

Correlation of Land Use Land Cover Dynamics and Soil Moisture Variability over Zaria-Nigeria

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Abstract

Soil moisture is an important part of the land water cycle. It affects ecosystem health, agricultural output, and climate regulation. Several factors influence its variability, especially land use and land cover (LULC). This study looked at how LULC relates to changes in soil moisture in Zaria, Nigeria. The study area is experiencing urban growth and agricultural expansion. Soil moisture data was retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF). LULC maps were created from satellite images taken from 2000 to 2020. Partial correlation analysis was employed to determine the relationship between various land cover types and soil moisture. The results show strong positive correlations between soil moisture and vegetated areas ($r = 0.9801$) and also with water bodies ($r = 0.9232$). These results indicate that thick vegetation and nearby water bodies help retain soil moisture by reducing evaporation, improving infiltration, and increasing water-holding capacity. On the other hand, soil moisture has a strong negative correlation with built-up areas ($r = -0.8723$) and bare soil ($r = -0.997$). The study shows that LULC characteristics greatly impact soil moisture changes. The study finally demonstrated the vital role of vegetation and water features in maintaining soil moisture, while also highlighting the negative effects of urban expansion and land degradation in semi-arid areas like Zaria.

1. Introduction

It is reported that human's activities have altered approximately 41% of the land surface by shifting from natural vegetation into agriculture and settlement (Sterling *et al.*, 2013). Land transformation induced by anthropogenic activities notably referred as urbanization causes changes on thermal surface properties and along with land use and land cover (LULC) thereby modifying surface energy and water balance (Hua and Ping, 2018). This phenomenon causes damage to environmental qualities such as, soil fertility (Rikimaru and Miyatake, 1997), biodiversity (McKinney, 2006), natural resources (Rashid *et al.*, 2018) and also have crucial effects on soil moisture (Feng *et al.*, 2023).

Soil moisture is of great importance to many disciplines, especially agriculture, hydrology, and atmospheric sciences. It plays a key role in the land-surface-atmosphere interaction (Mahmood, 1996; Yang *et al.*, 2007; Gentine, *et al.*, 2019). It can be defined as the amount of water stored in the unsaturated soil (Seneviratne *et al.*, 2010). While, surface soil moisture (SSM) is simply defined as the water that is stored in the uppermost layer (approximately top 0-10cm) of the soil (Pan *et al.*, 2003; Sharma and Hakkim, 2014). It is this thin layer of the soil that regulates most of the agricultural activity in the environment (Sharma *et al.*, 2018).

Modern geospatial technologies such as Remote Sensing (RS), Geographic Information System (GIS), and Global Positioning System (GPS) continue to provide very useful ways of identifying, mapping, monitoring, and tracking changes in the composition, extent, and distribution of several forms of earth resources (Mani and Varghese, 2018; Munthali, *et al.*, 2019). In the recent times, reanalysis data provides comprehensive snapshots of atmospheric conditions at regular intervals of time over long years or decades (Babre *et al.*, 2020). They are provided via data assimilation; a process that relies on both observations and model-based forecasts to estimate conditions (Dee *et al.*, 2011). It is now a popular approach in the estimation of soil moisture because of its capabilities in taking into account the problems of both soil roughness and vegetation cover inherently associated with microwave remote sensing - based methods (Said *et al.*, 2012; Li *et al.*, 2020).

Spatial distribution of soil moisture is affected by Landuse and Landcover (LULC) alteration, periods of the season (Donglian and Rachel, 2004; Jiang and Weng, 2015), topography (Majdar *et al.*, 2018) and vegetation (Zhou *et al.*, 2024). Several efforts were made on characterizing land use land cover globally (Aminu *et al.* 2013; Wang *et al.* 2018; Zhou *et al.* 2019; Azua *et al.* 2020; Peng *et al.* 2022; Abubakar *et al.* 2024; Moisa *et al.* 2025) through utilizing Normalized Difference Vegetation Index (NDVI) and Normalized Soil Moisture Difference Index (NSMDI) for soil moisture estimation and correlating it land cover dynamics with no such carried out in the study area.

Zaria is considered as one of the agricultural areas in the northern part of Nigeria and it is witnessing a remarkable increase in urbanization (Yakubu *et al.*, 2017), soil degradation (Aminu and Jaiyeoba, 2016), and high evapotranspiration activities and water stress (Emeribe *et al.*, 2021). The city also had transformed from an urban educational center to a rapidly growing city, having major agricultural, manufacturing, and industrial establishments (Abbas, 2018). Regrettably, no effort was made in investigating the relationship between soil moisture and LULC dynamics despite the noticeably land transformation that took place in the study area.

1.1 The Study Area

1.1.1 Location and extent

Zaria and environs is situated between latitudes $11^{\circ} 02' 00''$ and $11^{\circ} 12' 00''$ North of the Equator and between longitudes $7^{\circ} 36' 00''$ and $7^{\circ} 46' 00''$ East of the Greenwich Meridian at an average altitude of 670m above mean sea level as it covers an area of 542.9 square kilometres.

1.1.2 Climatic and weather

The area is blessed an abundance of fertile land for agriculture that is favorable for agricultural activities with an average annual rainfall of about 1000 mm (Sawa and Buhari, 2011; Suleiman *et al.*, 2021). The region lies within the tropical Savannah (Koppens classification). The study area experiences two distinct climatic seasons; the wet and dry seasons.

1.1.3 Soil

Based on the Food and Agriculture Organization (FAO) classification, Zaria soil is Ferric Luvisols, formed from basement complex rocks and quaternary deposits and it has very poor drainage due to its high percentage of fine materials in the upper layers (Yakubu and Mashi, 2019). It becomes waterlogged during heavy rains and tends to dry out and crack during the dry season. Due to its high clay content, the soil has good moisture retention capacity.

1.1.4 Vegetation of Study Area

The vegetation of the area was forest savannah however, due to settlement expansion, agricultural activities and other land uses, the natural vegetation has changed to guinea savannah (Azua *et al.*, 2018). Most of the crops produced in Zaria include guinea corn, maize, rice and millet, and cash crops such as cotton, groundnuts, soy beans and tobacco and also blessed with vast grazing land, wetland, grass land, farm land and abundant water resources (Kibbon *et al.*, 2016).

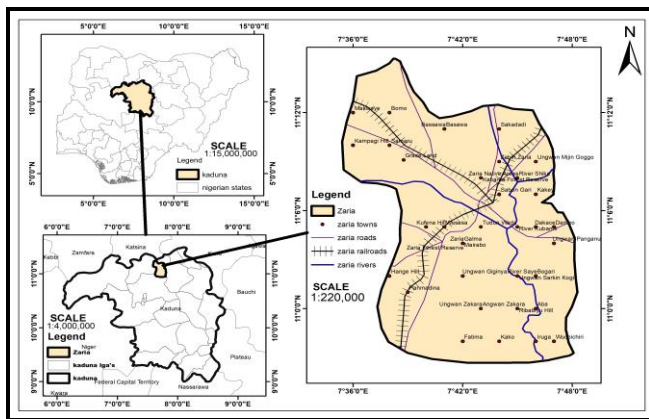


Figure 1: The Study Area. Top left: Map of Nigeria depicting Kaduna State. Bottom left: Kaduna State depicting Zaria/Sabon Gari L.G.A. Right: The Study Area

2. Material and Method

2.1. Dataset

The details of the datasets used for this study are shown in the Table 1. While the various software and their functions are highlighted in Table 2. The data acquired were from the European Reanalysis Interim (ERA-I), and the Landsat satellite images at three epochs: 2000, 2010 and 2020. The images were checked to ensure that the scenes had a minimum percentage of cloud cover (maximum cloud cover of 10 %) which was adopted.

Parameters	Data Type	Units	Spatial Resolution	Temporal coverage	Source of data
Monthly soil moisture	Secondary	m ³ /m ³	(0.125 ⁰ × 0.125 ⁰) grid	Global January 2000-December 2020	ECMWF NetCDF
Satellite Imageries	Secondary	N/A	30m	2000, 2010 and 2020	USGS

Table 1. Datasets and their Sources

Software	Function
Panoply 4.3.2	for viewing the spatial plot and numerical values of the data which are in Network Common Data Form (NetCDF) format
Matlab R2018b	for extracting gridded soil moisture values
QGIS 3.14.0	Used for Image classification
Microsoft Excel 2013	Used for correlation analysis
MathType Lite	Used for type setting of scientific equations

Table 2. Software and their Functions

2.2 Methods

2.2.1 Characterization of land use/land cover

The Landsat 7 ETM+ and Landsat 8 (OLI) images datasets (path: 189, Row: 52) with less than 10% cloud coverage courtesy of the United States Geological Survey (USGS) data hub (<http://www.usgs.gov/>) were downloaded, processed to generate land use/cover changes (LULC) maps for 2000, 2010 and 2020 epochs. In order to characterize the various land cover types in the study area, the following steps were followed (Nkeki, 2016).

2.2.2 Preprocessing

The accuracy and reliability of processed outputs depend on the quality of image being used. This is achieved through the removal of noise and unwanted defects acquired during the image acquisition stage. Both radiometric and geometric corrections were carried out on individual image scene. Before the image classification commenced, scan line correction was carried out in all the Landsat 7 ETM+ datasets using gap fill tool in the QGIS software in order to fill the existing gaps in the satellite data. The need for the gap-filling procedure is as a result of the unfortunate failure of the Landsat 7 ETM+ scan line corrector (SLC) in May 2003 (Asare *et al.*, 2020).

2.2.3 Image clip

The study area was clipped out as a subset from the Landsat full image to decrease the time consuming and storage space. The shape file of the study area was used to clip the study area during the image classification and was realized in the QGIS software (Theres and Selvakumar, 2022).

2.2.4 Image classification

The rectified image spanning twenty years at three epochs over the study area was characterized into four classification schemes namely; Built-up, Vegetation, Bare Soil and Water bodies (Isioye *et al.*, 2020) (Sharma and Vashishtha, 2023). The Maximum likelihood (ML) using supervised classification method was utilized for the different study periods in the QGIS software (Theres and Selvakumar, 2022). The LULC class description is summarized in Table 3 (Lie *et al.*, 2017)

S/N	LULC Class	Description
I	Urban/Built-up	residential, commercial etc
ii	Vegetation	Comprises agricultural lands, etc
iii	Bare land	Include all non-vegetated land
iv	Water body	Areas that comprises rivers, etc

Table 3. Landcover Description

2.3 Assessing Accuracy Assessment of Classified Images

Accuracy assessment is an important task when analyzing various image processing techniques for picture categorization (Al-aarajy *et al.* 2024). The accuracy of the categorized images is assessed using an error matrix (Mushore *et al.* 2017). The classified LULC images had been diagnosed with the simple random method (SRM), so one can compare the accuracy of LULC maps generated from Landsat images for 2000, 2010 and 2020 respectively as in equation 1 (Ullah *et al.* 2017).

$$\text{Overall Accuracy} = \frac{(\text{Observed Accuracy} - \text{Chance Assessment})}{(1 - \text{Chance Agreement})} \quad 1$$

The KHAT (k) values provide an assessment of how accurately the classification images matches the reference data. K can be conceptually described as equation (2) (Bazrafshan *et al.* 2022).

$$K = \frac{(\text{number sampling classes classified correctly})}{(\text{number of reference sampling classes})} \quad 2$$

This statistic shows how much of the ‘true’ vs. ‘chance’ agreement accounts for the percentage of accurate values in an error matrix.

2.4 Estimation of soil moisture

The soil moisture at 0-10cm was retrieved from European Centre for Medium-Range Weather Forecast (ECMWF), (<http://www.ecmwf.int>) for the period of 2000 to 2020 over the study area. To process the datasets, Panoply software version 4.3.2 was used to read the NetCDF datasets as well as preliminary visualize the spatial plot and gridded arrays of the soil moisture. The matrix form (latitude, longitude) for the study area was clipped, extracted, and exported as grid text files to Microsoft (MS-Excel), and Sorting and formulations were carried out to arrange all values in the required script-format in line with the geospatial coordinates of the study area (Ojigi and Opaluwa, 2019). The diagrammatic presentation of the methodology for the work is presented in Figure 2 as it shows the integrated method of assessing the correlation of land use land cover dynamics and soil moisture variability over the study area.

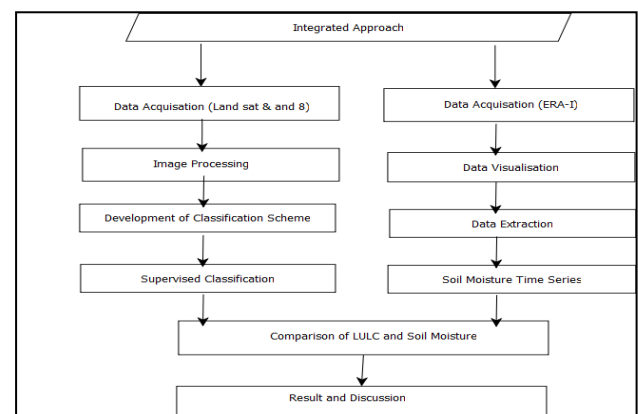


Figure 2. Methodological Flowchart

2.5 Relationship between LULC Classes and Soil Moisture

In order to determine the relationships of the four identified land cover types on soil moisture trend, Pearson correlation (r) was obtained between each land cover type of each epoch (2000, 2010 and 2020) with the corresponding soil moisture value of that period.

3. Result and Discussions

3.1 Characterization of LULC Classes

The results showed that the area of all the LULC classes have undergone changes, but with differing magnitude. Based on

image processing, the results revealed that study area was estimated to be 545.799 km² as presented in Table 4.

LULC	2000		2010		2020	
	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%
Built up	48.334	8.856	65.210	11.950	81.638	14.960
Vege	272.084	49.851	194.435	35.620	173.210	31.740
Bare soil	222.117	40.701	283.958	52.030	289.445	53.020
Water	3.264	0.590	2.196	0.400	1.506	0.280
Total	545.799	100	545.799	100	545.799	100

Table 4. Area statistics of LULC classes in the study area for the years under study

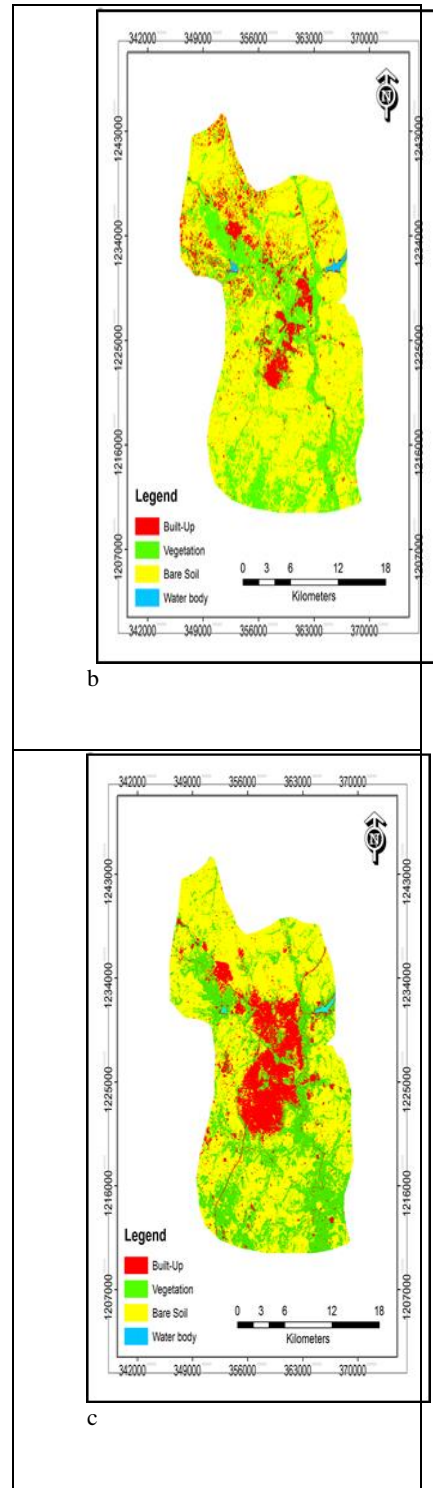
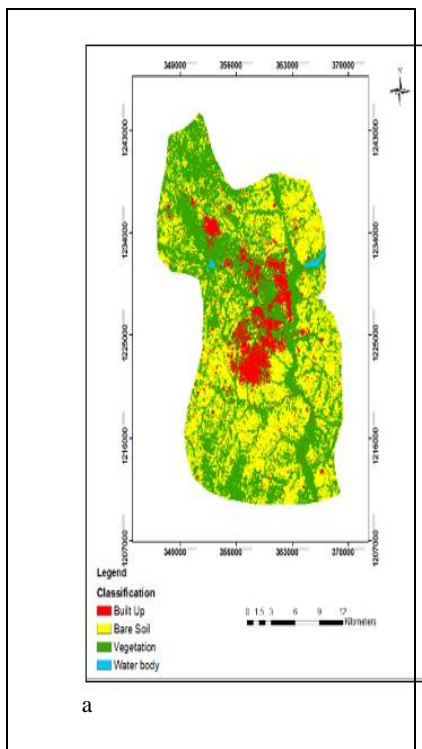


Figure 3. Classified landuse/landcover of the Study Area (a): October 2000 (b): December 2010 (c): December 2020.

In 2000, built up area covered about 48.334km² (8.86%) of the study area. Vegetation appears to be a predominant land cover type with a spatial extent of 272.084 km² (49.85%), bare soil covers about 222.177 km² (40.70%) and water bodies' covers 3.264 km² (0.59%). While in 2010, the built-up had showed a spatial extent of 65.210 km² (11.95%), vegetation drastically reduced to 194.435 km² (35.62%), bare soil increased to 283.958 (52.03%) while little decrease was noticed in water bodies of 2.196 km² (0.40%). In the last epoch, built-up covered 81.638 km² (14.96%) while vegetation, bare soil and water bodies had 173.210 km² (31.74%), 289.445 km² (53.02%), and 1.506 km² (0.28%), respectively. This can also be seen in Figures 3.

This may not be unconnected to the increase in population and expansion in settlement in Zaria as reported by Okewu (2016); Azua *et al.* (2020) who reported similar findings in the area, and Abubakar and Sawa (2016) in Birnin Kebbi-Nigeria This development had adversely affected the proportion of vegetation and bare soil (land covers) for the period under study. Figure 3 (a-c), display the results of classified images for 2000, 2010 and 2020 respectively.

LULC Classes	2000 P.A 100%	2000 U.A 100%	2010 P.A 100%	2010 U.A 100%	2020 P.A 100%	2020 U.A 100%
Built-up	96	98	96	92	96	97
Vege	98	96	94	96	96	96
Baresoil	92	92	98	98	96	98
Water body	98	98	94	94	98	94
Overall Acc	96		95		97	
Kappa Stat	0.947		0.935		0.963	

Table 5. Summary of the accuracy assessment of classified images (2000, 2010 and 2020)

3.2 Assessing Accuracy Assessment

The producer's accuracy of built-up class was determined as 96%, vegetation 98%, bare soil 92%, and water body 98%. While the user accuracy of built-up land was 98%, vegetation 96%, bare soil 92% and water body 98% with overall accuracy of 96 % and kappa coefficient of 0.9468 for year 2000. For the year 2010, the producer's accuracy of built-up class was 96%, vegetation 94%, bare soil 98%, and water body 94%. While the user accuracy of built-up land was 92%, vegetation 96%, bare soil 98% and water body 94% with overall accuracy of 95% and kappa coefficient of 0.9346. The results also show that, the user accuracy of built-up land was 96%, vegetation 96%, bare soil 96% and water body 98% while the user accuracy of built-up land was 97%, vegetation 96%, bare soil

98% and water body 94% with overall accuracy of 97 % and kappa coefficient of 0.96328 for the year 2020.

The Kappa coefficient measures the agreement between classification and truth values. Kappa value of 1 represents perfect agreement, while a value of 0 represents no agreement. The general range for Kappa values are if $K < 0.4$, a poor kappa value; while, if $0.4 < K < 0.75$, is a good kappa value and if $K > 0.75$, it is an excellent kappa value (Vieira *et al.*, 2010; Bharatkar and Patel, 2013).

3.3 Soil Moisture Variability

The estimated soil moisture values is presented in Table 6

Month/Year	2000	2010	2020	Monthly Aver
January	0.1725	0.1728	0.1741	0.1730
February	0.1723	0.1723	0.1722	0.1724
March	0.1712	0.1725	0.1724	0.1726
April	0.1898	0.1750	0.1756	0.1800
May	0.1980	0.1917	0.1887	0.1942
June	0.2411	0.2318	0.2088	0.2227
July	0.2712	0.2718	0.2295	0.2602
August	0.3108	0.3011	0.2815	0.3006
September	0.3081	0.3273	0.2895	0.3061
October	0.2354	0.2895	0.2414	0.2423
November	0.1739	0.2024	0.1754	0.1782
December	0.1726	0.1760	0.1738	0.1734
Annual Average	0.2181	0.2154	0.2069	0.2134

Table 6. Monthly Variability of Soil Moisture (m³/m³)

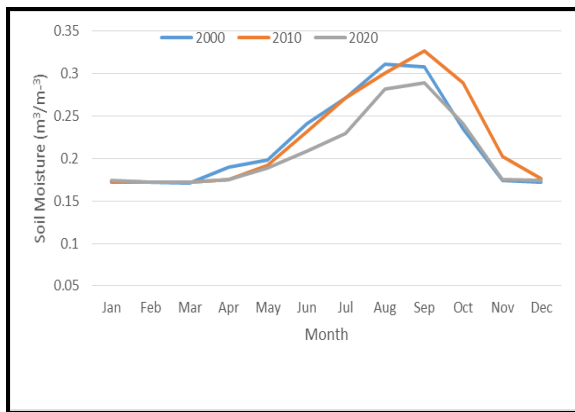


Figure 4. Monthly Soil Moisture Trend (2000-2020)

From Table 6 and Figure 4, over the (2000 – 2020) epochs, the month of September was observed to have the highest soil moisture values with an average of $0.3061 \text{ m}^3/\text{m}^3$ while February had the least soil moisture value with an average of $0.1724 \text{ m}^3/\text{m}^3$. This finding corroborates with Onwuka *et al.*, 2024 which attributed it to the influence of precipitation on soil moisture as a result of its intensity in August and September and its low values between January and March.

3.4 Relationship between LULC Classes and Soil Moisture Variability

The area of land covers types which were built up, vegetation, bare soil and water body and the estimated soil moisture values is presented in Table 7 while the trend relationship among them is depicted in Figure 5.

Var/Year	SM (m^3/m^3)	Built-up (km^2)	Bare soil (km^2)	Vegetation (km^2)	Water body (km^2)
2000	0.2354	48.338	222.117	272.084	3.264
2010	0.1760	65.210	283.958	194.435	2.196
2020	0.1734	81.638	289.445	173.210	1.506

Table 7. Surface moisture variation with corresponding land cover areas

Figures 5 (a-d) displayed the relationships between landcover and soil moisture over the study period. It can be seen that there was opposite relationships between soil moisture and built-up cover and soil moisture and bare soil between 2000 and 2020. Conversely, a noticeably positive relationship between soil moisture and water body and soil moisture and vegetation was discovered within same period.

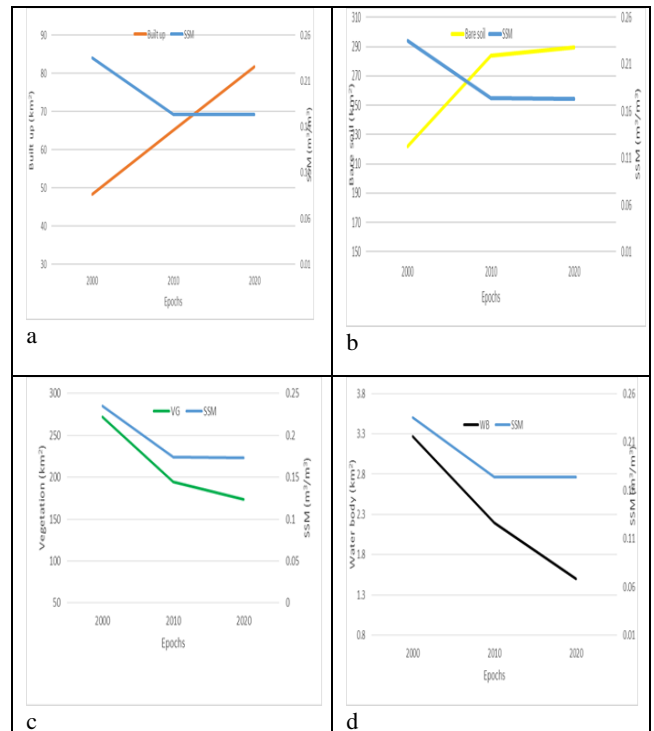


Figure 5. Trend relationships (a): SM vs Built-up (b): SM vs Bare soil (c): SM vs Vegetation (d): SM vs Water body.

In order to buttress the above relationship, the correlation coefficient (r) values were obtained between the surface soil moisture and each landcover types so as to ascertain the strength and direction of their relationship as shown in Table 8.

LULC/ SM	SM	Built-up	Veg	Bare soil	Water body
SM	1	-0.8723	0.9801	-0.9977	0.9232
Built-up	-0.8723	1	-0.9522	0.9038	-0.9903
Vege	0.9801	-0.9522	1	-0.9913	0.9811
Bare soil	-0.9977	0.9038	-0.9913	1	-0.9471
Water body	0.9232	-0.9903	0.9811	-0.9471	1

Table 8. Correlation coefficient (r) between Landcover classes and soil moisture variable

Strong positive correlation was noticed between vegetation cover and soil moisture ($r = 0.9801$), while water body and soil moisture had $r = 0.9232$. This could not be unconnected with convection which could also manifested in the reduction in area coverage of vegetation and water body area by 98.874 km^2 and 1.758 km^2 respectively. Conversely, negative relationships were witnessed between the built-up class and soil moisture ($r = -0.8723$) and, between bare soil and soil moisture ($r = -0.9977$) as it could be attributed to an increase in soil alteration via tar, and other materials replacement resulted to increase in built-up and bare soil by 33.304 km^2 and 67.228

km² respectively within same period of study as can be seen in Table 8. This shows that the transition from natural vegetation to impervious surfaces as a result of urbanization activities tends to introduce soil moisture depletion thereby causing increase in runoff and the decrease in infiltration rate. The result is in line with the findings of Nagne *et al.* (2019) and Masroor *et al.* (2022) who reported land cover dynamics as a factor influencing soil moisture changes.

4. Conclusion

The study aimed to use remote sensing and GIS to examine changes in land use and land cover (LULC), soil moisture variation, and their relationship in Zaria, Nigeria. Results showed significant LULC changes, with notable increases in built-up areas (68.97%) and bare soil areas (30.33%). These changes were likely due to urbanization and economic activities. On the other hand, vegetation and water bodies decreased by 36.34% and 53.86%, respectively. September had the highest average soil moisture at 0.3061 m³/m³, while February recorded the lowest at 0.1724 m³/m³, reflecting seasonal rainfall patterns. Strong positive correlations were found between soil moisture and vegetation ($r = 0.9801$) and water bodies ($r = 0.9232$). In contrast, negative correlations existed between soil moisture and both built-up areas ($r = -0.8723$) and bare soil ($r = -0.9977$), linked to increased land surface modification. These findings can help guide sustainable land use planning and environmental management.

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