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Modelling Land Use and Land Cover Changes Detection of Sokoto State, Nigeria Using Cellular Automaton and Markov Algorithm

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Abstract

Sokoto state has experienced extensive land degradation, leading to significant ecological and socio-economic impact on its population. This division on land has disrupted local ecosystem and affected the livelihoods of the people, creating challenges for both environmental sustainability and economic development in the State. Currently, desert features cover approximately 580,841 km² of Nigeria's landmass, accounting for 63.8% of the country's total area and affecting around 30 million people, or 17% of the national population. Sokoto State ranks second highest in desertification severity within Nigeria, leading to reduced land productivity, biodiversity loss, and ecological imbalance, which threaten the livelihoods of agrarian communities. This project aims to combat desertification in Sokoto State using advanced remote sensing and Geographic Information System (GIS) methodologies. The study will assess the extent and severity of desertification, identify contributing factors, and propose sustainable land management strategies. The research timeframe spans from 2000 to 2020, with data analysed at five-year intervals. Using multi-temporal satellite imagery from Landsat and integrating spatial data layers, including population and rainfall data from the Nigerian Meteorological Agency (NIMET), the project will conduct land use/land cover analysis, forecasting, and modelling. The findings aim to provide critical insights for local communities, policymakers, and stakeholders, enabling informed decisions and proactive measures to preserve and rehabilitate Sokoto State's fragile ecosystem.

Keywords: Land Degradation, Geographic Information System (GIS), Remote Sensing, Sokoto State, Sustainable Land management

1. Introduction

Land is fundamental to human existence, providing essential resources such as food, clothing, and shelter. Consequently, preventing land degradation is critical. Land degradation, a persistent decline in land productivity and biodiversity, poses a significant threat to ecosystems and human livelihoods. This degradation often results from climate change and anthropogenic activities, leading to the loss of soil fertility, water resources, and vegetation cover (Ahmad and Pandey, 2018; IPBES, 2018). Desertification, a severe form of land degradation, affects approximately 580,841 km² of Nigeria's landmass, impacting up to 63.8% of the country's total area and affecting around 30 million people (Ibrahim *et al.,* 2019). In Sokoto State, desertification manifests through land degradation, reduced agricultural productivity, loss of biodiversity, and ecological imbalance, threatening the livelihoods of agricultural communities. Despite numerous efforts, the absence of comprehensive and up-to-date data hinders effective monitoring and mitigation strategies. The necessity for precise and timely desertification monitoring has led to the increasing use of remote sensing and Geographic Information Systems (GIS). These technologies offer robust and cost-effective tools for assessing and tracking environmental changes over large areas, providing critical insights into desertification's spatial and temporal dynamics. Remote sensing and GIS techniques have been successfully employed in various studies to monitor desertification, identify key drivers, and propose mitigation strategies (Ekundayo et al., 2020).

Previous remote sensing studies have successfully monitored desertification in semi-arid regions, highlighting land cover changes, vegetation loss, and rainfall variability as key drivers. Research suggests that human activities such as overgrazing and deforestation significantly contribute to these environmental changes. For instance, Ibrahim et al. (2022) assessed desertification in northeastern Nigeria using Landsat TM, ETM, NigerSat-1, and NigerSat-X data over 25 years, employing land use/land cover analysis to track changes. Similarly, Ekundayo et al. (2020) utilized MODIS data to assess drought in the Sudano-Sahelian region of Nigeria through the Vegetation Health Index (VHI) from 2000 to 2010. Ahmad et al. (2019) examined desertification trends in Sokoto using MODIS data and the Enhanced Vegetation Index (EVI) over nearly two decades. Despite these efforts, there remains a lack of up-to-date studies focusing on Sokoto State specifically, with existing research predominantly concentrating on meteorological characteristics rather than geospatial analyses. Moreover, recent methodologies often focus on land use/land cover approaches, with relatively few studies employing vegetation indices such as NDVI and EVI. Maniyunda and Ya'u (2019) and Jibrillah et al. (2019) attempted to fill this gap by integrating land use/land cover analysis with anthropogenic and climatic factors. Yet, their studies were limited in temporal scope and resolution. Another important gap is the ability to predict and forecast possible geoaptaial events and distribution across a regio. Forecasting land use/land cover has been achieved by various approaches in research; one of the predominant approaches adopted is the Markov Cellular Automata (Markov CA) model; this model is suitable because it incorporates spatial interaction into its operation, compared to other approaches that focus on seasonality; Using the CA-Markov model for forecasting land use and land cover (LULC) changes has proven effective in various studies. Hamad et al. (2018) demonstrated its predictive capability under different scenarios. Karimi et al. (2018) successfully applied the model in Ravansar County, Iran, highlighting its monitoring potential. Rahnama (2021) used CA-Markov to forecast LULC changes in Mashhad Metropolitan, while Khawaldah et al. (2020) integrated GIS and remote sensing for simulation and prediction. El Haj et al. (2023) further confirmed the model's utility for simulating future LULC trends.This study aims to leverage remote sensing and GIS to track desertification in Sokoto State, focusing on the period from 2000 to 2020. The objectives include assessing the extent and severity of desertification, identifying contributing factors such as land cover changes and rainfall patterns, developing up-to-date desertification maps, and proposing mitigation strategies tailored to the local context.

1.1 Study Area

The study was conducted in Sokoto State, northwestern Nigeria, between latitudes 11°33'42"N and 13°59'7"N, and longitudes 4°9'36"E and 6°45'33"E. Covering about 32,000 km^2, it borders Niger to the north and Kebbi and Zamfara States to the south. The region has a dry sub-humid climate with an annual rainfall of 629 mm, peaking in August, and an average temperature of 28.4°C. The area's vegetation includes Acacia Parkland Savanna, and its soils range from Eutric Arenosols to Eutric Gleysols. Sokoto, known for its Islamic culture, experiences a rainy season from May to October and a dry season from November to February. It lies in the Sudan Savannah belt with a population of about 3.7 million, predominantly Hausa and Fulani, who practice Islam. The semi-arid climate and limited rainfall hinder agriculture and development.

Figure 1: Map of Sokoto State

2. Materials and Methods

The methodology involves data collection, processing, analysis, and forecasting. The supervised classification was done using the QGIS software, and the Markov CA model was used to forecast and predict land use/land cover for 2025 and 2030. Further details are described below.

2.1 Data and Data Processing

Landsat TM(2000), Lansat 4 (2005), Landsat 7(2010), and Landsat 8 OLI (2015,2018) were downloaded from the United States Geological Survey Department; the details of the path and row use are; Landsat Path 191 row 050, Path 191 row 051, Path 191 row 052 and Path 190 row 051, Path 191 row 050. The Landsat was orthorectified in GeoTIFF format and geographic WGS 84/UTM zone 32N-Minna Datum. The basic processing includes producing composite mosaic images using the Sokoto state shapefile as the input feature.

2.2 Land Cover Mapping and Accuracy Assessment

Due to insecurity, collecting field data in our study area is challenging, expensive, and risky. Recent studies have used auxiliary sources like Google Earth images for training and reference data to mitigate these issues, achieving significant success. These secondary data sources have proven essential for training and validating remote sensing maps, especially in Nigeria. Our study used expert knowledge and Google Earth images for the 2000 and 2020. Land cover maps for the study area were generated using supervised classification and the maximum likelihood algorithm, as recommended for Sub-Saharan Africa (Ekundayo et al. 2020). The classification utilized QGIS 3.4, covering classes like wetland, farmland, built-up areas, bare land, and vegetation. Accuracy was validated using sample points and fieldwork. For instance, the 2020 map, validated with high-resolution Google Earth data, achieved 89% accuracy.

In our study, the confusion matrix shows that the classification achieved an overall accuracy of 79%. The user accuracy was highest for built-up areas (90%) and lowest for wetlands (82%). Commission errors were lowest for built-up areas (10%) and highest for wetlands (18%). The producer's accuracy ranged from 82% to 90%. This indicates robust classification, with some misclassifications, particularly in wetlands and vegetation, suggesting areas for methodological refinement. A cross-description of the 2020 accuracy assessment is shown in Table 1.

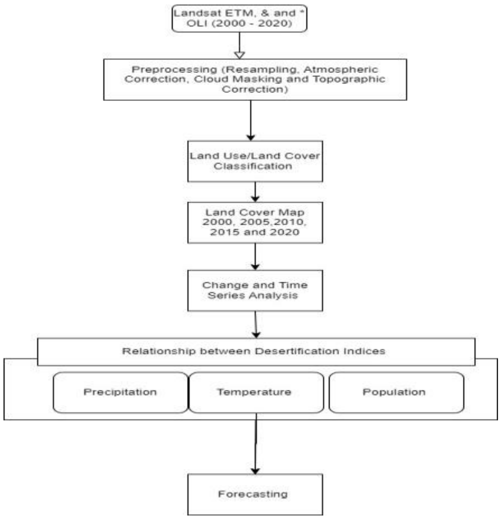

Figure 2: Methodology Flow Chart

Table 1: Cross Description of 2020 Accuracy Assessment

	Reference (Field Data)						
	Bareland	Built-Up	Vegetation	Waterbodies	Total	User Accuracy	Commission Error
Bare land	30	2	3	0	35	0.86	0.14
Built-Up	1	27	2	0	30	0.90	0.10
Vegetation	4	1	40	3	48	0.83	0.17
Waterbodies	0	0	3	14	17	0.82	0.18
Producer's Accuracy	0.86	0.90	0.83	0.82			
Omission Error	0.14	0.10	0.17	0.18			
Overall accuracy	0.79 (79%)						

2.3 Time Series and Forecasting

Cross-analysis was conducted to estimate the losses and gains for each land cover type and analyze the trends in land cover change. The assessment started by comparing the land cover map 2000 with that of 2020, evaluating the overall extent and trends of changes across the different land cover classes over the 20-year study period. Additionally, changes were continuously tracked between 2000 to 2005, 2005 to 2010, 2010 to 2015, and 2015 to 2020.

The process of Markov CA is such that the data is first normalized to turn initial data into proportion and probabilities. This generates the transition probabilities, also known as the transition matrix. The next operation is the CA transition function, which adopts the transition matrix; this function is then used to forecast the values for peculated time intervals. The relation for the transition probability matrix, state vector, and future state prediction is shown in equations 1, 2, and 3. The mathematical components of Markov Chain Algorithm are shown in the section below

i. ***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.

ii. ***State Vector (S)***

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

Where $S_{i(t)}$ represent the proportion of land in the state i at time t

iii. ***Future State Prediction***

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

3. Result and Discussion

3.0 Land Cover Changes from 2000 to 2020

Table 2 presents data on land cover changes from 2000 to 2020; this data is expressed in square kilometers and percentages of the total land area; the total land area is approximately 26,493.83 square kilometers. Over the two-decade period, there is a noticeable decline in vegetation, which decreased from 8,826.005 sq km (33.4%) in 2000 to 3,245.45 sq km (12.3%) in 2020. Conversely, bare soil initially decreases but then significantly increases from 10,972.19 sq km (41.6%) in 2015 to 13,972.253 sq km (52.8%) in 2020. Built-up areas consistently expand, growing from 3,999.475 sq km (15.1%) in 2000 to 8,563.671 sq km (32.3%) in 2020, reflecting urbanization trends. Water bodies, however, show a slight fluctuation, decreasing overall from 700.1631 sq km (2.6%) in 2000 to 412.453 sq km (1.6%) in 2020. These changes indicate significant environmental transformation, with a marked reduction in vegetated areas and an increase in urban and bare soil coverage, highlighting trends in land use and possibly human environmental impact. The full details are shown in table 2. The figure for land use/land cover classification for Sokoto state is shown in figure 3

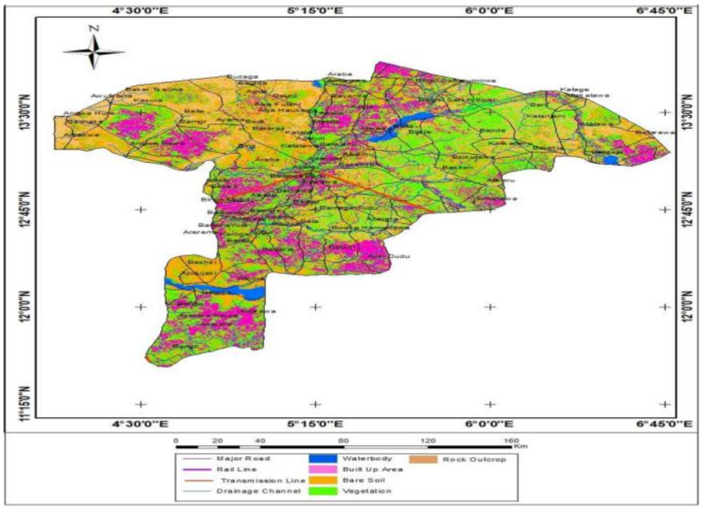

Figure 3: Land Use/Land Cover Classification for 2020

Table 2: Land cover changes from 2000 to 2020

Land Cover	2000	%	2005	%	2010	%	2015	%	2020	%
Vegetation	8826.00	33.	8216.02	31.	7026.11	26.	7351.28	27.	3245.45	12.
Bare Soil	12668.1	47.	11888.1	45.	11668.1	44.	10972.1	41.	13972.2	52.
Built-Up Area	3999.47	15.	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

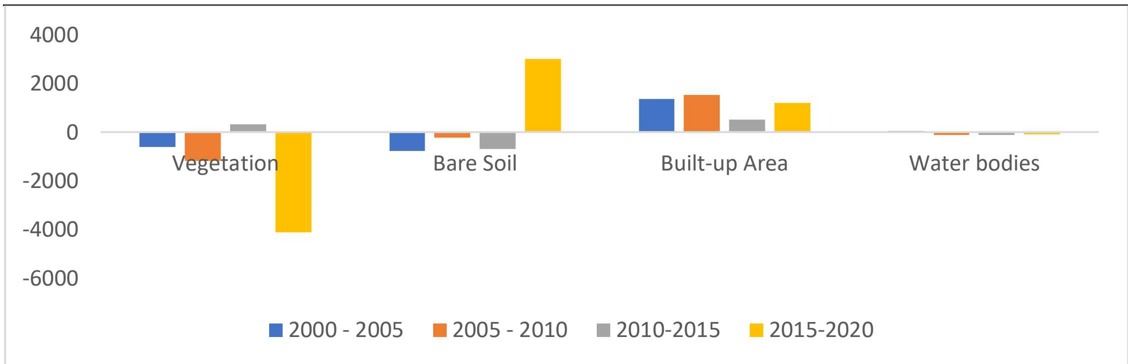

Figure 4: Change Detection Analysis

3.1 Land Cover Projections and Forcast for 2025 and 2030

The transition matrix data, which includes average growth rates and forecasted values for 2025 and 2030, provides insights into the expected changes in land cover types. Vegetation is forecasted to decrease, with a growth rate of 0.818455, leading to a decline from 2,656.256 sq km in 2025 to 2,174.026 sq km in 2030. On the other hand, built-up areas show significant growth with a rate of 1.214129, expanding from 10,397.400 sq km in 2025 to 12,623.782 sq km in 2030, indicating continuing urbanization. As seen in Figure 5, water bodies are expected to decrease slightly, with a growth rate of 0.881697, reducing from 363.659 sq km in 2025 to 320.684 sq km in 2030. Bare soil is projected to increase marginally, with a growth rate of 1.033424, rising from 14,439.264 sq km in 2025 to 14,921.889 sq km in 2030, as shown in Table 3. These projections highlight ongoing environmental trends, with urban areas expanding at the expense of vegetated and water-covered regions and a slight increase in bare soil areas, suggesting a potential for increased land degradation and reduced natural habitats. Figure 6 and 7 shows the projected maps for 2025 and 2030 respectively

Table 3: Transition Matirx

Transition Matrix (Average Growth Rates)		**Forecasted Value**	**2025**	**2030**
Vegetation	0.818455		2656.2555625	2174.026390
Built-up Area	1.214129		10397.399553	12623.782192
Water Bodies	0.881697		363.658634	320.683780
Bare Soil	1.033424		14439.264422	14921.888532

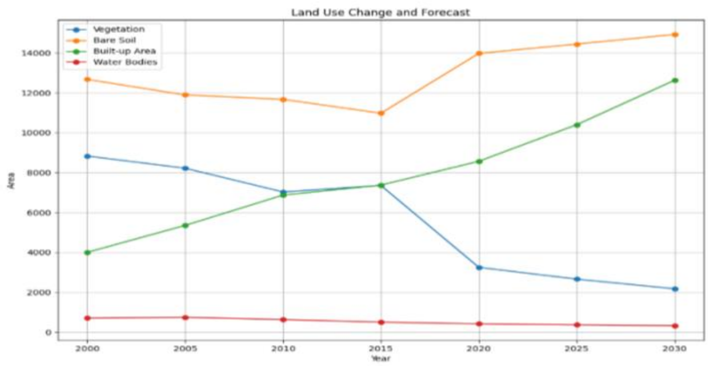

Figure 5: Land cover change trend from 2000 to 2020 and CA-Markov Forecasting

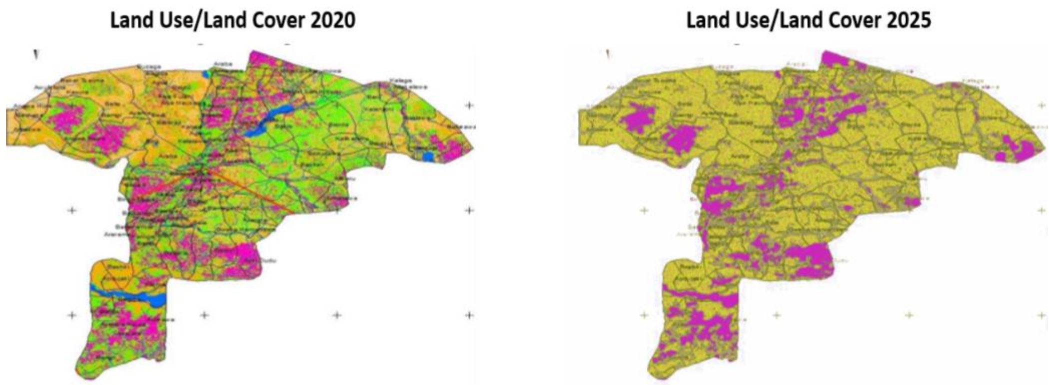

Figure 6: Land Cover Projection for 2030

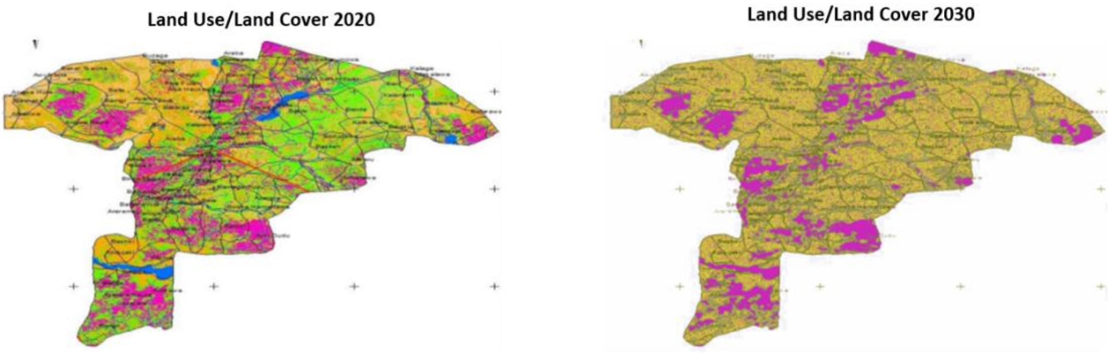

Figure 7: Land Cover Projection for 2030

3.2 Relationship between Desertification and Population, Temperature and Precipitation

The chart in Figure 8 displays data on rainfall and vegetation cover from 2000 to 2020. Rainfall shows a declining trend, starting at 700 mm in 2000 and 2005, dropping to 550 mm in 2010, slightly rising to 560 mm in 2015, and falling to 490 mm by 2020. Vegetation cover also declined, from 33.69% in 2000 to 12.39% in 2020, suggesting a link between reduced rainfall and vegetation loss. Figure 9 shows population growth from 1,050,000 in 2000 to 2,167,834 in 2020, alongside a decline in vegetation cover. This suggests population growth may contribute to vegetation reduction due to urbanization and other activities. Temperature data shown in figure 10 from 2000 to 2020 shows fluctuations, with an overall increase from 33.8°C in 2000 to 38°C in 2020, while vegetation cover consistently declined. This suggests rising temperatures may negatively impact vegetation due to climate-related factors like heat stress and changing precipitation patterns.

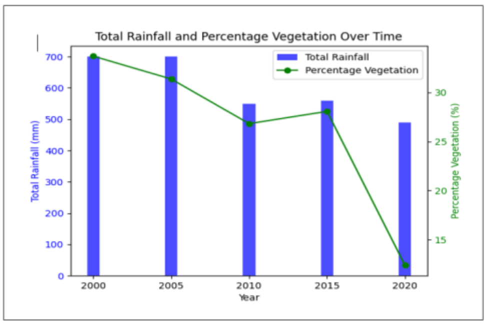

Figure 8: Relationship Between Total Rainfall and Percentage Vegetation from 2000 and 2020

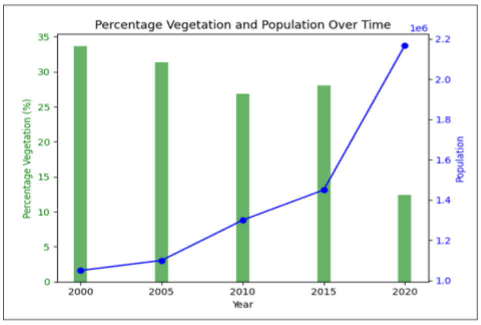

Figure 9: Relationship between percentage vegetation and population from 2000 and 2020

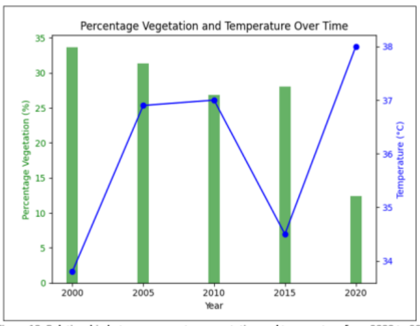

Figure 10: Relationship between percentage vegetation and temperature from 2000 to 2020

4. Discussion

4.1 Land Use Land Cover Analysis

The land use and cover analysis for Sokoto State from 2000 to 2020 reveals notable trends. Vegetation cover decreased by 63%, from 8826.005 hectares in 2000 to 3245.45 hectares in 2020. Bare soil initially declined from 12668.9 hectares in 2000 to 11668.19 hectares in 2010, but increased again to 13972.253 hectares by 2020. Ahmad et al. (2019) attributed this vegetation loss to overgrazing, deforestation, and climate change. Built-up areas showed a steady rise, from 3999.475 hectares in 2000 to 8563.671 hectares in 2020, indicating rapid urbanization and infrastructure development, though Oduwole (2018) warned of potential environmental impacts. Water bodies also declined by over 40%, from 700.1631 hectares in 2000 to 412.453 hectares by 2020, signaling a concerning reduction in surface water resources..

4.2 Land Cover Conversion from 2000 to 2020

The analysis of land cover conversion from 2000 to 2020 shows significant environmental changes in the study area. Vegetation cover declined by 63.23%, from 8,826.005 square kilometers in 2000 to 3,245.45 square kilometers in 2020, likely due to urbanization, agricultural expansion, and climate factors, as noted by Maniyunda and Yau (2019) and Ibrahim et al. (2022). Built-up areas increased from 3,999.475 square kilometers to 8,563.671 square kilometers, reflecting urban expansion into vegetated lands. Bare soil initially decreased but surged from 10,972.19 square kilometers in 2015 to 13,972.253 square kilometers in 2020, indicating increased land degradation, possibly from desert encroachment and deforestation. Water bodies declined from 700.1631 square kilometers in 2000 to 412.453 square kilometers in 2020, suggesting water scarcity due to drying bodies of water. Overall, the data highlights significant changes driven by natural and human activities, including vegetation loss, urbanization, and land degradation. Addressing these issues requires sustainable land use practices, afforestation, and effective environmental management.

4.3 Relationship between Desertification and Climate Parameters

The relationship between desertification and climate factors like rainfall, temperature, and population growth is key to understanding environmental changes in Sokoto. From 2000 to 2020, rainfall dropped from 700 mm to 490 mm, while vegetation decreased from 33.69% to 12.39%. Abubakar (2023) found a strong correlation (r = 0.90) between rainfall and vegetation, showing that declining rainfall impacts vegetation health and exacerbates desertification. Temperatures increased from 33.8°C in 2000 to 38°C in 2020, stressing vegetation due to higher evaporation rates, as noted by Ibrahim et al. (2022). Population growth, rising from 1,050,000 in 2000 to 2,167,834 in 2020, has increased land pressure, leading to deforestation and land degradation, with Abubakar (2023) reporting a negative correlation (r = -0.99) between population growth and vegetation cover. From 2000 to 2020, vegetation cover in Sokoto State fell by 63%, from 8,826 to 3,245 hectares, due to overgrazing, deforestation, and climate change (Ahmad et al., 2019). Bare soil initially decreased but rose again to 13,972 hectares by 2020. Built-up areas expanded by over 50%, reflecting urbanization, while water bodies decreased by over 40%, from 700 to 412 hectares, signaling water scarcity. The combined impact of declining rainfall, rising temperatures, and population growth has intensified desertification in Sokoto, driven by deforestation, unsustainable agriculture, and urbanization (Maniyunda & Yau, 2019). These changes threaten the region's ecosystem and local communities, highlighting the need for sustainable land use and climate adaptation strategies.

4.4 Land Cover Projection for 2025 and 2030

The projected decline in vegetation from 8,826.01 hectares in 2000 to 2,174.03 hectares by 2030 highlights severe land cover changes. This aligns with de Oliveira Barros et al. (2018), who found similar patterns in desertification-prone areas. The reduction is mainly driven by increased urbanization, as seen in Okafor et al. (2020), who observed significant forest loss due to settlement expansion in Burkina Faso. Bare soil areas are expected to grow from 12,668.19 hectares in 2000 to 14,921.89 hectares by 2030, signaling ongoing desertification. Falaki et al. (2020) linked this rise to land use changes and climate variability, posing ecological risks such as reduced soil fertility and increased erosion. Water bodies are forecasted to shrink from 700.16 hectares in 2000 to 320.68 hectares by 2030, reflecting historical trends. This decline, noted by Ma et al. (2021) in Central Asia, stresses local ecosystems and water availability, with significant consequences for biodiversity and agriculture. Urgent policy interventions are needed to address these changes. Sustainable land management, including reforestation and green space protection, is crucial to mitigate vegetation loss. Okafor et al. (2020) and Ma et al. (2021) stressed strategic land-use planning and adaptive policies to combat desertification and support Sustainable Development Goals (SDGs). Without action, environmental degradation will continue to escalate, threatening ecosystems and human livelihoods.4.4.2 Desertification and Bare Soil Increase

5. Conclusions

The analysis of land cover changes from 2000 to 2020 in Sokoto State reveals significant environmental transformations driven by natural and human factors. Over two decades, vegetated areas declined from 8,826.005 square kilometers (33.4%) in 2000 to 3,245.45 square kilometers (12.3%) in 2020, impacted by urbanization, agricultural expansion, and climate factors. Built-up areas grew from 3,999.475 square kilometers (15.1%) in 2000 to 8,563.671 square kilometers (32.3%) in 2020, reflecting rapid urbanization. Bare soil areas initially decreased but then rose to 13,972.253 square kilometers (52.8%) in 2020, suggesting land degradation due to desert encroachment and deforestation. Water bodies declined from 700.1631 square kilometers (2.6%) in 2000 to 412.453 square kilometers (1.6%) in 2020, raising concerns about water scarcity. Projected changes for 2025 and 2030 show further vegetation decline and expanded urban areas, indicating ongoing urbanization and highlighting the need for sustainable land management. The study explores the relationship between desertification, climate factors like rainfall and temperature, and population growth. Vegetation cover fell from 33.69% in 2000 to 12.39% in 2020, correlating with decreased rainfall and higher temperatures, showing climate change's impact on vegetation. Population growth, from 1,050,000 in 2000 to 2,167,834 in 2020, increased pressure on land, contributing to deforestation and degradation. The findings show profound environmental changes, urging policy interventions for sustainable land use, afforestation, and environmental management. Integrating remote sensing and GIS in monitoring land cover changes offers insights for developing strategies to mitigate these trends, ensuring a balanced environment for future generations.

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