnapping incidents, commencing in 2012, instigated the abandonment of agricultural plots, farmsteads, and residential zones within the kidnapping hotspots along the Kaduna-Abuja expressway. Consequently, this abandonment led to a notable augmentation in bare ground and vegetation cover. It is noteworthy that this study contrasts with the findings of Akingbogun, Oloyede, and Aborisade (2012), who reported a 14.12% increase in built-up areas and a 46.41% increase in farmland from 1984 to 2000 in the Eleyele forest reserve in Ibadan, Oyo State.

This incongruity can be ascribed to the dissimilarity in the nature of the respective locales. Unlike the Eleyele forest reserve, which is situated in the city center and is not a highly attractive zone for kidnappers, the Kaduna-Abuja expressway is located in peri-urban areas and serves as a vital transportation route connecting the Federal Capital Territory, Abuja, and other states of the Federation. Distinct commuting patterns, particularly inter-city mobility, coupled with inadequate security measures, contribute to the heightened vulnerability of commuters/residents along this route to kidnapping and other criminal activities.

The land use/land cover change/matrix along Kaduna-Abuja expressway in 2017 is presented in Figure 3, Table 8 and Table 9 respectively.

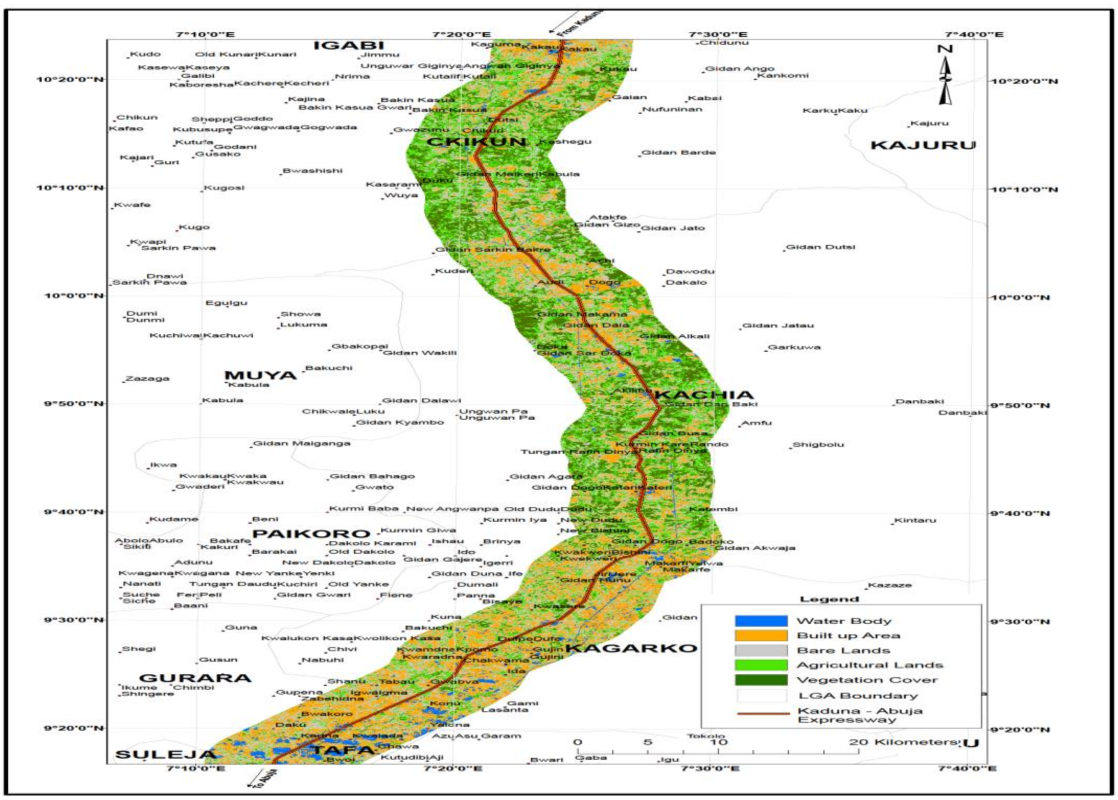

Figure 3: Land Use/Land Cover Changes along Kaduna-Abuja Expressway in 2017
Source: Author's Analysis from the 2017 NDVI of the study Area, (2024)

Table 8: Land Cover changes along Kaduna-Abuja Expressway for the Year 2017

Land Cover	Area Cover (km^2)	Percentage (%)
Water body	0.864	0.002
Built-up- Areas	4432.626	10.715
Bare-ground/Outcrop	10972.27	26.525
Agricultural Lands	11490.98	27.778
Vegetation Cover	14469.79	34.979
Total	**41366.53**	**100**

Source: Author's Analysis, (2024)

From Table 8, it is discerned that vegetation cover constituted 34.9% of the aggregate land cover. Agricultural lands were indicative of 27.7%, while bare lands comprised 26.5%. In an encompassing examination of the distribution of overall land cover, the combined presence of vegetation cover, agricultural lands, and bare lands exceeded 87%, with built-up areas and water bodies representing the remaining 13%. The transformative shifts in land cover during 2017 were predominantly influenced by a notable surge in kidnapping incidents, accounting for a substantial majority exceeding 95%.

This upheaval manifested primarily through discernible fluctuations in the expanse of bare ground, agricultural lands, and vegetation cover. The ramifications of pervasive criminal activities, particularly the escalating instances of kidnapping, reverberated across the landscape, precipitating alterations in land use dynamics. The resulting changes underscored the intricate interplay between security concerns and environmental transformations, painting a vivid narrative of the profound impact of societal challenges on the physical fabric of the terrain.

Table 9: Land Use/Land Cover Change Matrix along Kaduna-Abuja Expressway in 2012-2017

Land Cover	Area (km^2) for 2012	%	Area (km^2) for 2017	%	% Changes
Water body	0.121	2.925	0.864	0.002	0.743(-0.119)
Built-up-Area	11211.0	25.101	4432.626	10.715	-6778.374(-14.386)
Bare-ground/Outcrop	10122.1	24.352	10972.27	26.525	850.17(2.173)
Agricultural Lands	10002.21	24.175	11490.98	27.778	1488.77(3.603)
Vegetation Cover	10031.10	24.245	14469.79	34.979	4438.69(10.734)
Total	**41366.53**	**100**	**41366.53**	**100**	

Source: Author's Analysis (2024)

According to the outcomes presented in Table 9, a reduction of less than 14.38% is observed in built-up areas. Concurrently, there is a noteworthy escalation of more than 10.73% in vegetation cover, along with a recorded increase exceeding 3.6% in agricultural lands. The consequential significant decline of approximately 14.3% in built-up areas signifies a corresponding contraction in urban expansion and developmental activities. Conversely, the relatively modest 3% increment in agricultural lands contributes to an augmentation in both vegetation cover and bare lands. This correlation is rooted in the understanding that a reduction in agricultural lands results in a corresponding increase in vegetation cover, attributable to the prolonged abandonment of farmland due to the escalating and uncontrolled incidence of kidnapping in the study area (refer to Figure 9).

These findings agree with Gabriel and Audu (2017), who reported a 4% decrease (137.7021 km2) in built-up and bare land over a span of nearly two years in Donga, Taraba State. Furthermore, from 2012 to 2017, there was a 2.9% increase in bare ground and outcrop, a decrease of 10.7% in sparse vegetation from 2009 to 2014, an 8.06% rise in thick forest from 2012 to 2017, and a 1.28% increase in water bodies over the same period.

The Land use/Land Cover changes/matrix along Kaduna-Abuja expressway in 2022 is presented in Figure 4, Table 10 and Table 11 respectively.

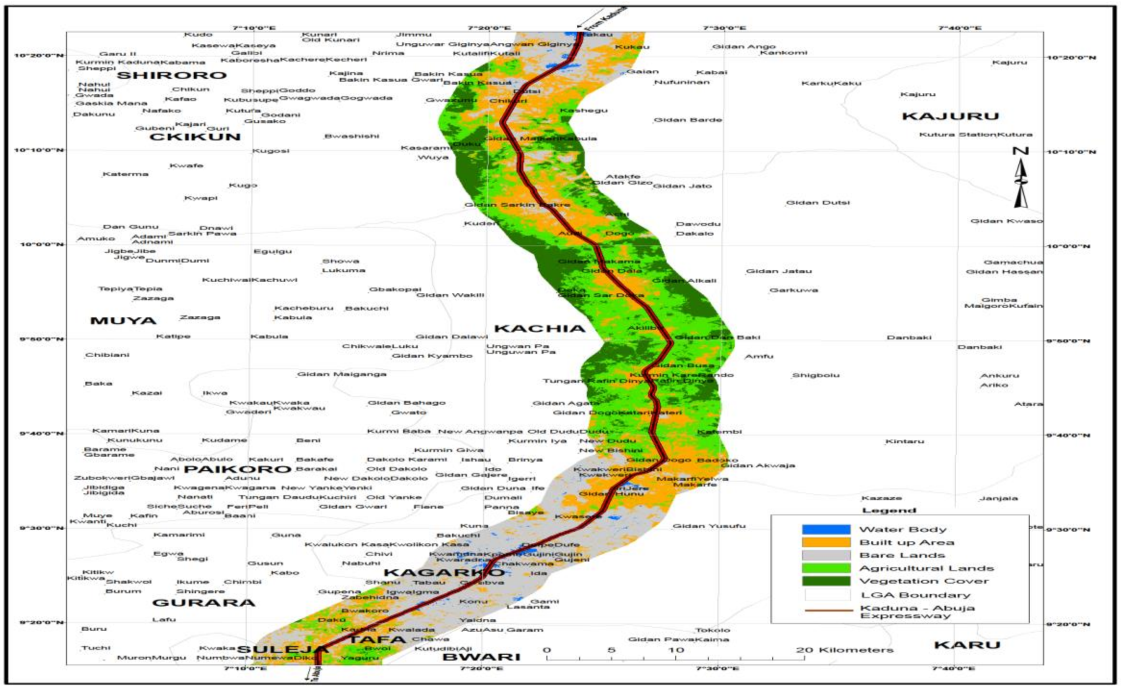

Figure 4: Land Cover along Kaduna-Abuja Expressway in 2022
Source: Author's Analysis from the 2022 NDVI of the Study Area, (2024)

Table 10: Land Cover changes along Kaduna-Abuja expressway for the year 2022

Land Cover	Area Cover (km^2)	Percentage (%)
Water body	3.501	0.008
Built-up- Areas	2432.007	5.879
Bare-ground/Outcrop	10070.8	24.345
Agricultural Lands	14152.81	34.213
Vegetation cover	14707.41	35.553
Total	**41366.53**	**100**

Source: Author's Analysis, (2024)

From Table 10, 35.5% accounts for vegetation cover and is the most represented, followed by 34.2% accounts for agricultural lands, 24.3% accounts for bare lands and is fairly represented, 5.8% account for built-up areas and 0.008% accounts for water body and are jointly the least represented. At the aggregate level, more than 72% of the land cover distributions are characterized by vegetation cover and agricultural lands and less than 6% are characterized by built-up areas and water body for the year 2022. This indicates that majority of the land cover changes in the study area for the year 2022 are vegetation cover, agricultural lands and bare lands and a very slow pace of urban expansion.

Table 11: Land Use/Land Cover Change Matrix along Kaduna-Abuja Expressway from 2017-2022

Land Cover	**Area Cover (km^2) 2017**	**%**	**Area Cover (km^2) 2022**	**%**	**% Change**
Water body	0.864	0.002	3.501	0.008	2.637(0.006)
Built-up-Area	4432.626	10.715	2432.007	5.879	-2000.619(-4.836)
Bare-ground/Outcrop	10972.27	26.525	10070.8	24.345	-901.47(-2.18)
Agricultural Lands	11490.98	27.778	14152.81	34.213	2661.83(6.435)
Vegetation Cover	14469.79	34.979	14707.41	35.553	237.62(0.574)
Total	**41366.53**	**100**	**41366.53**	**100**	

Source: Author's Analysis, (2024)

Based on results of the change matrix in Table 11, agricultural lands increased by 6.4% from 2017 to 2022; and vegetation cover increased by 0.5% from 2017 to 2022; Built up areas decreased by -4.8% from 2017 to 2022. It can be concluded that from 2017 and 2022, decrease in agricultural lands brings about appreciable increase in bare-ground and outcrop, and increased in thick vegetation. This is associated to abandoned farmlands, as a result of uncontrolled incidence of kidnapping and other criminalities in the study area. This decrease in agricultural lands brings about increase in bare-ground and increase vegetation cover. Vegetation cover provides a fertile ground for kidnappers to hide and perpetrate their criminal acts. This study agrees with the findings of Bariweni and Andrew (2017) that forest and sparse vegetation/grassland decreased from 73.34% and 10.32% to 51.34% and 8.08% between 2002 and 2015 respectively, while farmland and residential area increased from 10.71% and 0.44% to 30.575 and 1.72% for the same period respectively. Indicating that land use/cover changes was due to deforestation to provide raw materials for wood industries, and space for agriculture and building of house for the increasing population in the area.

Table 12: Land Cover Change Matrix along Kaduna-Abuja Expressway from 2012-2022

Land Cover	**Area (km^2) 2012**	**%**	**Area Cover (km^2) 2022**	**%**	**% Change**
Water body	0.121	2.925	3.501	0.008	3.38(-2.917)
Built-up-Areas	11211.0	25.101	2432.007	5.879	-8778.993 (-19.222)
Bare-ground/Outcrop	10122.1	24.352	10070.8	24.345	-51.3 (-0.007)
Agricultural Lands	10002.21	24.175	14152.81	34.213	4150.6 (10.038)
Vegetation Cover	10031.10	24.245	14707.41	35.553	4676.31(11.308)
Total	**41366.53**	**100**	**41366.53**	**100**	

Source: Author's Analysis, (2024)

Based on Table 12, a noteworthy augmentation of 11.3% in vegetation cover is observed, accompanied by a substantial 10.03% increase in agricultural lands. Conversely, there is a considerable decline of -19.22% in built-up areas and a marginal decrease of 0.007% in bare lands and outcrops. This pattern suggests that the interval from 2012 to 2022 witnessed a decline in bare lands, giving rise to an increase in vegetation cover and a corresponding decrease in built-up areas. The rise in bare grounds and outcrops is intricately linked to the phenomenon of abandoned farmlands, a consequence of prevalent kidnapping and other criminal activities in the study area.

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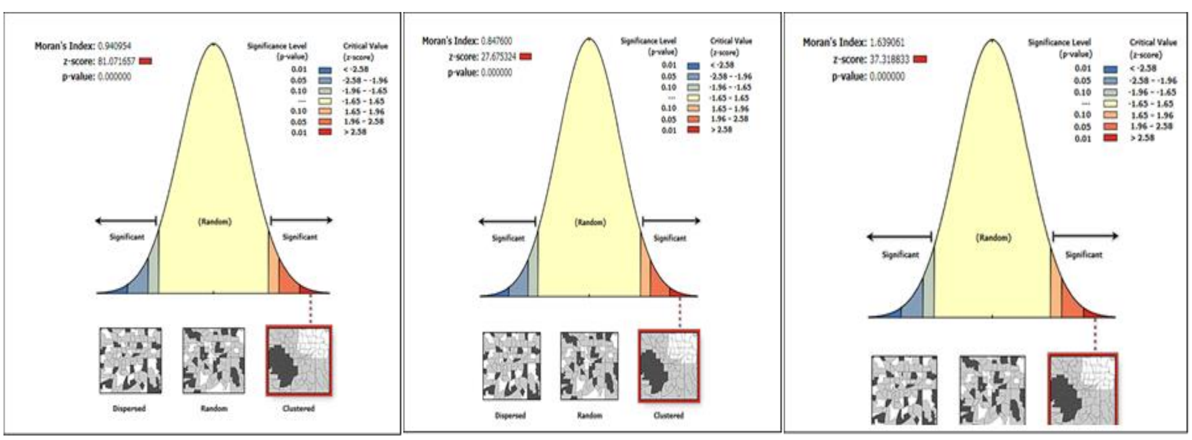
Consequently, a consistent correlation emerges between the decline in vegetation cover, the upsurge in bare-ground and outcrops, and the concurrent increase in vegetation juxtaposed with a diminished proportion of built-up areas. This phenomenon is a direct result of the unbridled escalation of kidnapping incidents in the study area.

The diminished built-up area observed from 2012 to 2022 is associated with a deceleration in the pace of urbanization, propelled by the escalating and uncontrolled nature of kidnapping. The encroachment of criminal activities, particularly in farming communities, has compelled inhabitants to abandon their farmlands, seeking refuge in relatively secure communities. Additional factors contributing to this observed pattern are linked to the study area's status as an expressway connecting various regions of the country. The instability in human mobility patterns within the study area further contributes to the limited expansion of built-up areas.

In essence, the uncontrolled surge in kidnapping incidents along the Kaduna-Abuja expressway, spanning from 2012 to 2022, engenders a fertile ground for diminished built-up areas and agricultural activities. Homesteads and farmlands are abandoned due to security threats, resulting in a decrease in built-up areas and a transformation from sparse vegetation to an increase in thick vegetation. It can be conclusively inferred that the uncontrolled incidence of kidnapping and associated criminalities along the Kaduna-Abuja expressway between 2012 and 2022 poses substantial threats to both human habitation and agricultural productivity within the study area.

The Global Spatial Autocorrelation (Moran's *I*)

The Global Spatial Autocorrelation (Moran's *I*) analysis of kidnapping rates, as presented in Figures 2 to Figure 4, shows Moran's *I* values of 0.94, 0.85, and 1.64, respectively. These values, being greater than zero, confirm a significant clustering of kidnapping incidents within the study area. The p-values (0.01), representing the significance test under the assumption that the distribution of Moran's *I* is normal, further reinforce the presence of clustering. The p-values (0.01) for all tests show statistical significance at the 99% confidence level, leading to the rejection of the null hypothesis. With z-scores of 81.07, 27.68, and 37.32 for the respective kidnapping rates, there is less than a 1% probability that the observed clustering is due to random chance. Figures 5 (a-c) summarizes the Global Autocorrelation (Moran's *I*) of kidnapping rates in the study area.



(a) (b) (c)

Figure 5 (a-c): Global Autocorrelation (Moran's *I*) of Kidnapping Rates in the Study Area
Source: Author's Analysis, (2024)

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Conclusion and Recommendations

The examination of the effects of kidnapping incidence on land use and land cover change along the Kaduna-Abuja expressway has yielded valuable insights into the spatial distribution of kidnapping activities within the study area. The study has disclosed noteworthy modifications in land cover dynamics, notably the abandonment of farmlands and the proliferation of vegetation, both directly influenced by incidents of kidnapping. The discerned patterns underscore the imperative for enhanced security measures along the expressway to effectively counter criminal activities. In essence, this analysis contributes substantively to an enhanced comprehension of the intricacies surrounding kidnapping incidences. Consequently, the research advocates for a constant monitoring of changes in land use and land cover (LULC) across the study area. This undertaking should extend beyond the confines of the study site, encompassing diverse local administrations within Kaduna State and extending to a national scale in Nigeria. To foster effective environmental planning and development in these regions, it is recommended that such assessments be conducted biannually and on a regular basis. This proactive methodology will establish a resilient groundwork for informed decision-making and sustainable growth within the confines of the study area.

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