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Full Length Research Article

INFLUENCE OF LAND USE AND LAND COVER CHANGES ON FLOOD SUSCEPTIBILITY IN KARADUA RIVER BASIN, KATSINA STATE, NIGERIA

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ABSTRACT
This study examines land use and land cover (LULC) changes and their impacts on flood susceptibility in the Karadua River Basin, Katsina State, Nigeria, between 2017 and 2023. Supervised classification of Landsat imagery was conducted, with spatial integration and extraction by polygon. Weighted and decomposition analyses were applied to deduce the influence of LULC on flood susceptibility in the study area. The results revealed that the classified LULC achieved high classification accuracy (overall accuracy > 84%, Kappa coefficient > 0.81). Additionally, agricultural land was identified as the dominant LULC type, covering over 98% of the area, though it declined slightly (-0.20%). Built-up areas increased significantly (118.06%), indicating rapid growth, while vegetation and water bodies declined by 50.40% and 26.47%, respectively. The decomposed weighted analysis of the Soil Conservation Service Curve Number (SCS-CN) method and LULC highlighted changes in infiltration and runoff across different LULC classes and soil types, with the growth of built-up areas and vegetation loss contributing to increased flood susceptibility. These trends underscore the need for sustainable land-use practices to mitigate environmental degradation and reduce flood risks in the basin.

Keywords: Land Use Land Cover, Flood, Susceptibility, Curve Number, Karadua, decomposition

INTRODUCTION
Flood disaster is not a recent phenomenon worldwide. It refers as an environmental hazard that substantially risks communities, their social, economic, and health implications as well as ecosystems worldwide, especially in developing countries (Babati et al., 2022). In India, every year, flood takes millions of lives, damage cultivation land, destroy communication infrastructures and affect the agricultural land (Sahoo & Ghose, 2021). This is certainly true for the Gorganrood Watershed (GW) in the northeast of Iran experiencing flooding events (Zhihuo et al., 2020). In Nigeria, the growing occurrences of flood events and their severity have raised concerns about the underlying factors contributing to this phenomenon (Babati et al., 2021; Cirella et al., 2019). One crucial issue that can be seen from the contemporary perspective is the influence of land use and land cover (LULC) changes on flood susceptibility (Ardiclioglu et al., 2022), particularly in river basins like the Karaduwa River Basin in Katsina State.
There are a number of natural and anthropogenic factors that define the hydrological characteristics within the Karaduwa river basin (Bishir et al., 2018). These characteristics have changed over the few decades due to urbanization, agricultural expansion and deforestation. These have been pointed out as the potential causes of the floods, as the land surfaces have been modified which increases runoff and reduces infiltration (Isa, et al., 2023). For instance, studies have shown that the conversion of natural vegetation to agricultural land significantly increases the Curve Number (CN), a parameter used to estimate runoff potential based on land cover types (Ezenwa et al., 2022). Higher CN values indicate a greater likelihood of flooding due to decreased moisture retention in soils.
Despite the growing body of research on LULC changes and their hydrological impacts globally (Cirella et al., 2019; Fawzy et al., 2020; Isa, et al., 2023; Ogarekpe et al., 2020), there remains a notable gap in localized studies focusing on specific regions such as the Karaduwa River Basin. This lack of detailed analysis hinders effective flood risk management and planning efforts. Therefore, this study aims to investigate the influence of LULC changes on flood susceptibility in the Karaduwa River Basin, employing geospatial analysis techniques. Understanding the dynamics of LULC changes and their implications for flooding is crucial for developing effective strategies to enhance community resilience against flood hazards. As the study area continues to face climate change and built-up development challenges, this research will provide essential information for policymakers, town planners, and environmental managers striving to balance development with sustainable resource management in flood-prone areas.

MATERIALS AND METHODS
Study Area
Karadua River Basin, situated in Katsina State in northern Nigeria. It is located between 12°00' and 12°30' north latitude and 7°30' and 8°00' east longitude with an area of about 1610 km^2 (see figure 1). The geological formation of the basing lies along the southern edge of the Mesozoic and Tertiary Iullameden of the Sahara region. The basin's crystalline foundation consists mainly of granite-migmatite and gneiss rocks with Unconsolidated Quaternary deposits overlying the basement rocks and Cretaceous sandstones (Bishir et al., 2018). The elevations reach up to 600 meters above sea level near the centre and gradually slope northwest toward Sokoto, averaging around 300 meters above sea level. As the basin is located in the Sudan savannah zone, it experiences a continental climate with wet and dry seasons, predominantly savannah, with grasses interspersed with scattered trees (Nwilo et al., 2020). The region's soils are ferruginous tropical brown and reddish-brown, derived from the basement complex rocks.

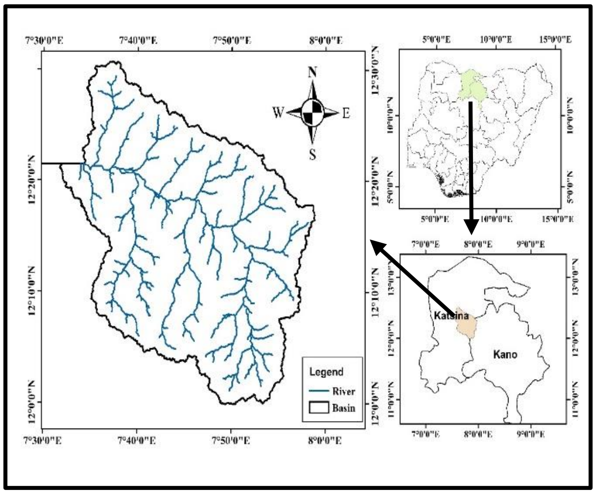

Figure 1: Karadua river catchment area

The Karadua Catchment follows a dendritic drainage pattern with a major tributary of the Bunsuru River within the main Sokoto River Basin. The watershed has a drainage density of 1.06 and an average slope angle of 1.5°. During the rainy season, the average monthly discharge is 356 m³/sec upstream of the dam and 253 m³/sec downstream. The suspended sediment load is 4.16 grams/litre above the dam (Hundu et al., 2021).

Material

Satellite imagery was obtained from www.earthexplore.usgs.org. This includes Landsat (OLI-2017, 2020 and 2023). These were chosen because they provide just the necessary detail required and at no cost. Radiometric and geometric restoration processes was applied to restore image since it is expected to have systematic errors, such as sensor spectral properties, and atmospheric scattering to creep into the data acquisition process and can degrade the remote sensor data quality.

Method of Data Analysis

Image classification

For this study, supervised classification of LULC imageries was utilised. The training samples were collected based on the researcher's personal experience and physiographic knowledge of the study area for each land cover class. The image classification was conducted using the Google Earth engine. The land use was classified for 2017, 2020 and 2023.

Subsequently, the accuracy assessment was conducted which is a comparison of a classification to actual geographic data to determine the correctness of the classification process. Kappa statistics is calculated using the following equation:

$$Kappa = \frac{\mathrm{OA} - \mathrm{EA}}{1 - \mathrm{EA}}$$

Where OA: is observed accuracy, and EA: is expected accuracy. The Kappa statistics between 0.61-0.80 are often considered substantial and values >0.81 are almost perfect (Bashariya et al., 2022). Furthermore, the change analysis panel in the Land Change Modeller algorithm provides a rapid quantitative assessment of changes, allowing the generating evaluations of gains and losses and specific transitions in both map and graph Therefore, the LULC maps were subjected to the change analysis

The SCS-CN method was originally developed by the SCS (US Department of Agriculture), this implies that the level of flood susceptibility and retention of water by different land use can be ascertained. The SCS CN of each other kind of land use land cover under different soil types were present in Table 1:

Table 1: soil curve number of different land use land cover under different soil type

LULC Type	Soil A	Soil B	Soil C	Soil D
Urban areas	77	85	90	92
Agricultural cropland	67	78	85	89
Grassland/Pasture	49	69	79	84
Shrubland	35	56	70	77
Bare land	77	86	91	94
Forest (sparse)	30	55	70	77
Water bodies	100	100	100	100

Sources: (Ezenwa et al., 2022)

The SCN-CN was further modified to suit the aim of this research and to provide a comprehensive level of the water retention power of the classified land use in the Karadua River catchment area, Katsina State, Nigeria. This is presented in the table 2:

Table 2: soil curve number for different land use land cover under different soil type in the study area.

LULC Type	Soil A	Soil B	Soil C	Soil D
Agricultural Area	72	82	88	92
Built up Area	77	85	90	92
Vegetation	38	60	73	79
Water Bodies	100	100	100	100

The soil groups are expressed as Soil Group A: Sandy or gravelly soils with high infiltration rates. Soil Group B: Moderately permeable soils like loamy soils. Soil Group C: Soils with slow infiltration rates, such as sandy clay loam. Soil Group D: Heavy clay soils or soils with a shallow water table and prolonged infiltration.

Spatial statistical analysis was employed to assess the variation and determine how each land use corresponds to its retention and how it changes as the land use and land cover change for a particular location and time. This was follow by Calculate the Weighted SCN for Each Year, Use the formula:

$$\text{Weighted SCN} = \sum \frac{(\text{Area of LULC Class} \times \text{SCN Value})}{\text{Total Area}}$$

Perform this calculation for each year using the respective SCN values and LULC areas.

Analyze the Contribution of Each LULC to SCN: Multiply the proportion of each LULC class in the total area by its SCN value. Compare changes over the years to identify which LULC class drives the most significant SCN changes was conducted using a decomposing approach.

RESULTS AND DISCUSSION

Land Use Land Cover of Karadua River Catchment Area

After Classifying land use land cover the accuracy assessment is conducted until it reaches the minimum threshold i.e. acceptable threshold (table 3).

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Table 3: Accuracy assessment of land use land cover of 2017, 2020 and 2023

Year	User Accuracy	Producer Accuracy	Overall Accuracy	Kappa Coefficient
2017	84.04	83.15	84.00	0.83
2020	85.06	84.20	84.15	0.81
2023	84.18	85.15	86.00	0.84

Table 3 reveals the accuracy levels of land use/land cover classification for the years 2017, 2020, and 2023. Both User Accuracy and Producer Accuracy for each period of land use classification are above 80%. The Kappa values for the classified land use/land cover images are consistently greater than 0.80 (80%) for 2017, 2020, and 2023, as shown in the table. These results indicate that the classification model has maintained a high level of accuracy over the three years. The Kappa values, which reflect the agreement between the predicted and true classifications, suggest strong performance, with minimal misclassifications relative to what would be expected by chance. This is similar to the finding of (Akın & Erdoğan, 2020; Bashariya et al., 2022) found that the high accuracies across the user and producer metrics also suggest that the model reliably identifies land cover types (Producer Accuracy) and accurately classifies those types when assigned (User Accuracy).

Characteristics of Land Use Land Cover of 2017, 2020 And 2023

Table 4: land use land cover characteristics of the study area

	2017		2020		2023	
LULC CLASS	Area Km²	%	Area Km²	%	Area Km²	%
Agricultural Land	1585.2	98.4	1584.9	98.4	1582.0	98.2
Built-up Area	8.0	0.5	12.6	0.8	17.4	1.1
Vegetation	7.4	0.5	5.0	0.3	3.7	0.2
Water	9.6	0.6	7.7	0.5	7.1	0.4
Total	1610.20	100	1610.20	100	1610.20	100

The table 4 shows the characteristics of classified land use/land cover for 2017, 2020, and 2023. The results reveal that agricultural land consistently covers about 98% of the total area, with a slight decrease in 2023 (from 98.4% to 98.2%). This trend can be observed in the figure below. Additionally, the built-up area shows an increasing trend, rising from 8.0 km² (0.5%) in 2017 to 17.4 km² (1.1%) in 2023. The growth of built-up areas indicates urban expansion and development in the study area over time. This increase is likely linked to population growth, infrastructure projects, and the growing demand for shelter.

Furthermore, the vegetation area has decreased from 7.4 km² (0.5%) in 2017 to 3.7 km² (0.2%) in 2023. This decline can likely be attributed to land use changes, particularly the conversion of vegetated areas into agricultural or built-up land. Similarly, water areas have decreased slightly, from 9.6 km² (0.6%) in 2017 to 7.1 km² (0.4%) in 2023, as shown in the figure below.

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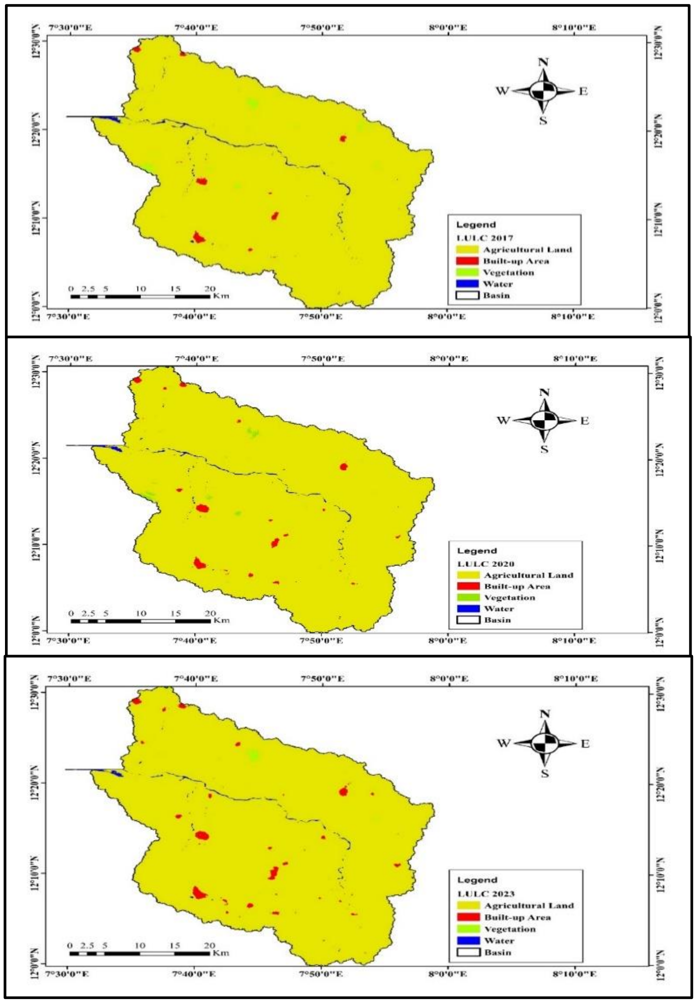

Figure 2: Classified Land Use Land Cover of The Study Area

The Change Detection Between Land Use Land Cover of 2017, 2020 And 2023

The analysis of the land use/land cover (LULC) changes between 2017 and 2023, as shown in Table 5 and Figure 3 provides a clear picture of how the landscape has evolved. Each land cover class exhibits different trends over the periods 2017-2020, 2020-2023, and 2017-2023. The Agricultural land decreased by 0.3 km² (a 0.02% loss) between 2017 to 2020, a small decline that is not significant when compared to other LULC classes. In the Change of agricultural land from 2020 to 2023 there was a more substantial reduction with a loss of 2.9 km² (a 0.18% decrease). For the entire period from 2017 to 2023, agricultural land lost 3.2 km² (0.20%), reflecting a steady decline. The relatively small overall loss suggests that agricultural activities remain dominant in the area, but this trend of slight reduction may indicate a gradual conversion of agricultural land for other uses, especially urban development.

Table 5: Land Use Land Cover Changes in the Study Area

	2017-2020		2020-2023		2017-2023	
LULC CLASS	Area Km²	%	Area Km²	%	Area Km²	%
Agricultural Land	-0.3	-0.02	-2.9	-0.18	-3.2	-0.20
Built-up Area	4.6	36.37	4.9	38.76	9.4	118.06
Vegetation	-2.4	-47.76	-1.3	-26.71	-3.7	-50.40
Water	-1.9	-24.96	-0.6	-8.12	-2.5	-26.47

The Built-up Area increased by 4.6 km² (a 36.37% rise) from 2017 to 2020, indicating significant urban expansion or infrastructure development. This was clearly shown in the figure 5. Also the built-up area continued to grow, increasing by 4.9 km² (a 38.76% rise) from 2020 to 2023 while over the entire period, built-up areas increased by 9.4 km² (a remarkable 118.06% increase). This large growth highlights a trend of rapid urbanization, with built-up areas more than doubling over six years. This urban sprawl has likely encroached on agricultural land and vegetation areas, driving much of the observed land cover changes.

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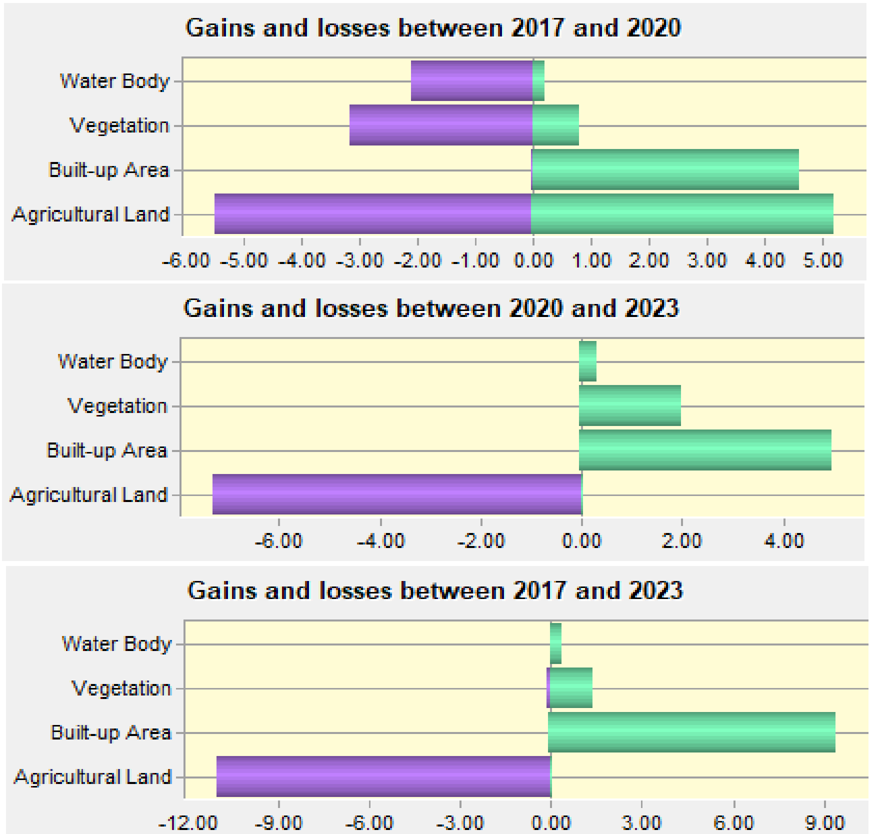

Figure 3: Gains and Losses of Land Use Land Cover Changes in the Study Area

Furthermore, the vegetation area decreased by 2.4 km² (a 47.76% decline), from 2017 to 2020 a significant loss in just three years, from 2020 to 2023 the Vegetation continued to decrease, with a loss of 1.3 km² (a 26.71% decline). This further reduction is consistent with the ongoing loss of natural habitats, reflecting the growing pressures from urbanization and agriculture. While over the entire period, the vegetation area decreased by 3.7 km² (a 50.40% loss). The substantial overall loss of vegetation raises concerns about environmental degradation, including reduced biodiversity and ecosystem services (Bashariya et al., 2022). This shift may be a result of land use conversion, particularly to agricultural and built-up areas (Nwilo et al., 2020).

The water area decreased by 1.9 km² (a 24.96% loss) from 2017 to 2020. Also water area Changed from 2020 to 2023 with a loss of 0.6 km² (8.12%). Over the entire period, water areas decreased by 2.5 km² (a 26.47% reduction). This overall decline in water bodies could be attributed to a variety of factors, including land use changes (such as urban expansion or agricultural development), or potential environmental management practices that have reduced water availability.

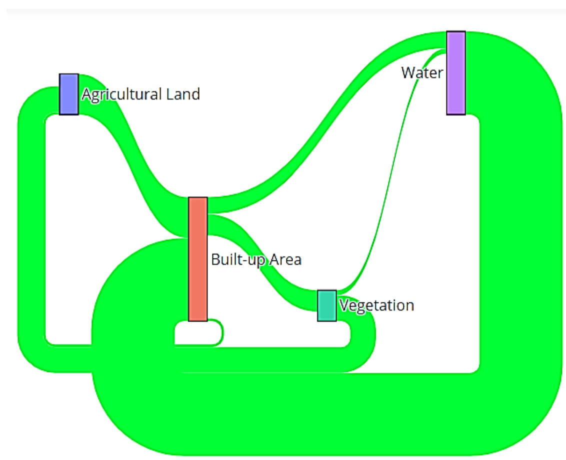

Figure 4: transition of land use land cover changes in the study area

The dynamic land use transitions between 2017 and 2023 are shown in Figure 4. The result revealed significant contributions to urbanization from multiple land use types. Some water bodies have been converted to built-up areas, possibly through reclamation or urban expansion near lakes or rivers. A substantial portion of farmland has been urbanized, likely due to population growth and

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infrastructure development. Also, Natural areas like forests or grasslands have been lost to urban expansion. The flow indicates that some vegetated areas were cleared or converted to farmland, potentially for food production or economic activities (Bishir et al., 2018). this result emphasizes that all land use types are interconnected, with changes in one category impacting others. This reflects the competing demands for land and resources.

Land use influenced on flood susceptibility

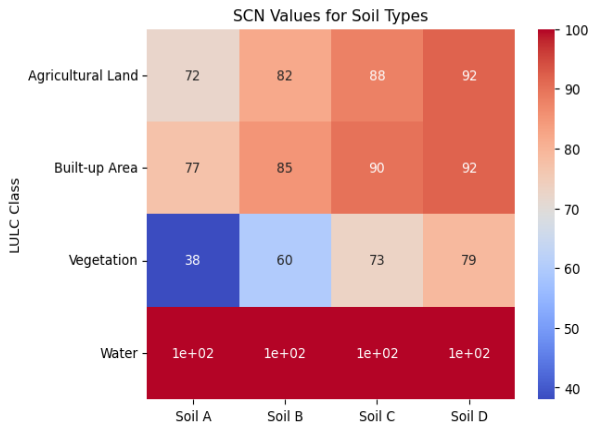

Figure 5: Distribution of Soil Curve Number of Different Land Use Across Soil Types in the Study Area

Figure 5 revealed that the Vegetation land use under Soil A shows the highest infiltration, as indicated by the low SCN value (38). This reflects the permeable nature of Soil A combined with vegetation cover, which promotes infiltration and reduces runoff. While under Soil B also exhibits good infiltration, though slightly lower than under Soil A, with an SCN value of 60. This is due to the moderate permeability of Soil B. The Agricultural land under Soil A (SCN = 72) allows higher infiltration compared to vegetation under Soil C (SCN = 73). This suggests that agricultural land benefits more from the high permeability of Soil A than vegetation under the less permeable Soil C. the Built-up areas across all soil types have higher SCN values (77–92), indicating low infiltration and significant runoff. Despite the high SCN values, your observation suggests these areas retain water due to impervious surfaces.

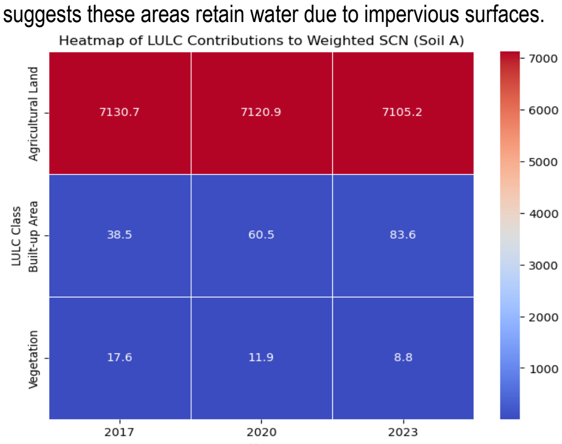

Figure 6: impact of land use land cover changes on flood susceptibility

The decomposition analysis of the SCN (Soil Conservation Number) changes over time, driven by changes in Land Use Land Cover (LULC) areas, provides insight into how different land use types influence flood susceptibility (see Figure 6). The SCN values are influenced by the type of land use and the extent of its changes over the periods (2017–2020, 2020–2023, and 2017–2023).

Changes in agricultural land show a negative trend in SCN over the 2017–2020 and 2020–2023 periods. This suggests that agricultural land contributes negatively to SCN changes, which might reflect that agricultural practices (such as tilling, overgrazing, or monoculture cropping) can lead to soil degradation, increasing the soil's retention capacity and, consequently, the probability of flood occurrences.

Built-up areas exhibit changes in SCN values, particularly during the 2017–2023 period. This result is counterintuitive, as urbanization typically results in increased impervious surfaces, thereby increasing the likelihood of flood susceptibility. Additionally, vegetation loss to agricultural land and built-up areas is detrimental to the soil's infiltration capacity, leading to higher flood susceptibility, increased erosion rates, loss of organic matter, and overall soil degradation.

Conclusion

The Karadua River Basin in Katsina State, Nigeria, has undergone notable changes in land use and land cover (LULC) between 2017 and 2023, significantly affecting its hydrology and flood susceptibility. The agricultural land remained the predominant LULC type, covering over 98% of the area. However, it experienced a slight decline of 3.2 km² (-0.20%) over six years, indicating gradual conversion to urban areas. Built-up areas more than doubled, increasing by 9.4 km² (118.06%) between 2017 and 2023. This growth reflects urban expansion and infrastructure development, which likely encroached on agricultural and vegetative land, reducing permeable surfaces and increasing flood risks. Vegetation cover reduced significantly by 3.7 km² (-50.40%), while water bodies decreased by 2.5 km² (-26.47%). These losses suggest deforestation and reduced water availability, potentially due to land conversion and environmental pressures. As such the Changes in LULC have significantly influenced flood susceptibility since the Agricultural land and Vegetation Loss contributed to reduced SCN (Soil Conservation Number), exacerbated soil erosion and reduced infiltration, further increasing flood risks. Therefore, sustainable land-use management and reforestation could mitigate these impacts by improving soil retention and reducing runoff. In addition, the study emphasizes the urgent need for integrated land-use planning, focusing on balancing urban development with environmental conservation to minimize adverse hydrological impacts and enhance flood resilience.

REFERENCE

Akın, A., & Erdoğan, M. A. (2020). Analysing temporal and spatial urban sprawl change of Bursa city using landscape metrics and remote sensing. *Modeling Earth Systems and Environment*, *6*(3), 1331–1343. https://doi.org/10.1007/s40808-020-00766-1

Ardicliogiu, M., Hadi, A. M. W. M., Periku, E., & Kuriqi, A. (2022). Experimental and Numerical Investigation of Bridge Configuration Effect on Hydraulic Regime. *International Journal of Civil Engineering*, *20*(8), 981–991. https://doi.org/10.1007/s40999-022-00715-2

Babati, A.-H., Abdussalam, A. F., Baba, S. U., & Isa, Z. (2022).

Prediction of flood occurrences and magnitude in Hadejia-Jama'are river basin, Nigeria. *Sustainable Water Resources Management*, *8*(6), 188. https://doi.org/10.1007/s40899-022-00781-3

Babati, A., Saleh, Y. I., Isa, Z., Baba, B. M., Dabo, A. A., & Yahya, M. I. (2021). Simulation of Groundwater Level in River Mallam Sule Catchment Area of Potiskum , Yobe State Using SWAT. *Science World Journald*, *16*(3), 363–368.

Bashariya, M. B., Zaharaddeen, I., Auwal, F. A., & Abu-Hanifa, B. (2022). MODELLING THE SIGNATURE OF HUMAN INFLUENCE ON VEGETATION DYNAMIC IN KAMUKU NATIONAL PARK, NIGERIA. *Science World Journal*, *17*(2).

Bishir, G. S., Julius, A., Michael, B. K. darkoh, & Bothepha, M. (2018). Impact of Desertification on Livelihoods in Katsina State, Nigeria. *Journal of Agriculture and Life Science*, *5*(1), 34–52.

Cirella, G., Iyalomhe, F., & Adekola, P. (2019). Determinants of Flooding and Strategies for Mitigation: Two-Year Case Study of Benin City. *Geosciences*, *9*(3), 136. https://doi.org/10.3390/geosciences9030136

Ezenwa, K. O., Iguisi, E. O., Yakubu, Y. O., & Ismail, M. (2022). A SCS-CN TECHNIQUE FOR GEOSPATIAL ESTIMATION OF RUNOFF PEAK DISCHARGE IN THE KUBANNI DRAINAGE BASIN, ZARIA, NIGERIA. *FUDMA JOURNAL OF SCIENCES*, *6*(1), 314–322. https://doi.org/10.33003/fjs-2022-0601-901

Fawzy, S., Osman, A. I., Doran, J., & Rooney, D. W. (2020). Strategies for mitigation of climate change: a review. *Environmental Chemistry Letters*, *18*(6), 2069–2094. https://doi.org/10.1007/s10311-020-01059-w

Hundu, W. T., Anule, P. T., Kwanga, G. ., & Dam, D. P. (2021). Assessment of Land Use and Land Cover Change Using GIS And Remote Sensing Techniques in Katsina-Ala Local Government Area of Benue State, Nigeria. *Journal of Research in Forestry, Wildlife & Environment*, *13*(4).

Isa, Z., Abdussalam, A. F., Sawa, B. A., Ibrahim, M., Isa, U. A., & Babati, A.-H. (2023). Identifying major climate extreme indices driver of stream flow discharge variability using machine learning and SHaply Additive Explanation. *Sustainable Water Resources Management*, *9*(4), 119. https://doi.org/10.1007/s40899-023-00897-0

Isa, Z., Sawa, B. A., Abdussalam, A. F., Ibrahim, M., Babati, A. H., Baba, B. M., & Ugya, A. Y. (2023). Impact of climate change on climate extreme indices in Kaduna River basin, Nigeria. *Environmental Science and Pollution Research*, *30*(31), 77689–77712. https://doi.org/10.1007/s11356-023-27821-5

LV, Z., Zuo, J., & Rodriguez, D. (2020). Predicting of Runoff Using an Optimized SWAT-ANN: A Case Study. *Journal of Hydrology: Regional Studies*, *29*, 100688. https://doi.org/https://doi.org/10.1016/j.ejrh.2020.100688

Nwilo, P. C., Olayinka, D. N., Okolie, C. J., Emmanuel, E. I., Orji, M. J., & Daramola, O. E. (2020). Impacts of land cover changes on desertification in northern Nigeria and implications on the Lake Chad Basin. *Journal of Arid Environments*, *181*, 104190. https://doi.org/https://doi.org/10.1016/j.jaridenv.2020.104190

Ogarekpe, N., Obio, E., Tenebe, I., Emenike, P., & Nnaji, C. (2020). A dataset for the flood vulnerability assessment of the upper Cross River basin using morphometric analysis. *Data in Brief*, *30*, 105344. https://doi.org/https://doi.org/10.1016/j.dib.2020.105344

Sahoo, A., & Ghose, D. K. (2021). Flood Frequency Analysis for Menace Gauging Station of Mahanadi River, India. *Journal of The Institution of Engineers (India): Series A*, *102*(3), 737–748. https://doi.org/10.1007/s40030-021-00544-x