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MONITORING DESERTIFICATION AND ITS ENVIRONMENTAL EFFECTS IN SOKOTO STATE USING GEOSPATIAL APPROACH

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Abstract: *Report by the International Food Policy Research Institute highlights that Nigeria loses approximately 0.35% of its total land area estimated at 923,768 km² to desertification annually. As of the year 2020, about 35% of the country's landmass is under threat, putting the livelihoods of over 40 million land dependent individuals at risk. This study employs Remote Sensing and Geographic Information System (GIS) techniques to monitor the rate of desertification in Sokoto State, Nigeria. Multi-temporal satellite imagery, including Landsat TM (2000), Landsat 4 (2005), Landsat 7 (2010), and Landsat 8 OLI (2015, 2018), was obtained from the United States Geological Survey (USGS). Geometric and atmospheric corrections were applied to enhance image accuracy. Supervised classification using the Maximum Likelihood algorithm was adopted, and desertification indicators precipitation, temperature, and population were integrated with land use/land cover (LULC) outputs for comprehensive analysis. Findings reveal a substantial decline in vegetated areas from 33.4% in the year 2000 to 12.3% in the year 2020, largely driven by urbanization, agricultural encroachment, and possible climate factors. Built-up areas significantly increased from 15.1% to 32.3% over the same period, indicating rapid urban development. Bare soil coverage exhibited fluctuations, with a notable rise from 41.6% in the year 2015 to 52.8% in 2020. Water bodies declined from 2.6% in 2000 to 1.6% in 2020, raising concerns over water availability. Projections using Markov cellular automata algorithm for the year 2025 and 2030 indicated continued degradation, with vegetated areas recording a decrease trend pattern by 8.2% to 10% and built-up areas to record an increasing trend of 40% to 53% by 2030. These trends underscore the urgent need for strategic interventions and policies aimed at mitigating desertification and restoring degraded lands to sustainable productivity.*

Key words: Desertification, Deforestation, Soil Fertility, Urbanization and Remote Sensing and Geographical Information System (GIS)

1 Introduction

Desertification remains one of the most pressing environmental challenges confronting dryland regions globally, with profound implications for ecological sustainability, agricultural productivity, and human livelihoods. It is broadly defined as the land degradation in arid, semi-arid, and dry sub-humid areas, primarily driven by climatic variations and anthropogenic activities (Ibrahim et al., 2022). to the misconception that it entails the physical expansion of deserts, desertification is better understood as the progressive degradation of land in drylands due to unsustainable human activities and environmental pressures (Bayati, 2017). This complex and multidimensional phenomenon involves the deterioration of soil quality, loss of vegetative cover, and a decline in the overall productivity of ecosystems that were once biologically diverse and agriculturally viable (Higginbottom and Symeonakis, 2014).

Several interlinked natural and human-induced factors contribute to desertification. According to Carvalho (2024), understanding these causative

BJET, 2025, Vol. 20 (1), 64-76

elements is crucial to designing effective mitigation strategies. Jibrillah et al. (2019) identify climate change, overgrazing, deforestation, unsustainable agricultural practices, urban expansion, and mining as primary drivers. Changes in temperature and precipitation patterns often result in prolonged droughts and increased evaporation, accelerating the degradation of already fragile ecosystems (Trenberth, 2011). Unregulated livestock grazing, for instance, leads to the excessive removal of vegetation cover, reducing soil fertility and enhancing erosion risks (Milazzo et al., 2023; Abdelsalam, 2021). Deforestation for fuelwood and agricultural land not only exposes soil surfaces but also disrupts biodiversity and microclimatic conditions (Olijrra, 2019; World Bank, 2019). Moreover, poor land management practices such as monocropping, overuse of agrochemicals, and inefficient irrigation further exacerbate soil exhaustion and salinization (Elouattassi et al., 2023; Khan et al., 2024). Urbanization and resource extraction also result in the loss of vegetation and increased susceptibility to wind and water erosion (Abdul-Rahaman et al., 2016). The consequences of desertification are far-reaching and multifaceted. It leads to significant biodiversity loss, reduction in arable land, depletion of freshwater resources, and destabilization of socio-economic systems (Li et al., 2024; Fekadu, 2023). Fertile lands transform into barren wastelands, forest ecosystems disappear, and grasslands contract, thereby undermining ecological functions and habitat integrity (Anjum et al., 2010). As vegetation cover diminishes, the topsoil becomes more vulnerable to erosion, diminishing agricultural outputs and endangering food security (McLaughlin and Kinzelbach, 2015). Additionally, reduced vegetation cover impairs groundwater recharge by limiting rainfall infiltration, which exacerbates water scarcity and intensifies competition for dwindling resources (Jasechko et al., 2024). Mitigating desertification necessitates a multi-pronged approach, including sustainable land management, afforestation, conservation agriculture, and policy frameworks that promote responsible land use (Islam et al., 2025; AbdelRahman, 2023). Central to these strategies is the ability to monitor and detect desertification trends effectively.

In this regard, remote sensing and Geographic Information Systems (GIS) offer powerful tools for large-scale, cost-effective monitoring. Remote sensing enables the detection of land cover changes, vegetation health, and surface water availability, while GIS facilitates spatial analysis and decision-making (Dubovyk, 2017; Mashala et al., 2023). Field-based assessments provide direct observations but are typically labor-intensive and geographically limited. Emerging technologies such as unmanned aerial vehicles (UAVs) and sensor networks now offer high-resolution data and real-time environmental monitoring capabilities (Andresen and Schultz-Fellenz, 2023). A growing body of research has demonstrated the effectiveness of geospatial technologies in assessing and combating desertification. For instance, Bayati (2017) and Al-Timimi (2021) applied remote sensing and GIS to detect vegetation loss and expanding sand dunes in Iraq. Similarly, Wang (2008) and Kundu (2015) utilized these tools to investigate the influence of climate and anthropogenic factors on desertification in China and India, respectively. These studies underscore the critical role of geospatial techniques in generating accurate, timely data to guide intervention strategies. In the context of Nigeria, particularly Sokoto State, desertification presents an urgent environmental and socio-economic threat. Characterized by an arid to semi-arid climate and extensive land degradation, Sokoto is increasingly vulnerable to the adverse impacts of desert encroachment. These include declining agricultural productivity, water scarcity, and ecological imbalance all of which compromise food security and livelihoods. Therefore, a geospatial assessment of desertification in Sokoto is not only timely but essential for informing sustainable land use planning and resilience-building strategies.

2 Study Area

Sokoto is a northwestern state in Nigeria, renowned for its distinctive cultural heritage, historical significance, and unique geographical features. Situated within the Sahelian ecological zone, Sokoto State experiences a semi-arid climate characterized by high temperatures, limited and erratic rainfall, and an extended dry season (Atedhor, 2015). These environmental conditions render the region particularly vulnerable to desertification and land degradation. Geographically, Sokoto State is located at approximately latitude 13°05′ N and longitude

5°15′ E (Mahmuda et al., 2014), encompassing an estimated land area of 32,000 km². It shares boundaries with Kebbi State to the southwest, Zamfara State to the southeast, and the Republic of Niger to the north. The climate is defined by two major seasons: a rainy season occurring between May and September, and a dry season extending from October to May (Anon, 2001). Relative humidity levels are typically 20% or lower, while average temperatures range between 22°C and 43°C (Iloeje, 1971). Figure depict the map of the study area.

Figure 1.: Map of Sokoto state

3 Methodology

The methodology adopted for this study involves the integration of Remote Sensing (RS) and Geographic Information System (GIS) techniques to investigate the extent and progression of desertification in Sokoto State, Nigeria. The region's semi-arid climate characterized by high temperatures, irregular rainfall patterns, and extended dry seasons makes it particularly prone to desertification processes (Ikpe and Ajiya, 2021; Atedhor, 2015). The step-by-step workflow of the methodological approach is illustrated in Figure 2. Additionally, the sources of the datasets utilized for this research are summarized in Table 1.

3.1 Data Acquisition

Landsat satellite imagery acquired for the years 2000 (Landsat TM), 2005 (Landsat 4), 2010 (Landsat 7 ETM+), and 2015 and 2018 (Landsat 8 OLI) were sourced from the United States Geological Survey (USGS) database. The scenes covered multiple Landsat paths and rows, specifically Path 191/Row 050, Path 191/Row 051, Path 191/Row 052, and Path 190/Row 051.

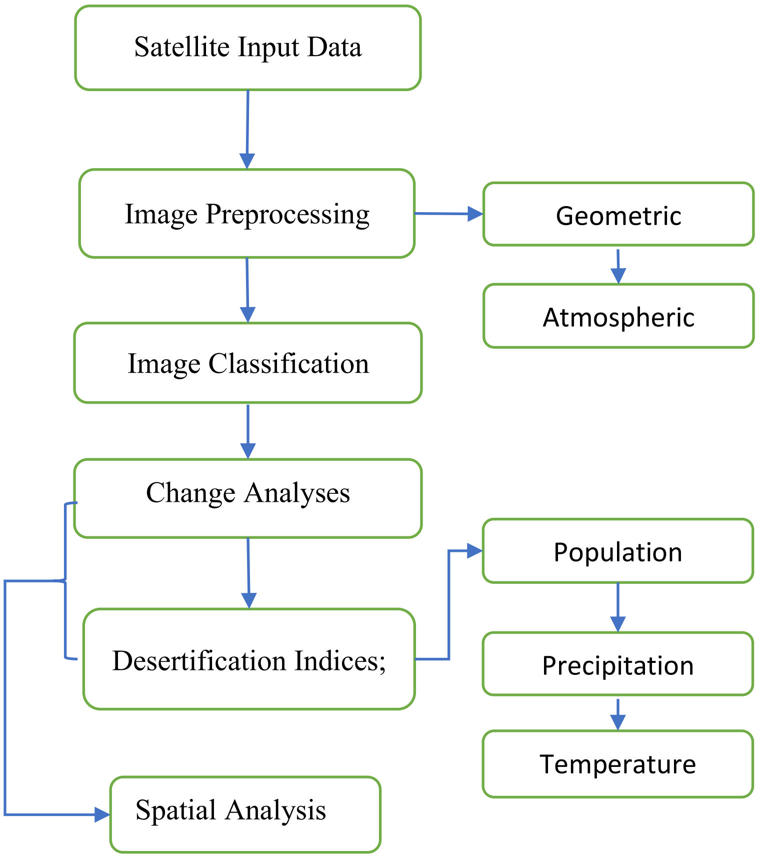

Figure 2. Conceptual Design

All images were orthorectified and provided in GeoTIFF format, referenced to the WGS 84/UTM Zone 32N coordinate system (Minna Datum). The pre-processing stage involved mosaicking the satellite scenes and clipping them using the Sokoto State administrative boundary shapefile as a reference. The selected spectral bands for each Landsat sensor were optimized to detect changes in land cover, vegetation condition, and surface soil moisture across the study period. This approach enabled a consistent temporal analysis of desertification trends. A summary of the datasets, including sensor type, acquisition dates, spatial resolution, and sources, is presented in Table 1.

Table 1. *Data Characteristics and Sources*

S/N	Data name	Data Type	Epochs	Resolution	Data Sources
1	Landsat Satellite Imagery	Raster data	2000, 2005, 2010, 2015 &2020	30m	USGS Earth Explorer
2	Climate parameters	Vector Data	2000-2020		Nigeria Meteorological Agency (NIMET)
3	Administration Map	Vector data	20years	1:300,000	OSGF
4	Demographic	Vector	20years		NPC&INEC

The details of the satellite datasets used in this study are presented in Table 1. For land use/land cover (LULC) classification, bands 2, 4, 5, and 6 were utilized for Landsat 8 OLI, while bands 1, 3, 4, and 5 were applied for Landsat 4–5 ETM imagery. In addition to the satellite data, supplementary geospatial datasets were integrated to examine other contributing factors to desertification in Sokoto State. These included rainfall, temperature, and population data. The climatic parameters were sourced from the Nigerian Meteorological Agency (NiMet), while demographic data were obtained from both the National Population Commission (NPC) and the Independent National Electoral Commission (INEC). To prepare the satellite image data for postprocessing, geometric correction was carried out to mitigate terrain-induced distortions and restore the true spatial representation of surface features. This step addressed the effects of terrain displacement, Earth curvature, and sensor rotation, thereby ensuring accurate geometric alignment (Green et al., 2014). Radiometric correction was also performed by converting digital number (DN) values into radiance. To reduce atmospheric noise and enhance spectral quality, top-of-atmosphere (TOA) correction was applied across all Landsat bands. This process transformed DN values into surface reflectance, as recommended by Baba et al. (2025) and validated by earlier studies (Kobayashi and Sanga-Ngoie, 2008; Paolini et al., 2006).

Land use/land cover change maps for the study area were generated through supervised classification, employing the maximum likelihood algorithm, which is widely recommended for Sub-Saharan African landscapes due to its robustness. The classification was executed using QGIS 3.4 and categorized the landscape into five major classes: wetland, farmland, built-up areas, bare land, and vegetation.

3.2 Land Cover Mapping and Accuracy Assessment

Due to prevailing security challenges in the study area, field data collection is both logistically difficult, costly, and potentially hazardous. To overcome these constraints, recent studies have increasingly relied on auxiliary sources such as high-resolution Google Earth imagery for training and validation purposes, with documented success (Hu et al., 2013; Burke et al., 2021). These secondary data sources have proven invaluable in supporting the development and validation of remote sensing-based land cover maps, particularly within the Nigerian context (Mengistu and Salami, 2008; Ishaya and Ifatimehin, 2009).

In this study, a combination of expert knowledge and Google Earth imagery was employed to generate training and reference data for the years 2000 and 2020. Accuracy assessment was conducted using stratified random sampling and a set of reference points. The 2020 classification epoch, which was validated against high-resolution Google Earth imagery, achieved an overall accuracy of 89%, demonstrating the reliability of this approach in the absence of extensive field data.

3.3 Image Classification

Supervised image classification technique was employed to categorize land cover types within the study area. This process involves training the classifier using reference data (ground truth points) that represent specific land cover classes (e.g., bare soil, vegetation, water). Maximum Likelihood algorithm was utilized based on data characteristics and its ability to classify pixel efficiently even at lower resolution. Change detection techniques were applied to Landsat imagery acquired for different time periods. This will enable the identification and quantification of land cover changes that have occurred over time. Commonly used methods include post-classification change detection and spectral change analysis.

3.4 Time Series and Forecasting

A cross-tabulation analysis was carried out to estimate the gains and losses across each land cover class and to assess the spatio-temporal trends of land cover change. The analysis began by comparing land cover maps from 2000 to 2020, providing an overview of the cumulative changes over the 20-year study period. To gain further insights into the progression of land use/land cover (LULC) transitions, change detection was also conducted between individual time intervals. 2000–2005, 2005–2010, 2010–2015, and 2015–2020. Forecasting future LULC dynamics has been approached using various modeling techniques in the literature. One of the most widely adopted models is the Cellular Automata–Markov Chain (CA-Markov) model, which is particularly effective due to its incorporation of spatial interactions, unlike other models that primarily emphasize temporal or seasonal patterns (Asif et al., 2023; Luan et al., 2024). The CA-Markov model has demonstrated strong predictive capabilities in numerous case studies. For instance, Hamad et al. (2018) illustrated its robustness under varying scenarios; Karimi et al. (2018) successfully applied it to monitor land dynamics in Ravansar County, Iran; and Rahnama (2021) used the model for LULC forecasting in Mashhad Metropolitan. Similarly, Khawaldah et al. (2020) integrated CA-Markov with GIS and remote sensing tools to simulate future land cover changes, while El Haj et al. (2023) confirmed its effectiveness in projecting long-term LULC trends.

The CA-Markov modelling process begins with the normalization of land cover data, converting categorical data into proportional and probabilistic values. This step generates the transition probability matrix, which quantifies the likelihood of land cover types converting from one class to another. The Cellular Automata (CA) transition function is then applied to incorporate spatial dependencies, using the transition probabilities to simulate future land cover states over predefined time intervals. The mathematical relationships among the transition probability matrix, state vector, and future state prediction are expressed in Equations 1, 2, and 3, respectively.

3.4.1 Markov Chain Components

Transition Probability Matrix (P)

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \qquad (1)$$

Where p_{ij} Represent the probability of transitioning from state i (land use type I) to state j (land use type j) over a specified period.

State Vector:

$$S_t = \begin{bmatrix} S_{1(t)} \\ S_{2(t)} \\ \vdots \\ S_{n(t)} \end{bmatrix} \qquad (2)$$

$$S_{(t-1)} = P.S_{(t)} \qquad (3)$$

Where $S_{i(t)}$ represent the proportion of land in the state i at time t, *Future State Prediction*

4 Results and Data Analysis.

4.1 Discussion and Analysis of LULC Change Data in Sokoto State, Nigeria

The land use/land cover (LULC) analysis of Sokoto State from 2000 to 2020 reveals significant spatial and temporal changes in key land cover types, including vegetation, bare soil, built-up areas, and water bodies. These shifts serve as critical indicators for assessing the extent and progression of desertification in the region. The results underscore patterns that merit detailed evaluation and discussion. Table 2 presents the classification accuracy achieved during the image classification process, while land cover changes over the 20-year period are expressed in both square kilometers and percentage of total land area. The study area encompasses a total landmass of approximately 26,493.83 km² (see Table 1). Over this period, vegetation cover experienced a sharp decline, reducing from 8,826.01 km² (33.4%) in 2000 to just 3,245.45 km² (12.3%) in 2020. This represents a substantial reduction of approximately 63%, signalling an alarming trend consistent with severe desertification processes. This decline is likely driven by a combination of factors, including overgrazing, deforestation, and the impacts of climate variability. The loss of vegetative cover not only threatens biodiversity but also increases soil erosion and diminishes soil fertility, with significant implications for agricultural productivity in the region (Doso Jnr, 2014; Telo-da-Gama, 2023).

Conversely, while bare soil initially declined in earlier epochs, a marked increase was observed between 2015 and 2020, rising from 10,972.19 km² (41.6%) to 13,972.25 km² (52.8%). This upward trend in bare soil, particularly within the last decade, serves as a strong indicator of escalating land degradation. It suggests that previously vegetated areas are becoming increasingly barren, likely due to unsustainable land use practices and the advancing effects of desertification.

***Table 2.** Vector Data from Map of Sokoto State from The Year 2000 to 2020*

	2000		2005		2010	
Category	UA	CE	UA	CE	UA	CE
Bare Land	0.89	0.11	0.88	0.12	0.85	0.15
Builtup areas	0.93	0.07	0.88	0.12	0.93	0.07
Vegetation	0.84	0.16	0.88	0.12	0.87	0.13
Water bodies	0.83	0.17	0.84	0.006	0.88	0.12
OA	86%		88%		85%	
	2015		2020			
	UA	CE	UA	CE		
Bare Land	0.85	0.15	0.86	0.14		
Built up areas	0.83	0.17	0.9	0.1		
Vegetation	0.78	0.22	0.83	0.17		
Water bodies	0.79	0.21	0.82	0.18		
OA	76%		79%			
UA	User accuracy					
CE	Commission error					
OA	Overall accuracy					

Built-up areas exhibited a consistent expansion across all epochs analyzed, increasing from 3,999.48 km² (15.1%) in 2000 to 8,563.67 km² (32.3%) in 2020. This steady growth reflects the ongoing trend of urbanization within Sokoto State. While urban expansion is often indicative of socio-economic development, it also poses several challenges, including the loss of arable land, increased pressure on food supply and natural resources, and the potential for environmental degradation (Marzuki and Jais, 2020). Figure 3 illustrates the land use/land cover (LULC) change maps for Sokoto State between 2000 and 2005, highlighting the spatial distribution and transition of various land cover types during this period

The expansion of built-up areas often results in the displacement of natural habitats and contributes to the urban heat island effect, which can alter local climatic conditions and further accelerate desertification processes (Han et al., 2023). In contrast, water bodies exhibited minor fluctuations over the study period, showing a net decline from 700.16 km² (2.6%) in 2000 to 412.45 km² (1.6%) in 2020 (see Table 3). This reduction may be attributed to factors such as declining rainfall, increased evaporation rates driven by rising temperatures, and the over-extraction of water resources for agricultural and urban demands. The decline in surface water not only compromises human water

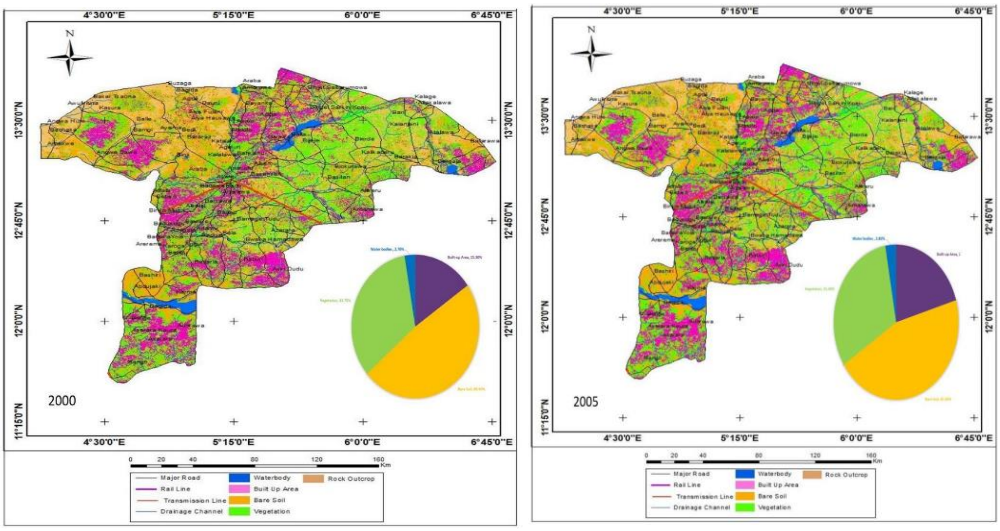

Figure 3. land used land cover Classification map of Sokoto state, Nigeria from the year 2000 to the year 2005

+availability but also poses significant risks to aquatic ecosystems and local biodiversity. Collectively, these land cover changes marked by decreasing vegetated areas and increasing urban and bare soil extents reflect a profound environmental transformation likely driven by climate variability and human land use practices. Importantly, the accuracy assessment of the land cover classification results across the four epochs demonstrates a high level of reliability. The lowest overall accuracy was recorded in 2015 at 76%, while all other classification years exceeded 80% accuracy, underscoring the robustness and validity of the classification outputs. Figures 4 and 5 present the classified land use/land cover maps for the years 2010, 2015, and 2020, illustrating the spatial patterns and transitions across different land cover types

Table 3. Vector Data for the LULC Change Maps for the year 2000 to 2020

Land Cover	2000	%	2005	%	2010	%	2015	%	2020	%
Vegetation	8826.005	33.4	8216.021	31.1	7026.116	26.6	7351.28	27.9	3245.45	12.3
Bare Soil	12668.19	47.9	11888.19	45.0	11668.19	44.2	10972.19	41.6	13972.253	52.8
Built-Up Area	3999.475	15.1	5349.523	20.2	6869.365	26.0	7369.365	27.9	8563.671	32.3
Water	700.1631	2.6	740.1	2.8	630.1631	2.4	5000.992	1.9	412.453	1.6
Total	26493.83	100	26493.83	100	26493.83	100	26493.83	100	26493.83	100

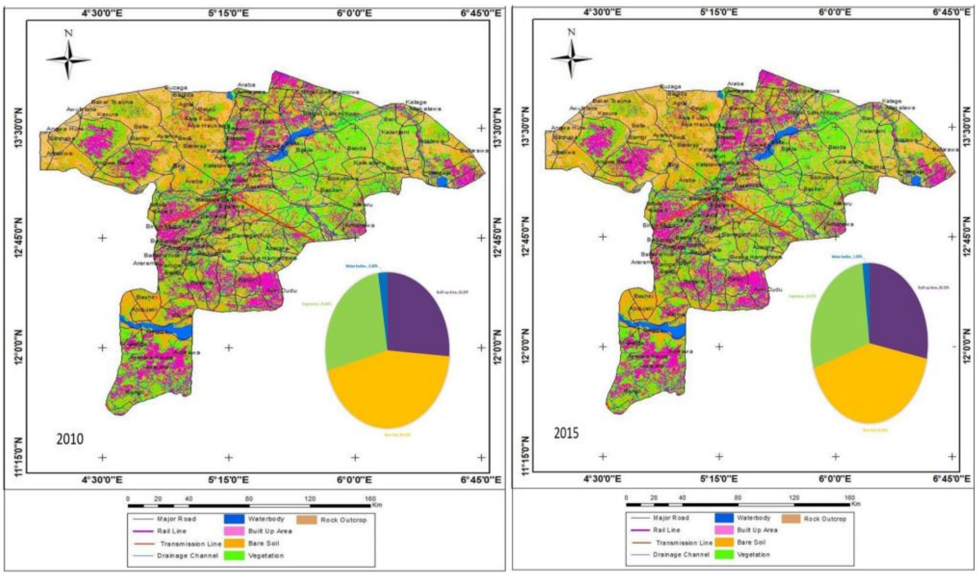

Figure 4. LULC change classification maps of Sokoto state, Nigeria from the year 2010 to the year 2015.

4.2 Land Cover Projection and Forecast For the year 2025 and 2030.

The transition matrix, incorporating average growth rates and forecasted land cover values for the years 2025 and 2030, offers valuable insights into projected changes across the study area. The model predicts a continued decline in vegetation cover, with an average growth rate of 0.818455, decreasing from 2,656.26 km² in 2025 to 2,174.03 km² by 2030. This trend underscores the persistence of vegetation loss, likely due to ongoing anthropogenic pressures and climatic stress. In contrast, built-up areas are projected to experience substantial growth, reflecting a growth rate of 1.214129, increasing from 10,397.40 km² in 2025 to 12,623.78 km² in 2030. This notable expansion is indicative of sustained urbanization trends in the region. Water bodies are expected to decline modestly, with a growth rate of 0.881697, shrinking from 363.66 km² in 2025 to 320.68 km² by 2030, likely due to continued climatic variability and water resource exploitation.

Similarly, bare soil is projected to increase slightly, with a growth rate of 1.033424, rising from 14,439.26 km² in 2025 to 14,921.89 km² in 2030. These projections, presented in Table 4, highlight critical environmental trends, the expansion of urban areas at the expense of vegetation and water resources, accompanied by a gradual increase in bare soil. Figure 6. Depicts the graphical representation of the patches trend pattern to the year 2030. Together, these changes suggest a trajectory of increasing land degradation, habitat loss, and reduced ecological resilience in the study area

Table 4. Projection Transition Matrix

Categories	Grow rate	2025	2030
Vegetation	0.8184	2656.255	2174.026
Built-up Area	1.2141	10397.399	12623.782
Water Bodies	0.8816	363.658	320.683
Bare Soil	1.0334	14439.264	14921.888

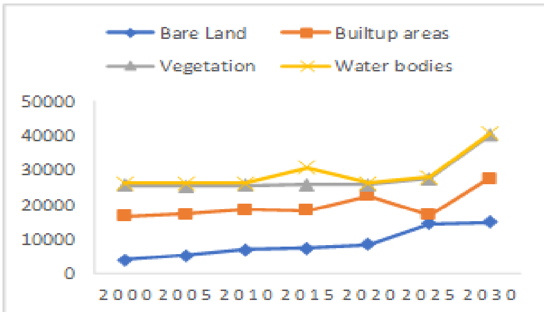

Figure 6. LULC change trend Pattern from the year 2000 to 2020 using CA-Markov

4.3 The Integration of LULCC of the Study Area to Desertification Parameter.

4.3.1 Relationship Between Vegetation and Rainfall

Figure 7 presents a comparative chart illustrating total annual rainfall and the percentage of vegetation cover in Sokoto State from 2000 to 2020. During this period, a notable declining trend in rainfall is observed remaining at 700 mm in both 2000 and 2005, then decreasing to 550 mm in 2010, showing a slight increase to 560 mm in 2015, before further dropping to 490 mm in 2020. In parallel, the percentage of vegetation cover also declined significantly, from 33.69% in 2000 to 12.39% in 2020. This consistent reduction in vegetative cover appears to correlate with the decreasing trend in rainfall, suggesting a potential relationship between precipitation variability and vegetation dynamics. The observed pattern supports the hypothesis that declining rainfall may be a key factor contributing to the loss of vegetation cover, further exacerbating desertification processes within the region.

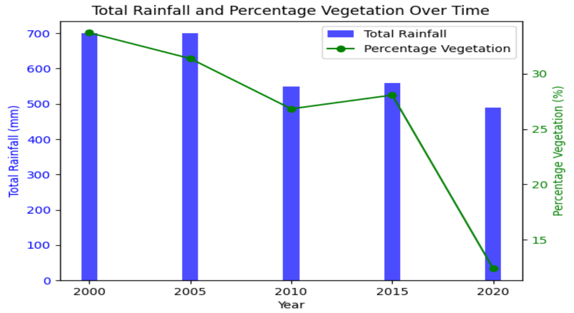

***Figure** 7. Relationship between total rainfall and percentage vegetation from 2000 and 2020*

4.3.2 Relationship Between Vegetation and Population

The chart presented in Figure 48 illustrates the relationship between population growth and the percentage of vegetation cover in Sokoto State from 2000 to 2020. Over this two-decade period, the population increased steadily from approximately 1,050,000 in 2000 to 2,167,834 in 2020. In contrast, the proportion of land covered by vegetation declined markedly, decreasing from 33.69% to 12.39% over the same timeframe. This inverse relationship suggests that population growth may be a significant driver of vegetation loss in the region. The increasing population likely exerts pressure on land through urban expansion, agricultural encroachment, and other human-induced land use changes, contributing to the degradation of natural vegetation. The observed trend underscores the environmental consequences of demographic growth, particularly its impact on natural resources, land cover, and ecosystem integrity.

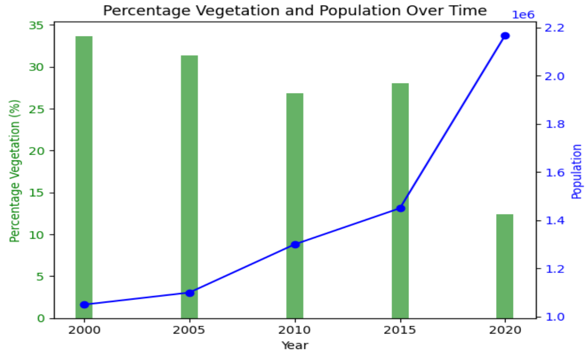

***Figure 8**. Relationship between percentage vegetation and population from the year 2000 to 2020*

4.3.3 Relationship Between Vegetation and Temperature

Figure 9 presents a comparative analysis of temperature trends and the percentage of vegetation cover in Sokoto State between 2000 and 2020. Throughout this period, temperature exhibited notable fluctuations with an overall increasing trend rising from 33.8°C in 2000 to 36.9°C in 2005, slightly increasing to 37.0°C in 2010, dropping to 34.5°C in 2015, and peaking at 38.0°C in 2020. Concurrently, the percentage of vegetation cover declined steadily, falling from 33.69% in 2000 to 12.39% in 2020. This inverse relationship observed in Figure 9 suggests that as temperatures have risen, vegetation cover has decreased significantly. The decline may be attributed to the adverse effects of heat stress, altered precipitation patterns, and other climate-related stressors that inhibit plant growth and survival. These findings emphasize the negative impact of rising temperatures on vegetative health and point to the broader ecological consequences of climate change on terrestrial ecosystems.

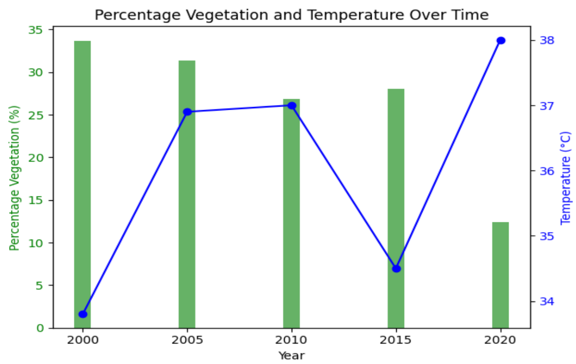

***Figure 9**. Relationship between percentage vegetation and temperature from the year 2000 to 2020*

BJET, 2025, Vol. 20 (1), 64-76

4.4 Discussion

4.4.1 Land Use Land Cover Analysis

The land use/land cover (LULC) analysis for Sokoto State from 2000 to 2020 reveals critical environmental trends that warrant in-depth evaluation. One of the most significant findings is the continuous decline in vegetation cover over the two-decade period. In 2000, vegetation covered approximately 8,826.01 hectares, but by 2020, this figure had declined by nearly 63%, reducing to just 3,245.45 hectares. This dramatic loss of vegetative cover indicates a heightened vulnerability to desertification and environmental degradation in the region. A similar pattern is observed in the bare soil category, which initially showed a modest decline from 12,668.90 hectares in 2000 to 11,888.19 hectares in 2005, and further to 11,668.19 hectares by 2010. However, this trend reversed in subsequent years, with bare soil areas increasing substantially to 13,972.25 hectares by 2020. This resurgence in exposed soil may be linked to vegetation loss, poor land management practices, and increased anthropogenic pressure. Ahmad et al. (2019), in a study on desertification in Sokoto State, similarly identified overgrazing, deforestation, and climate change as major contributors to vegetation degradation and the exposure of bare soil.

In contrast, the built-up area exhibited a consistent upward trend over the study period. From 3,999.48 hectares in 2000, it more than doubled to 8,563.67 hectares in 2020, reflecting the region's rapid urbanization and infrastructure development. While urban growth can signify economic progress, it also introduces a range of environmental challenges. As noted by Beckers et al. (2020), urban expansion often leads to the conversion of agricultural and natural land, increasing pressure on natural resources and contributing to environmental degradation. Moreover, the displacement of vegetative cover due to urban development can intensify the urban heat island effect, further exacerbating local climate conditions.

The trend in water bodies also raises concerns. In 2000, surface water bodies covered approximately 700.16 hectares, but this area declined to 412.45 hectares by the year 2020, a reduction of more than 40%. This substantial loss suggests a decline in surface water availability, which may be attributed to factors such as reduced rainfall, increased evapotranspiration, and excessive withdrawal of water for agricultural and urban uses. The depletion of water resources not only threatens local ecosystems but also poses a serious challenge to human water security in a region already vulnerable to climate variability.

Overall, these land cover dynamics declining vegetation and water bodies, rising bare soil, and expanding urban areas reflect the interplay between environmental stressors and human activities. They underscore the urgent need for sustainable land management strategies, reforestation efforts, and integrated environmental planning to mitigate further degradation and support ecological resilience in Sokoto State.

5 Conclusion and Recommendation

5.1 Conclusion

The comprehensive assessment of land cover changes in Sokoto State, Nigeria, from 2000 to 2020, reveals substantial environmental transformations driven by both natural processes and anthropogenic activities. Over the two-decade period, there has been a pronounced decline in vegetated areas, reducing from approximately 8,826.01 km² (33.4%) in 2000 to 3,245.45 km² (12.3%) in 2020. This trend highlights the profound impacts of urban expansion, agricultural encroachment, and potentially climate-induced stressors such as increased temperature and declining precipitation. Simultaneously, built-up areas have expanded significantly, more than doubling from 3,999.48 km² (15.1%) to 8,563.67 km² (32.3%), reflecting the rapid pace of urbanization and infrastructure development in the region. The bare soil category experienced initial reductions, followed by a sharp increase, rising from 10,972.19 km² (41.6%) in 2015 to 13,972.25 km² (52.8%) in 2020. This reversal points to increasing land degradation, potentially due to deforestation, unsustainable land practices, and desert encroachment. Additionally, surface water bodies witnessed a gradual decline, shrinking from 700.16 km² (2.6%) in 2000 to 412.45 km² (1.6%) in 2020, suggesting growing water scarcity concerns in the face of changing climatic and land use patterns.

Future projections for 2025 and 2030 reinforce these findings, with vegetation expected to decline further to 2,174.03 km², while built-up areas are anticipated to reach 12,623.78 km² by 2030. These projections underscore a continued trajectory of urbanization occurring at the expense of natural ecosystems, emphasizing the urgent need for sustainable land management strategies. This study also examined the interrelationship between desertification and key climate and demographic variables, including rainfall, temperature, and population growth. The decline in vegetation from 33.69% in 2000 to 12.39% in 2020 closely correlates with reduced rainfall and rising temperatures, illustrating the compounded effects of climate change on vegetative health and distribution. Additionally, population growth, which surged from 1,050,000 in 2000 to 2,167,834 in 2020, has intensified pressure on land resources, accelerating deforestation, land degradation, and habitat loss.

Overall, the findings highlight the intensifying environmental challenges facing Sokoto State, driven by a combination of human-induced land use changes and climatic variability. Addressing these issues demands immediate policy interventions aimed at promoting sustainable land use, implementing reforestation and afforestation programs, and strengthening environmental governance. The integration of remote sensing and GIS technologies has proven invaluable in monitoring and analysing land cover dynamics, providing a robust scientific basis for designing effective strategies to mitigate environmental degradation and ensure the long-term sustainability and resilience of the region's ecosystems.

6 Recommendation

i. The restoration of vegetation through reforestation and afforestation is a vital strategy for combating desertification. These interventions contribute significantly to reducing soil erosion, enhancing soil fertility, and supporting biodiversity conservation. By stabilizing the soil surface, increasing organic matter, and improving the land's capacity to retain water and nutrients, reforestation efforts foster a more resilient and ecologically stable environment.

ii. The adoption of sustainable land management practices, including crop rotation, agroforestry, and conservation tillage, plays a key role in maintaining soil health and agricultural productivity. These practices help alleviate pressure on land resources, enhance soil structure, and increase the land's resilience to degradation. Promoting SLM ensures the long-term viability of productive landscapes, reducing susceptibility to desertification while supporting livelihoods.

iii. Effective water resource management is critical in arid and semi-arid environments. Techniques such as rainwater harvesting, efficient irrigation systems, and the protection of natural water bodies are essential for sustaining both agricultural activities and ecological functions. By minimizing water loss and optimizing usage, water conservation practices help mitigate land stress, reduce degradation risks, and contribute to climate adaptation and desertification control.

iv. Enhancing public understanding of desertification and its environmental implications through awareness campaigns and educational initiatives is essential for fostering responsible land stewardship. Community-based education programs can empower local populations to adopt sustainable practices, actively protect their natural environment, and contribute to desertification mitigation efforts. Building a culture of environmental responsibility at the grassroots level is crucial for achieving long-term ecological sustainability.

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