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ANALYSING THE ENVIRONMENTAL CONSEQUENCES OF URBANIZATION ON CLIMATE CHANGE IN KADUNA STATE, NIGERIA

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ABSTRACT

The rapid urbanization experienced by many regions like Kaduna state, Nigeria, has become a major issue of concern due to its potential effects on the local climate. This research aimed to analyse the environmental consequences of urbanization on climate change in Kaduna State, Nigeria, from 2008 to 2023 to provide future projections of these consequences. This was done by analysing the spatio-temporal Land Use and Land Cover (LULC) changes in Kaduna, analysing the relationships between the LULC, Land Surface Temperature (LST) and Normalized Difference Built-Up index (NDBI) trends in the state, examining the correlation between LST and NDBI. Landsat imageries for 2008, 2013, 2018 & 2023 were used for determining the LULC, LST & NDBI over Kaduna state, precipitation, and relative humidity data from NASA's POWER (Prediction of Worldwide Energy Resources). The study leveraged the ability of Artificial Neural Network (ANN) and Cellular Automata (CA) within the Modules for Land Use Change Evaluation framework to model complex, non-linear relationships for prediction analysis. The model's accuracy was measured using Kappa and had an accuracy level of 0.67. Some key findings include doubling the developed areas from 12.37% to 24.85% from 2008-2023 with a corresponding decrease in cultivated and rocky areas. A strong positive correlation was also identified between urbanization and land surface temperature within the study area, suggesting the presence of urban heat island effects. The projection for 2043 shows that urban growth would most likely continue with developed areas expected to reach 35.54% in 2043, precipitation and humidity are also likely to decline. The study provides valuable insights for urban planners and policymakers by emphasizing the need for sustainable urban development strategies and climate resilience measures within Kaduna state.

Keyword: Precipitation; Urbanization; Land surface temperature; Climate change

1.0 Introduction

The rapid urbanization in Kaduna State, Nigeria, has significant implications for the local climate, primarily due to changes in land use and cover. As more than half of the world's population lives in urban areas, and with projections indicating that urban land cover will triple by 2030, understanding these dynamics is essential for sustainable development [20]. Urbanization leads to heat stress conditions, exacerbated by the Urban Heat Island effect, which increases the vulnerability of urban dwellers compared to rural populations [7]. The growth of urban areas often leads to loss of vegetation and more impervious surfaces, which increases greenhouse gases, disrupts ecosystems, diminishes biodiversity, and affects essential ecosystem service [22]. Studies such as "Assessing the impact of climate on the built environment in Kaduna metropolis and environ" [12] and "Assessment of urban Heat Island in Kaduna metropolis between 2000 and 2018" [11] have established a foundation for understanding the current and historical effects of urbanization on climate change within Kaduna metropolis. However, these studies do not consider future projections, and this is essential in a world of rapid urbanization and increasing climate concerns. As the urban area continues to evolve, there is a pressing need to comprehend how these transformations contribute to shifts in surface temperature. The utilization of Landsat data offers a valuable opportunity to quantify these changes and derive essential metrics such as land surface temperature and Normalized Difference Building Index (NDBI). By analyzing these parameters, the study seeks to unravel the nuanced connections between urbanization, land surface temperature, and vegetation dynamics. The investigation into the correlation between land surface temperature and NDBI values holds promise for uncovering the environmental repercussions of urban expansion in Kaduna. This research strives to contribute to the broader understanding of the interplay between human activities, land use changes, and climate dynamics, fostering knowledge that can inform sustainable urban planning and environmental management practices.

The aim of this study is to analyze the environmental consequences of urbanization on climate change in Kaduna State, Nigeria, from 2008 to 2023 with a view to providing future projections of these consequences by analyzing the spatio-temporal Land Use and Land Cover (LULC) changes in Kaduna, analyzing the relationships between the LULC, Land Surface Temperature (LST) and Normalized Difference Built-Up index (NDBI) trends in the state, examining the correlation between LST and NDBI.

1.1 Study Area

Kaduna State, located in Northern Nigeria, spans a land mass of 46,053 km² at latitudes 8°45'0" N to 11°15'0" N and longitudes 6°15'0" E to 8°45'0" E. It shares borders with Kano, Zamfara, Katsina, Niger, and Bauchi states.

The region is characterized by an undulating plateau with various rivers and a foundation of ancient rocks like gneisses and granites [2]. The soil is primarily red-brown to red-yellow ferruginous, weathered and influenced by laterization [1,17]. Kaduna experiences a tropical dry-and-wet climate, with a wet season from April to mid-October and dry season from mid-October to April, averaging around 1323 mm of rainfall annually [1]. Vegetation includes tropical grassland, diminishing in density northward, transforming into the northern Guinea Savanna in the metropolis. Human activities like cultivation and grazing have impacted natural vegetation. The region faces challenges from climate change, including increased temperatures, altered rainfall patterns, and extreme weather events, posing threats to ecosystems and human populations [12].

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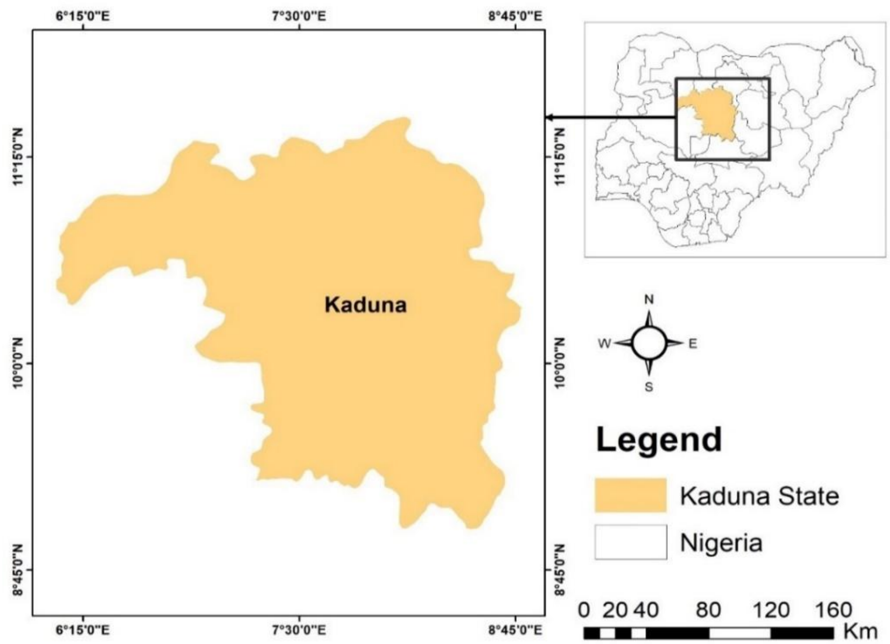

Figure 1: Map showing the study area (Kaduna State)

2. METHODS

The data acquisition, data quality, data processing and data presentation employed to achieve the aim and objectives are described. The flowchart of framework of methodology is shown in figure

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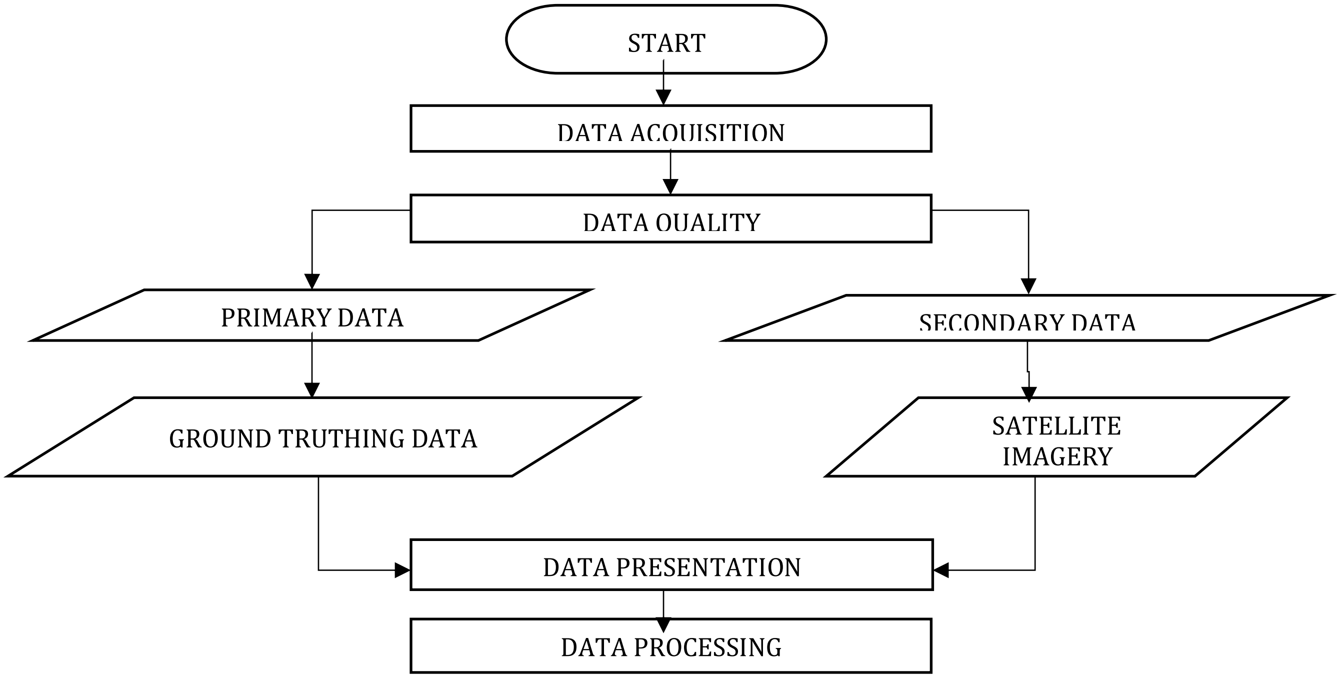

Figure1: Framework of Methodology.

2.1 Data Acquisition

The study majorly involves the collection secondary data. The secondary data were gathered from existing datasets, such as satellite imagery (Landsat) and Precipitation data. Landsat satellite imagery was acquired with appropriate spectral bands and temporal coverage to the study area. Precipitation data was acquired for the study area from NASA's Prediction of Worldwide Energy Resources (POWER) website. The process by which these data were collected is explained below in Table 1.

Table 1: Data type, Source, Mode of acquisition, Resolution, format and usefulness

S/N	Data type	Data Source	Resolution	Derived Usage
1	Landsat imagery	USGS	30	Land Use and Land Cover Maps (LULC)
2	Base map, Topography, and relief map of the study area	Diva GIS	30	Administrative map

3	Precipitation	NASA's Prediction of Worldwide Energy Resources (POWER)	-	Precipitation pattern

2.2 Data Processing

Radiometric and geometric corrections were applied to the Landsat images, which were projected to UTM Zone 32. These images enabled land use mapping and change detection, processed in ArcMap 10.7 using a supervised classification technique that categorized land into four classes: cultivated land, rock, developed areas, and water. The NDBI was employed to assess built-up areas, highlighting man-made structures by utilizing the NIR and SWIR bands to reduce terrain and atmospheric effects. Positive NDBI values indicate built-up areas, while negative values represent vegetation or water. Additionally, thermal band images were utilized to map LST in Kaduna State. The spatial resolutions were 120m for TM band 6, 60m for ETM+ band 62, and 100m for OLI, enabling effective analysis of urban climate. Pre-processed relative humidity and precipitation data from NASA's POWER database, covering the years 2008 to 2023, were used to identify trends related to urban growth and climate impacts. The MOLUSCE Plugin was used to analyze LULC changes in Kaduna State from 2008 to 2023, predicting future changes for 2043 based on an Artificial Neural Network (ANN). The LULC classes included Developed, Water, Cultivated, and Rock, with additional spatial variables to enhance accuracy. For forecasting precipitation and humidity, an Auto-Regressive Integrated Moving Average (ARIMA) model was applied. This involved data preprocessing and validation through RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). Additionally, a Long Short-Term Memory (LSTM) model was developed using historical data from NASA's POWER, with an emphasis on optimizing the architecture. The accuracies of both models were assessed using RMSE and MAE for comparison.

3.0 Result and Discussion

Kaduna State has undergone significant urbanization and land use changes from 2008 to 2023, reflecting broader national trends. Developed areas increased from 5,515.872 km² (12.37% of the total area) in 2008 to 11,010.22 km² (24.85%) in 2023, averaging a growth rate of 6.64% per year. The period between 2013 and 2023 saw intensified urban development, indicating a rapid expansion in both urban and infrastructure development.

A considerable decline in cultivated areas has accompanied the urban expansion in Kaduna state. In 2008, cultivated areas which are very valuable for agricultural activities and food security covered 39.80% of the state had shrunk to 33.45% by 2023, which equals a loss of 2,922.22 km² as shown in Figure 1 and Figure 4 respectively. This reduction in cultivated land raises a lot of concerns about the food production capacity, rural livelihoods, and changing economic structure within the region [9]. The highest decrease in the amount of cultivated within the region occurred between 2008 and 2013, which could be a pointer to a period of rapid land use transition at the beginning of the study period. Concurrently, rocky areas which play a crucial role in the ecosystem and biodiversity experienced a significant amount of reduction. These areas decreased from 46.86% of the state's land in 2008 to 41.26% in 2023, a loss of 2,607.31 km² as shown in Table 2. Water bodies, although they cover only a small portion of the state's area, have shown intriguing fluctuations. An overall increase of 0.8% was recorded between 2008 and 2023, with a total growth of 35.1909 km². However, this growth was not linear, because there was a decrease from 2008 to 2018, which was followed by a significant increase from 2018 to 2023 as shown in Table 2 and Table 3. The changes observed in water bodies could be attributed to various factors such as changes in water management practices, or shifts in rainfall patterns possibly linked to climate change [8]. The interrelation between the land cover changes portrays the image of rapid urbanization, where development is happening at the expense of agricultural land. The Normalized Difference Built-up Index (NDBI) and Land Surface Temperature (LST) data provide further evidence for the observed transformation. For the NDBI, there is a slight increase in the high values and some fluctuations within the low values. It is interesting to note that the LST data shows a significant increase in both the high and the low-temperature values, with a maximum temperature of 37°C in 2008 and 54.9774°C in 2023, the minimum temperature increased from 0.299945°C to 15.5634°Cover the same period of time as shown in Table 4. These temperature changes suggest the development of urban heat island effects, which a frequently associated with rapid urbanization [3].

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The implications of these land use changes are profound and multifaceted. This rapid urbanization is likely to mount more pressure on existing urban infrastructure, facilities, health care and other services, which would necessitate significant investments in urban planning and development [18]. The loss of agricultural land may significantly affect the rate of food production and rural economies, and this can now serve as a driving force for rural-to-urban migration and cause changes in the demographic makeup of the state [16]. The reduction of rocky areas may negatively impact the ecosystem. Additionally, rising land surface temperatures in the region raise concerns, as they can affect human health by increasing cooling energy demands and altering local rainfall patterns [6].

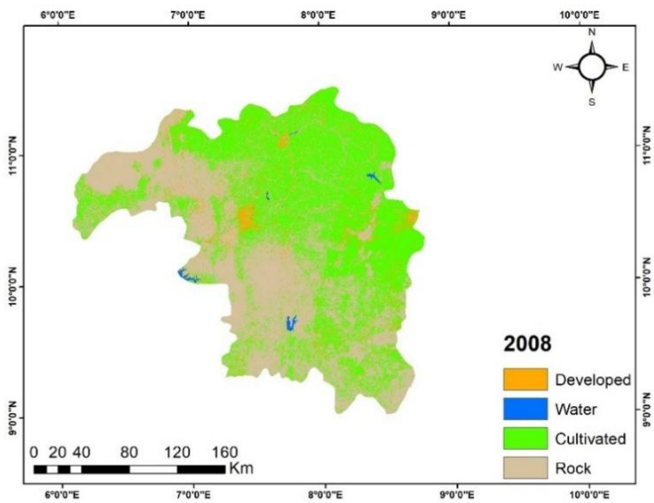

Figure 3: Land Use Land Cover of Kaduna State for 2008

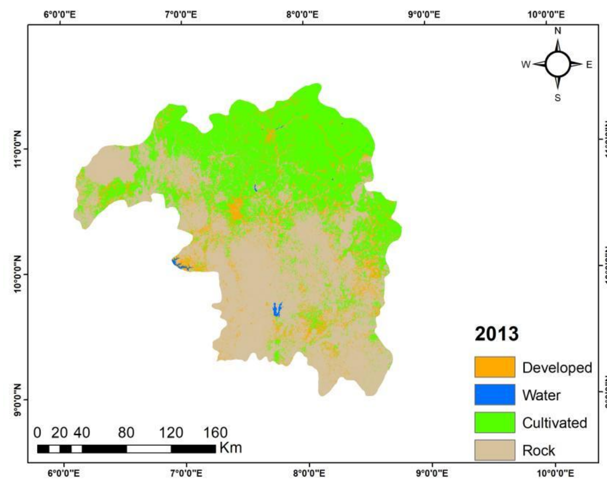

Figure 4: Land Use Land Cover of Kaduna State for 2013

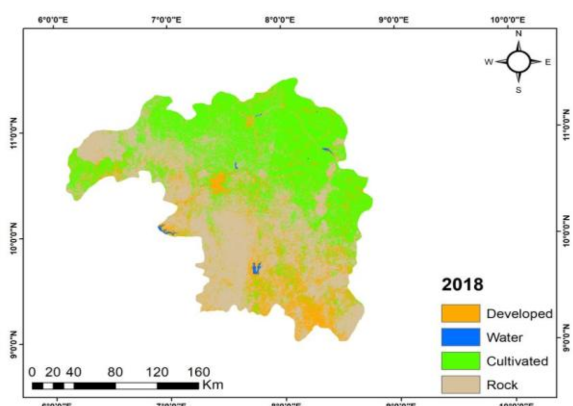

Figure 5: Land Use Land Cover of Kaduna State for 2018

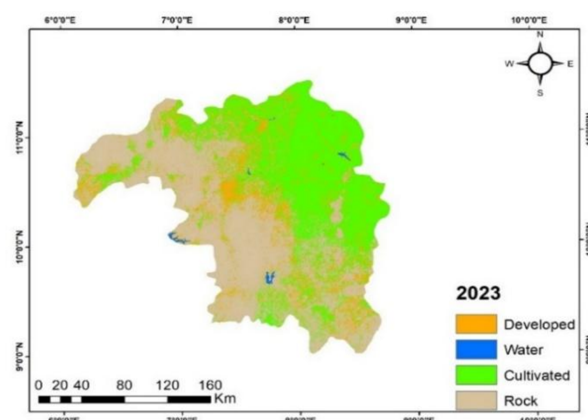

Figure 6: Land Use Land Cover of Kaduna State for 2023

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Table 2: Land Use Land Cover classification for the study

	2008			2013	
Class name	Area (sqkm)	%	Class name	Land Use class	%
Developed	5515.872	12.37	Developed	6532.337	14.65
Cultivated	17740.54	39.80	Cultivated	15804.45	35.45
Rock	20889.3	46.86	Rock	21830.19	48.97
Water	158.6168	0.36	Water	138.1209	0.31

Table 3: Land use land cover classification for the 2018 and 2023

	2018			2023	
Class name	Area (sqkm)	%	Class name	Area (sqkm)	%
Developed	8997.659	20.18	Developed	11010.22	24.85
Cultivated	15728.66	35.28	Cultivated	14818.32	33.45
Rock	19713.55	44.22	Rock	18281.99	41.26
Water	133.7271	0.30	Water	193.8077	0.44

Table 4: NDBI and LST results for the study period

Year	High NDBI	Low NDBI	High LST	Low LST
2023	0.712267	-0.35167	54.9774	15.5634
2018	0.689999	-0.32675	54.9715	6.1376
2013	0.669016	-0.30865	43.12724	0.58886
2008	0.652696	-0.27692	37	0.299945

3.1 Humidity and Precipitation in Kaduna State

The climate data from Kaduna State (2008-2023) show a significant increase in humidity, rising from 59.56% to 69.53%, particularly between 2018 and 2023. Precipitation patterns reveal dramatic fluctuations, initially declining from 1,096.56 mm in 2008 to 615.45 mm in 2013, before surging to 3,966.09 mm in 2023, indicating a threefold increase. Both humidity and precipitation exhibit upward trends, with a strong positive correlation (0.997) between them, although they do not correlate linearly. The Mann-Kendall test confirms significant positive trends for both variables, suggesting that urbanization may be influencing local climate conditions. The analysis indicates urbanization impacts hydrology and local microclimates, contributing to an increase in precipitation and humidity, which could result in flooding, agricultural challenges, and higher energy demands due to the urban heat island effect. These changes highlight the need for improved urban infrastructure, including drainage systems and flood management, as well as adaptive agricultural practices to manage extreme rainfall variability. Overall, effective water resource management is crucial in addressing the challenges posed by these shifting climate patterns.

Table 5: Correlation between Humidity, Precipitation, and Land Surface Temperature.

Correlation between Humidity, Precipitation and Land Surface Temperature						
		Humidity	Precipitation	High LST	Low LST'	Mean LST
Humidity	Pearson Correlation	1	.997**	-.864	-.561	-.959*
	Sig. (2-tailed)		.003	.136	.439	.041
	N	4	4	4	4	4
Precipitation	Pearson Correlation	.997**	1	-.839	-.497	-.961*
	Sig. (2-tailed)	.003		.161	.503	.039
	N	4	4	4	4	4
High LST	Pearson Correlation	-.864	-.839	1	.813	.925
	Sig. (2-tailed)	.136	.161		.187	.075
	N	4	4	4	4	4
Low LST'	Pearson Correlation	-.561	-.497	.813	1	.556
	Sig. (2-tailed)	.439	.503	.187		.444
	N	4	4	4	4	4
Mean LST	Pearson Correlation	-.959*	-.961*	.925	.556	1
	Sig. (2-tailed)	.041	.039	.075	.444	
	N	4	4	4	4	4
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

Table 6: Mann Kendall trend test for Precipitation and humidity from 2008 - 2023

Mann Kendall trend test for Precipitation and humidity from 2008 - 2023				
Variable	Z	P value	Tau	Sen's slope
Precipitation	2.331	0.0198**	0.6	120.48

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Humidity	2.2534	0.0242**	0.425	0.48
**. P-value is significant at the 0.01 level (2-tailed).				
*. P-value is significant at the 0.05 level (2-tailed).				

3.2 Future Projection

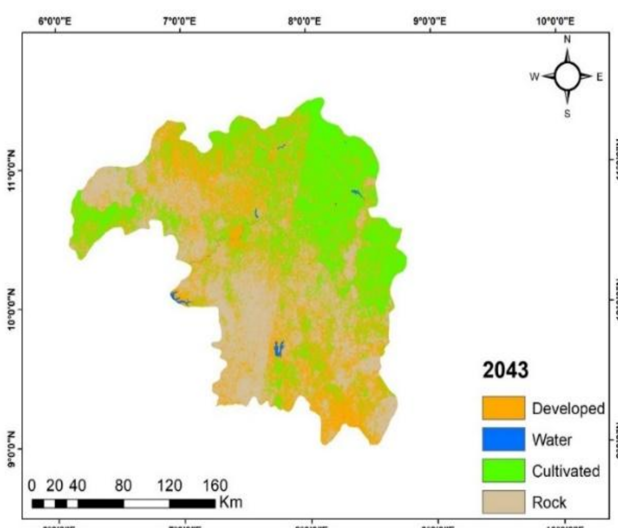
3.2.1 Land Use Land Cover Prediction

The analysis of land use and cover in Kaduna state from 2008 to 2023 reveals significant changes. Developed areas increased from 5,515.87 sq km (12.37%) in 2008 to 11,010.22 sq km (24.85%) in 2023, with projections showing growth to 15,745.59 sq km (35.54%) by 2043. In contrast, agricultural land decreased from 17,740.54 sq km (39.80%) in 2008 to 14,818.32 sq km (33.45%) in 2023, with a further decline to 13,592.50 sq km (30.68%) expected by 2043. Similarly, rocky areas reduced from 20,889.30 sq km (46.86%) in 2008 to 18,281.99 sq km (41.26%) in 2023, projected to decline to 14,794.88 sq km (33.39%) by 2043 see Table 7 and Figure 5. This indicates a trend of increasing urbanization at the expense of agricultural land. Changes in natural landscapes can harm local biodiversity [21]. Water bodies remained stable, fluctuating between 0.30% and 0.44% of the total area, throughout the study.

Urban area expansion may worsen heat island effects, impacting local climate change [5]. Urban surfaces like asphalt and concrete absorb and hold more heat than natural landscapes [14]. Rapid urbanization often brings increased human activities, like transport and industry. These can emit greenhouse gases [13]. This could lead to much higher temperatures in urban areas than in the surrounding rural areas [5]. A kappa statistics value of 67% was obtained, this level of accuracy suggests that the model prediction is reliable although some variability exists due to the complex nature of land-use dynamics.

Table 7: Projected Land use land cover for 2043

Class name	Area (Sq. km)	%
Developed	15745.59	35.5396
Water	162.9512	0.3678
Cultivated	13592.5	30.67984
Rock	14794.88	33.39374



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3.2.2 Autoregressive Integrated Moving Average (ARIMA)

The 2043 forecasts for precipitation and humidity show that precipitation is predicted to be 3,901.09mm and humidity at 64.53%. However, the accuracy of these predictions varies significantly. The precipitation model has a high Mean Absolute Percentage Error (MAPE) of 25.11, indicating greater variability, while the humidity model has a much lower MAPE of 4.02 [19]. Additionally, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are also higher for precipitation (RMSE: 504.06, MAE: 343.86) compared to humidity (RMSE: 3.01, MAE: 2.47). Both models have similar Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, but the humidity model has lower values (AIC: 78.55, BIC: 79.26), suggesting a better fit without overfitting. The ARIMA (0,1,0) model used ensures data stationarity but limits flexibility in the precipitation model, contributing to its lower accuracy [10]. The precipitation model's predictions are less reliable, while the humidity model offers more accurate and stable forecasts. Future decisions should prioritize humidity predictions while using precipitation forecasts cautiously and consider refining the precipitation model for improved accuracy.

Figure 5: Projected Land Use and Land Cover Map

Table 8: Future Projection of Precipitation and Humidity Using ARIMA

Parameter	Precipitation Model	Humidity Model
Forecast Year	2043	2043
Predicted Value	3901.09mm	64.53%
Model Accuracy Metrics		
MAPE (Mean Absolute Percentage Error)	25.11	4.02
RMSE (Root Mean Square Error)	504.06	3.01
MAE (Mean Absolute Error)	343.86	2.47
Model Quality Indicators		
AIC	232.22	78.55
BIC	232.93	79.26
Model Type	ARIMA (0,1,0)	ARIMA (0,1,0)

3.2.3 Long Short-Term Memory (LSTM)

The LSTM model forecasts a gradual decline in both precipitation and humidity from 2024 to 2043, with precipitation decreasing from 1775.96 mm to 1289.97 mm and humidity from 67.78% to 60.58%. Accuracy metrics indicate that humidity predictions (RMSE of 3.11, MAE of 2.65) are significantly more reliable than precipitation predictions (RMSE of 1097.53, MAE of 723.55). This discrepancy suggests that precipitation may have higher variability or irregularities in historical data, while humidity trends are smoother and easier for the model to capture. As a result, decision-making should prioritize humidity forecasts over precipitation forecasts, which may require further validation [4].

Table 9: Prediction of future Precipitation and Humidity using LSTM

Metric	LSTM (Precipitation)	LSTM (Humidity)
Forecast Year	2043	2043
Predicted Value	1289.97	60.58
RMSE	1097.53	3.11
MAE	723.55	2.65
Model Type	LSTM	LSTM

3.2.4 Evaluating ARIMA and LSTM Models for Precipitation and Humidity Predictions in 2043

The comparison between LSTM and ARIMA models reveals their distinct capabilities in predicting precipitation and humidity. For precipitation, ARIMA forecasts a total of 3,901.09 mm for the year 2043, while LSTM predicts only 1,289.97 mm, indicating a substantial difference in the trends identified by each model. ARIMA exhibits superior accuracy, with a lower Root Mean Square Error (RMSE) of 504.06 and Mean Absolute Error (MAE) of 343.86, compared to LSTM's RMSE of 1,097.53 and MAE of 723.55 [15]. In terms of humidity, the forecasts from both models are more aligned: LSTM predicts 60.58%, while ARIMA predicts 64.53%. The accuracy metrics (RMSE and MAE) for both models are relatively close, although ARIMA has slightly lower error rates [23]. Overall, ARIMA is the more accurate model for precipitation, showing better alignment with historical data, while both models perform effectively in predicting humidity [23].

Table 10: LSTM vs. ARIMA (0,1,0): Performance Assessment for 2043 Precipitation and Humidity Forecasts

Metric	LSTM (Precipitation)	ARIMA (Precipitation)	LSTM (Humidity)	ARIMA (Humidity)
Forecast Year	2043	2043	2043	2043

Predicted Value	1289.97	3901.09	60.58	64.53
RMSE	1097.53	504.06	3.11	3.01
MAE	723.55	343.86	2.65	2.47
MAPE	N/A	25.11	N/A	4.02
AIC	N/A	232.22	N/A	78.55
BIC	N/A	232.93	N/A	79.26
Model Type	LSTM	ARIMA (0,1,0)	LSTM	ARIMA (0,1,0)

4.0 Conclusion and Recommendations

This study examines the environmental consequences of urbanization and its impact on climate change in Kaduna State, Nigeria, from 2008 to 2023, with future projections. It highlights the significant transformation of both climate and landscape patterns in the region. The research shows that the area designated for urban development in Kaduna has nearly doubled, increasing from 12.37% of the total area in 2008 to 24.85% in 2023. This trend is expected to continue, with projections indicating that urban areas will comprise 35.54% of the total area by 2043. This urban expansion comes at the cost of cultivated and rocky areas, which have experienced notable declines over the years. A strong positive correlation was found between the expansion of developed areas and the increase in Land Surface Temperature (LST), indicating urban heat island effects. This correlation persists across both high and low-temperature values. Additionally, the study observed a statistically significant upward trend in precipitation and humidity from 2008 to 2023. For forecasting future precipitation and relative humidity, the study utilized two models: ARIMA and LSTM. ARIMA performed better for predicting precipitation, while both models showed good performance in forecasting humidity. However, both models suggest a downward trend in precipitation and humidity levels by 2043. The findings suggest that urbanization is linked to rising temperatures, reduced cultivated areas, and changes in rainfall and humidity. These environmental changes are expected to have broader implications for the economy and society, potentially threatening food security, biodiversity, and public health due to increasing temperatures. Therefore, it is recommended that smart growth strategies be implemented to manage urban expansion and protect agricultural land.

References

1. Abaje, I. B., Sawa, B. A., Iguisi, E. O., & Ibrahim, A. A. (2015). Assessment of rural communities' adaptive capacity to climate change in Kaduna State, Nigeria. *J. Environ. Earth Sci.*, *5*(20).
2. Abaje, I., Sawa, B., Iguisi, E., & Ibrahim, A. (2016). Impacts of climate change and adaptation strategies in rural communities of kaduna state, nigeria. Ethiopian Journal of Environmental Studies and Management, 9(1), 97. https://doi.org/10.4314/ejesm.v9i1.9
3. Chu, W., Qiu, S., & Xu, J. (2016). Temperature change of Shanghai and its response to global warming and urbanization. *Atmosphere*, *7*(9), 114.
4. Hu, S., Zhang, Z. X., Zhao, X. L., Wang, X., Liu, B., Yi, L., ... & Xu, J. Y. (2017, February). Suitability evaluation of urban terrain in China. In *IOP Conference Series: Earth and Environmental Science* (Vol. 57, No. 1, p. 012037). IOP Publishing.
5. Huang, B., Ni, G. H., & Grimmond, C. S. B. (2019). Impacts of urban expansion on relatively smaller surrounding cities during heat waves. *Atmosphere*, *10*(7), 364.
6. Husain, T., & Chaudhary, J. R. (2008). Human health risk assessment due to global warming–a case study of the Gulf countries. *International journal of environmental research and public health*, *5*(4), 204-212.
7. Kovats, R. S., & Hajat, S. (2008). Heat stress and public health: a critical review. Annu. Rev. Public Health, 29, 41-55
8. Krishan, R., Nikam, B. R., Pingale, S. M., Chandrakar, A., & Khare, D. (2018). Analysis of trends in rainfall and dry/wet years over a century in the Eastern Ganga Canal command. *Meteorological Applications*, *25*(4), 561-574.
9. Kushwaha, S., Sinha, D. K., Yadav, A., & Ahmad, N. (2020). Changes in Land Use Pattern in Uttar Pradesh: a zone-wise analysis. *Int J Curr Microbiol App Sci*, *9*(1), 1689-1699.
10. Lai, Y., & Dzombak, D. A. (2020). Use of the autoregressive integrated moving average (ARIMA) model to forecast near-term regional temperature and precipitation. *Weather and forecasting*, *35*(3), 959-976.
11. Mande, H. K., & Abashiya, O. D. (2020). Assessment of Urban Heat Island in Kaduna Metropolis between 2000 and 2018. FUDMA JOURNAL OF SCIENCES, 4(4), 166-174.
12. Mande, K. H. (2020). Assessing the impact of climate change on the built environment in Kaduna Metropolis and environs. Science World Journal, 15(3), 78-84.
13. Mathew, A., Khandelwal, S., & Kaul, N. (2016). Spatial and temporal variations of urban heat island effect and the effect of percentage impervious surface area and elevation on land surface temperature: Study of Chandigarh city, India. *Sustainable Cities and Society*, *26*, 264-277.
14. Mohajerani, A., Bakaric, J., & Jeffrey-Bailey, T. (2017). The urban heat island effect, its causes, and mitigation, with reference to the thermal properties of asphalt concrete. *Journal of environmental management*, *197*, 522-538.
15. Mungale, N., & Shinde, J. (2024). Rainfall Forecasting: A Comparative Analysis of Deep Learning and Machine Learning Models with Application to Environmental Data. *International Journal of Intelligent*

Systems and Applications in Engineering, *12*(12s), 380–393. Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/4524

16. Ofuoku, A. (2015). Examination of urban-rural migration in Delta State, Nigeria: Implications for the agricultural extension service. *Journal of Agricultural Faculty of Gaziosmanpaşa University (JAFAG)*, *32*(2), 79-85.
17. Okafor, G. C., & Ogbu, K. N. (2018). Assessment of the impact of climate change on the freshwater availability of Kaduna River basin, Nigeria. *Journal of Water and Land Development*.
18. Ramadan, E. (2015). Sustainable urbanization in the Arabian Gulf region: Problems and challenges. *Arts and Social Sciences Journal*, *6*(2), 1-4.
19. Sankalp, S., & Panda, P. K. (2023). A comparative evaluation of machine learning and ARIMA models for forecasting relative humidity over Odisha districts. *Developments in Environmental Science*, *14*, 91-105.
20. Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, *109*(40), 16083-16088.
21. Wang, Y., Rao, Y., & Zhu, H. (2022). Revealing the Impact of Protected Areas on Land Cover Volatility in China. *Land*, *11*(8), 1361.
22. Yang, S., Yang, J., Shi, S., Song, S., Luo, Y., & Du, L. (2023). The rising impact of urbanization-caused CO_2 emissions on terrestrial vegetation. Ecological Indicators, 148, 110079.
23. Zaharieva, S., Georgiev, I., Georgiev, S., Borodzhieva, A., & Todorov, V. (2025). A Method for Forecasting Indoor Relative Humidity for Improving Comfort Conditions and Quality of Life. *Atmosphere*, *16*(3), 315. https://doi.org/10.3390/atmos16030315.