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Research Article

Geospatial Analysis of The Relationship Between Land Use/Land Cover and Surface Water Quality in Southern Yobe, Nigeria

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ABSTRACT

Surface water quality in semi-arid regions is increasingly threatened by land use and land cover (LULC) changes, yet limited integrated assessments exist in Southern Yobe, Nigeria. This study examined the influence of LULC patterns on surface water quality using a geospatial-statistical approach. Satellite imagery from USGS was processed in ArcGIS version 10.0 for supervised classification into agricultural land, bare surfaces, vegetation, built-up areas, and water bodies. Thiessen polygon interpolation was applied to delineate zones of influence, while water samples were collected across Fune, Fika, and Nangere LGAs and analyzed for electrical conductivity (EC), chemical oxygen demand (COD), chloride, total nitrogen (TN), and total phosphorus (TP) following APHA (2017) standards. Correlation and regression analyses in SPSS 26 established relationships between LULC types and water quality parameters. Results revealed agricultural land and bare surfaces as dominant covers, significantly elevating EC, TN and temperature through nutrient enrichment and sedimentation. Conversely, vegetation cover revealed strong buffering capacity, reducing and EC, while built-up areas showed emerging but limited impacts on water quality. Chloride, COD, and TP exhibited weak or no significant associations with LULC under current conditions. The findings highlight agriculture and soil exposure as key drivers of water degradation, while vegetation acts as a critical stabilizer. The study recommends adopting sustainable farming practices, afforestation, erosion control, urban runoff management, and integrated land-water governance. Continuous monitoring of nutrient and sediment-related parameters is essential. The study concludes that water quality sustainability in Southern Yobe depends on proactive land management aligned with catchment protection strategies.

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1 Introduction

Water is fundamental to human survival, food production, and ecosystem functioning. Globally, surface water bodies are increasingly under pressure from anthropogenic activities, particularly land-use and land-cover (LULC) changes. Land use practices determine the types and intensities of pollutants entering water bodies, while land cover influences hydrological processes such as infiltration, runoff, and sediment transport (Rey-Romero et al., 2022). Agricultural expansion, deforestation, bare soil exposure, and rapid urbanization are among the most significant drivers of water quality deterioration. These processes often lead to nutrient enrichment, eutrophication, and higher levels of chemical oxygen demand (COD) and total dissolved solids (TDS), which in turn threaten aquatic life and human water supplies (Juncal et al., 2023).

Water quality degradation is a global issue, but it is particularly acute in developing regions where population growth, weak regulation, and poverty increase the intensity of land use pressures on fragile ecosystems. The World Health Organization [WHO] (2017) stresses that catchment protection is one of the most effective strategies for ensuring safe drinking water. Therefore, understanding the spatial links between land cover patterns and water quality is critical for achieving the United Nations Sustainable Development Goals (SDGs), especially Goal 6 on clean water and sanitation.

Across sub-Saharan Africa, rapid land use changes have intensified water quality problems. High rates of agricultural expansion, logging, and settlement growth are contributing to soil erosion, sedimentation of rivers, and nutrient runoff. These processes are compounded by climate variability, which alters rainfall intensity and hydrological cycles.

In the Ikpa River Basin of Nigeria, Oluwaseun et al. (2023) reported that climate variability, land cover change, and soil erosion risk significantly impaired water quality, leading to elevated nutrient loads and reduced aquatic ecosystem health. Similarly, studies in East Africa have documented how catchments with higher forest or vegetation cover tend to produce water with lower nutrient concentrations compared to degraded or agricultural catchments (Mathews et al., 2020).

Semi-arid and transitional regions of Africa face unique challenges because rainfall is seasonal, soils are fragile, and vegetation cover is often sparse. When land cover is altered, runoff increases dramatically, carrying sediments and dissolved ions into rivers and reservoirs.

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These processes accelerate the degradation of already scarce surface water resources. This reality underscores the importance of localized, spatially explicit assessments of LULC and water quality in African watersheds.

Nigeria has witnessed significant land cover changes over the past four decades, driven largely by agricultural expansion, urban growth, and population increase. Several Nigerian studies demonstrate strong links between these changes and water quality deterioration. For instance, Ogundairo et al. (2025) showed that urban expansion in the Eleyele catchment, Ibadan, was associated with increased nutrient enrichment and organic loading of water bodies. Likewise, Ogbozige and Alfa (2019) found that agricultural and built-up land uses in the River Kaduna watershed were strongly correlated with elevated EC, TDS, COD, total nitrogen (TN), and total phosphorus (TP), while vegetation cover had a mitigating effect.

Other studies confirm similar patterns in different ecological zones of Nigeria. In the Osun River catchment, land clearing and farming activities were linked to sedimentation and nutrient enrichment (Akinbile & Yusoff, 2011). In urban Kano, poor land use practices contributed to degraded water quality in streams and reservoirs, while in rural areas, intensive farming practices increased non-point source pollution (Edokpayi et al., 2017). These findings collectively show that vegetation cover acts as a natural buffer, stabilizing soils, filtering pollutants, and reducing surface runoff, while agricultural and urban land uses often exacerbate water quality problems.

Yobe State, located in northeastern Nigeria, lies within a transitional semi-arid to sub-humid climatic zone. It experiences highly seasonal rainfall, with most precipitation occurring between June and September, while the rest of the year is marked by dryness and high evapotranspiration. This climatic regime makes water resources highly vulnerable to fluctuations and land management practices. The Komadugu-Yobe Basin, which drains much of Yobe State, is a critical hydrological system supporting agriculture, livestock, and domestic water supply. However, it faces increasing pressures from population growth, over-cultivation, and land degradation.

Recent research highlights water quality concerns in this region. Audu and Boso (2025) reported significant variability in surface water quality across rural micro-watersheds in Southern Yobe, noting that EC, dissolved oxygen, and COD were strongly influenced by surrounding land cover. Shuaibu (2024) conducted a hydrogeochemical analysis of the Komadugu-Yobe Basin and found that catchment land uses influenced groundwater chemistry, underscoring the strong link between surface processes and water resources in the basin.

Studies in towns such as Gashua further confirm these challenges. Yuguda et al. (2020) documented elevated concentrations of heavy metals in river water and sediments, which they attributed to anthropogenic activities and runoff from surrounding lands. Suleiman (2021) also reported high levels of heavy metals in drinking water sources in the Bade Local Government Area of Yobe State, highlighting risks to human health from water contamination. Collectively, these studies demonstrate that water resources in Southern Yobe are highly vulnerable to LULC change. Agricultural expansion, dominance of bare surfaces, and limited vegetative cover intensify soil erosion and nutrient runoff, leading to declining water quality. Yet, despite these concerns, there has been little integrated research that combines geospatial LULC analysis with comprehensive field water quality assessment in Southern Yobe. This study aims to bridge that gap by applying geospatial techniques (remote sensing, GIS, and Thiessen polygon interpolation) alongside field water quality measurements to assess the influence of LULC patterns on surface water quality in Southern Yobe.

2 Materials and Methods

2.1 Study Area

The research was carried out in the three Local Government Areas of Southern Yobe, namely Fune, Fika, and Nangere. The study area covers approximately 8,686.37 km² and is situated within the semi-arid zone of northeastern Nigeria (Figure 1). The climate is marked by a single rainy season from June to September and a long dry season from October to May. Subsistence agriculture is the predominant activity, with scattered settlements, bare surfaces, sparse vegetation, and seasonal water bodies. These land use and land cover conditions strongly influence the quality of available surface water resources.

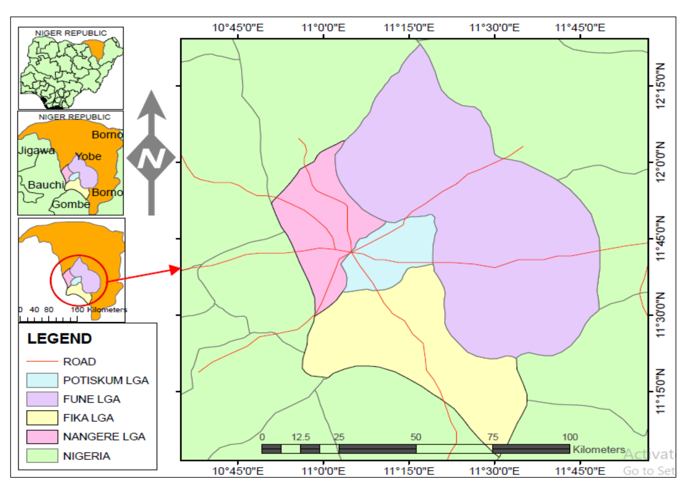

Figure 1: Study Area

Source: Adapted from the administrative map of Yobe State (2025).

2.2 Data Sources

2.2.1 Water Sampling and Laboratory Analysis

Water samples were collected from twenty-five (25) strategically selected sampling locations distributed across the three Local Government Areas. The study area lies between latitudes 11° 20′00′′ to 12°20′00′′ North of the Equator and longitudes 10°40′00′′ to 12°00′00′′ East of the Greenwich Meridian. Geographic coordinates of each sampling point were recorded in situ using a handheld Global Positioning System (GPS) receiver referenced to the World Geodetic System 1984 (WGS 84). The coordinates were compiled and exported in CSV format for subsequent GIS-based spatial analysis. Sampling was conducted in October, corresponding to the late wet season–early dry season transition period characteristic of the Sudano-Sahelian climatic regime of northern Nigeria. This timing was selected to capture residual runoff effects following the rainy season while minimizing peak dilution influences, thereby reflecting representative ambient water quality conditions. The sample size (25) was considered sufficient to ensure spatial representation across dominant land use/land cover categories and hydrological segments (upstream, midstream, and downstream) within the study area. Sampling locations were proportionally distributed to capture varying anthropogenic influences and environmental conditions, thereby enhancing spatial representativeness and supporting robust statistical interpretation.

A grab sampling technique was employed in accordance with established environmental monitoring protocols. Samples were collected in pre-cleaned polyethylene bottles, properly labeled, and stored in an ice chest at approximately 4 °C immediately after collection to minimize physicochemical alteration during transport. All samples were transported under controlled conditions and delivered within recommended holding times to the laboratory for analysis.

Physicochemical analyses were conducted at the Central Laboratory, Bayero University, Kano. The laboratory was responsible for sample preparation, preservation verification, instrument calibration, and analytical measurements. Parameters analyzed included electrical conductivity (EC), temperature, chloride (Cl^-), chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP). Analytical procedures followed the Standard Methods for the Examination of Water and Wastewater prescribed by the American Public Health Association (APHA, 2017).

Quality assurance and quality control (QA/QC) procedures were implemented by the laboratory in accordance with its standard operating procedures. This included instrument calibration using certified reference standards, analysis of reagent blanks, and duplicate measurements to ensure analytical reliability. Method detection limits (MDLs) and analytical precision values for each parameter were determined by the laboratory and considered in the interpretation of results to ensure data accuracy and reproducibility. Method detection limits (MDLs) and analytical precision values for each parameter were determined and reported by the laboratory as part of its quality control procedures.

2.3 Satellite Data and Image Processing

The high-resolution satellite imagery, Landsat 9 Operation Land Imager 1 (OLI 1) with 30m resolution, was imported into the ArcGIS version 10.0 environment, and it underwent pre-processing to correct for various distortions. The first step, radiometric correction, adjusts the satellite images to compensate for sensor and atmospheric effects, ensuring that the pixel values accurately represent surface reflectance. Following this, geometric correction is performed to align the images with a map coordinate system, ensuring spatial accuracy and consistency across the dataset. All datasets were georeferenced to a uniform spatial reference system, and resampling was performed to achieve a consistent spatial resolution across the imagery. With pre-processed imagery, the next step is image classification; each pixel is based on its spectral characteristics. This process involves categorizing the imagery into different land cover/ land use types (LC/LU) relevant to the study, such as agricultural land, vegetation, built-up area, water body, and bare surface, as seen in Table 1.

Table 1: Land use land cover classification scheme

Land Use-Land Cover Type	Description
Agricultural land	All cultivated lands
Vegetation	All vegetated lands, such as grassland, shrubs, forests, and other natural vegetation, are not yet cultivated.
Built-up Area	Areas used for both urban and rural residential land use
Water Body	All water surfaces, such as rivers, streams, and ponds.
Bare surface	Rocky land and land without vegetation

The classified imagery was converted into thematic maps representing the spatial distribution of LULC classes. Thiessen polygons were used to extract the percentages of different Land Use/Land Cover (LU/LC) types within the study area. This method ensures that each polygon represents the dominant land cover type surrounding a specific water sampling location, facilitating the analysis of LU/LC influences on surface water quality; zonal statistics were applied to extract the percentage of each LU/LC type within each polygon.

2.4 Statistical Analysis

Statistical analyses were performed using SPSS version 26. Spearman's correlation was applied to test the strength and direction of relationships between land use and land cover classes and the measured water quality parameters. Multiple regression analysis was then used to quantify the extent to which variations in land use and land cover explained changes in water quality. All statistical tests were conducted at a 95% confidence level, with significance considered at $p < 0.05$.

3 Results and Discussions

3.1 Land Use/Land Cover Patterns in the Study Area

The analysis of Table 2 and Figure 2, where the percentage of land use/land cover (LU/LC) types was extracted using Thiessen polygon interpolation, provides important insights into how different LU/LC patterns influence water quality across the study area. The spatial distribution highlights the dominance of agricultural land, significant presence of bare surfaces, and varying levels of vegetation and built-up areas, all of which play an important role in shaping surface water quality.

The whole study area is 8686.37 km^{2,} of which agricultural land constitutes the most widespread land cover across many villages, particularly in Garin Makera (87.58%), Pakarau Magala (86.73%), and Garin Barde (82.35%), indicating a high dependence on farming activities. The prevalence of croplands has major implications for water quality, as agricultural runoff often contributes to increased levels of nutrient enrichment, particularly nitrogen (TN) and phosphorus (TP) (Adeyemi et al., 2019). This is consistent with global studies showing that watersheds dominated by agriculture experience higher concentrations of suspended sediments and dissolved ions due to soil erosion and fertilizer application (Mathews et al., 2020). The negative correlation between agricultural land and dissolved oxygen (DO) observed in the study suggests that farming activities increase organic loading in water bodies, leading to microbial decomposition and oxygen depletion, a trend widely reported in previous research (Alkhatib et al., 2021).

Bare surfaces are another major land cover type, particularly in Garin Tango (42.25%), Basirka (40.52%), and Chana (37.42%), where minimal vegetation cover exposes soil to erosion and runoff. The high proportion of bare surfaces increases sediment transport into surface water sources, contributing to elevated total suspended solids (TSS) (Edokpayi et al., 2017). This aligns with findings by Odikamnoro et al. (2019), who reported that watersheds with high bare surface percentages exhibited degraded water quality due to increased sedimentation, which affects aquatic life and raises water treatment costs.

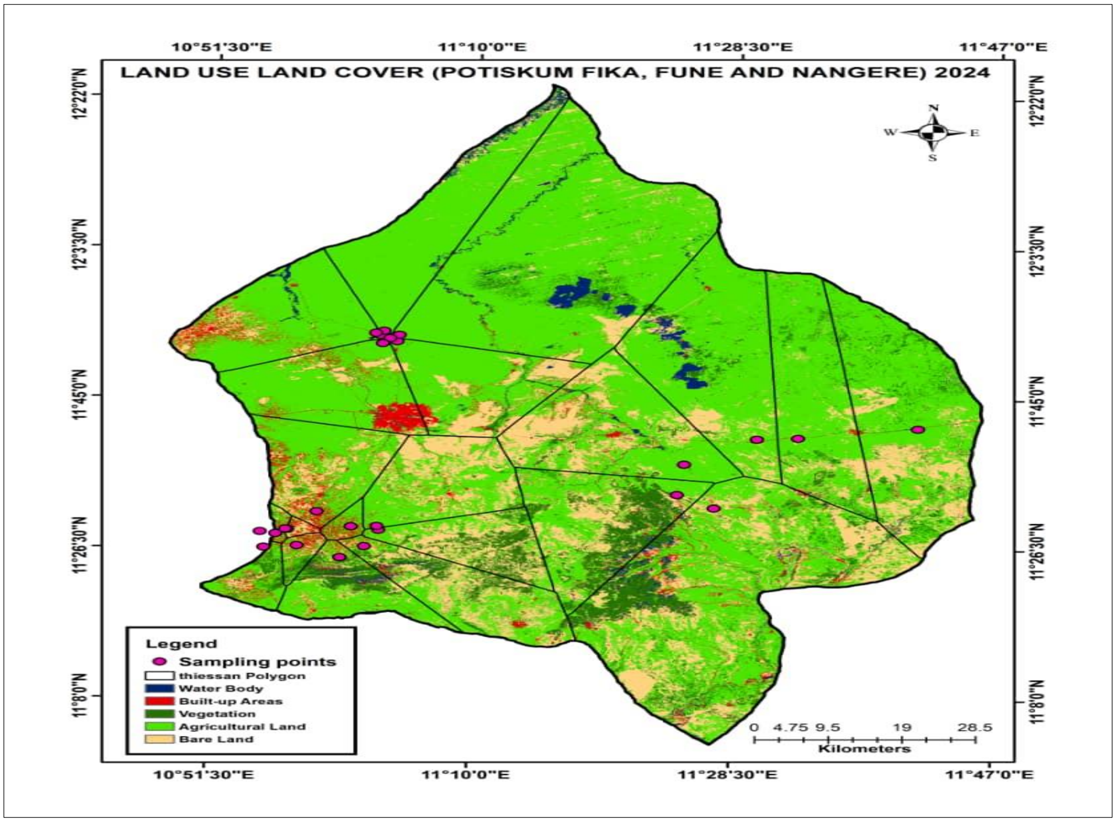

Figure 2: Spatial pattern of LU/LC

The built-up areas, concentrated in settlements such as Siminti (33.85%) and Baino (24.43%), introduce another layer of influence on water quality. Urbanization alters hydrological cycles by increasing impervious surfaces, reducing infiltration, and intensifying surface runoff, which often carries pollutants such as heavy metals, hydrocarbons, and organic matter from domestic waste (WHO, 2017). The relatively low percentage of built-up areas in many villages, such as Garin Tango (0.75%) and Pakarau Magala (0.54%), suggests that direct anthropogenic pollution from urban runoff is currently limited. However, as urbanization expands, stormwater management measures, such as green infrastructure and wastewater treatment, will be necessary to maintain water quality (Armah et al., 2018).

Vegetation cover varies across the study area, with some villages such as Garin Tango (27.17%) and Male (16.53%) exhibiting relatively high vegetation coverage. The presence of vegetation is important for maintaining water quality, as it acts as a natural filter for pollutants, stabilizes soil, and reduces surface runoff (Akinbile & Yusoff, 2011). The negative correlation between vegetation and electrical conductivity (EC) in this study aligns with findings from global research, which indicate that watersheds with extensive vegetative cover tend to have lower dissolved ion concentrations and improved water clarity due to reduced erosion (Mathews et al., 2020). Villages with minimal vegetation cover, such as Garu (0.08%) and Kukawa (0.65%), are more susceptible to soil degradation and water quality deterioration, emphasizing the need for afforestation and soil conservation initiatives.

Water bodies are scarce across the study area, with Old Nangere I (15.80%) and Bai (4.26%) having the highest proportions. The limited surface water availability suggests heavy reliance on seasonal streams, micro-watersheds, and groundwater sources, making water scarcity a significant concern. Previous studies have shown that regions with limited surface water bodies experience greater seasonal water quality fluctuations, particularly in nutrient concentrations and microbial contamination (Adekunle et al., 2007). This underscores the need for integrated water resource management to ensure a sustainable water supply.

Table 2: Land Use/Land Cover Distribution (%) in Sampled Villages

S/N	Villages	Water body (%)	Built-up Area (%)	Vegetation (%)	Agricultural Land (%)	Bare Surface (%)
1	Old Nangere	1.46	5.25	1.70	67.67	23.92
2	Old Nangere I	15.80	4.50	2.34	76.82	0.54
3	Pakarau	3.83	0.35	1.06	90.62	4.14
4	Siminti	1.61	33.85	1.54	15.99	47.01
5	Buramo	0.45	18.47	6.12	54.21	20.76
6	Buramo Dan Hajja	0.33	12.88	10.46	58.88	17.46
7	Didim	1.82	10.98	15.64	59.58	11.99
8	Baino	0.73	24.44	10.45	43.19	21.19
9	Male	2.01	21.46	16.53	40.96	19.04
10	Bai	4.26	4.68	19.42	58.93	12.71
11	Chana	2.53	3.37	14.96	41.72	37.43
12	Garin Tango	0.79	0.76	27.17	29.03	42.26
13	Basirka	0.30	2.98	1.94	54.25	40.53
14	Garu	1.59	27.95	0.08	64.95	5.42
15	Kukawa	0.55	13.30	0.66	64.40	21.09
16	Pakarau Magala	3.47	0.54	3.80	86.73	5.46
17	Garin Makera	3.35	5.59	1.79	87.58	1.71
18	Garin Barde	1.77	7.91	0.26	82.35	7.71
19	Garin Bijimi	1.03	12.46	0.23	78.22	8.07
20	Mil Biyar	0.84	0.76	8.19	67.99	22.22
21	Funai	0.57	0.78	6.31	81.22	11.11
22	Sabon Sara	3.75	0.45	4.34	81.10	10.36
23	Daura	2.39	1.93	27.46	42.75	25.48
24	Abakire	2.76	3.50	13.12	50.99	29.62
25	Lukunde	1.48	3.32	3.43	58.98	32.79

The findings from Figure 2, generated using Thiessen polygon interpolation, validate the statistical trends observed in Table 2, providing spatial clarity on LU/LC variations and their water quality implications. The combination of correlation and regression analyses in this study confirms that agricultural expansion and bare surface coverage significantly influence water pollution, while vegetation plays a protective role in stabilizing surface water quality. These results align with broader research on land use impacts, highlighting the need for sustainable land management policies (WHO, 2017; Alkhatib et al., 2021).

The analysis of Table 2 and Figure 2, derived from Thiessen polygon interpolation, provides a detailed understanding of LU/LC patterns and their implications for surface water quality. The dominance of agricultural land and bare surfaces poses significant risks of water pollution, while vegetation acts as a buffer to mitigate degradation. The findings align with existing literature on land use impacts on water resources, emphasizing the need for integrated land and water management approaches (Mathews et al., 2020; Alkhatib et al., 2021). Sustainable agricultural practices, erosion control, urban water management, and improved conservation strategies are essential for ensuring long-term water quality and availability in the study area.

3.2 Relationship between Electrical Conductivity (EC) and Land Use/Land Cover

A strong relationship was observed between EC and LU/LC patterns (Table 3). Vegetation (-0.474, p = 0.037) exhibited a significant negative correlation with EC, suggesting that denser vegetation reduces dissolved ion concentrations in water by acting as a buffer that minimizes soil erosion and nutrient leaching. This finding is consistent with Alkhatib et al. (2021), who found that increased vegetation reduces EC levels by stabilizing soil and preventing excessive ion transport into water bodies. Conversely, agricultural land showed a positive correlation (0.457, p = 0.027) with EC, indicating that farming activities contribute to increased ion concentration, likely through fertilizer application and soil disturbances. Akinbile and Yusoff (2011) reported similar findings in agricultural regions, where EC levels were higher due to the presence of dissolved salts from fertilizers and organic waste decomposition.

Table 3: Spearman's Correlation coefficients between EC (µs/cm) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with EC (µs/cm)	Sig. (2-tailed)
Water Body	0.117	0.578
Built-up Area	-0.115	0.583
Vegetation	-0.474*	0.037
Agricultural land	0.457*	0.027
Bare Surface	-0.035	0.867

**. Correlation is significant at the 0.05 level (2-tailed).*
***. Correlation is significant at the 0.01 level (2-tailed).*

In the regression model for electrical conductivity (EC), LU/LC predictors (Table 4) explained only a small portion of variation (R^2 = 0.140), and none were statistically significant at $p < 0.05$. This suggests that broad classes of land use, such as agricultural and built-up areas, had limited explanatory power for EC in this study's context. However, empirical research indicates that increases in agricultural land and urban development are generally associated with higher electrical conductivity due to runoff carrying dissolved ions (e.g., salts and nutrients) from disturbed landscapes into aquatic systems (Gani et al., 2023). Indeed, land use impacts on water quality have been consistently demonstrated in river systems globally, with agricultural and built-up land contributing to elevated conductivity through enhanced solute transport, whereas natural and vegetated land use tends to mitigate such increases through physical filtration and stabilization of soils (Gani et al., 2023). These broader findings help contextualize why agricultural land showed a positive yet non-significant coefficient in the regression model.

Table 4: Regression Analysis of Electrical Conductivity (EC) and Land Use/Land Cover

Predictor Variable (%)	B (Unstandardized Coefficient)	Std. Error	Beta (Standardized Coefficient)	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	-0.129	2.651	-0.011	-0.049	0.962	
Built-up Area	-1.078	0.799	-0.295	-1.350	0.192	
Vegetation	-1.381	0.963	-0.033	-1.434	0.032	
Bare Surface	0.198	0.639	0.076	0.310	0.760	
Agricultural Land	0.758	0.023	0.034	0.105	0.041	
Model Summary	R = .374	R^2 = 0.140	Adj. R^2 = -0.032	Std. Error = 0.344		Regression = 0.337
ANOVA (Residual)						Residual = 0.200
ANOVA (Total)						Total = 0.537

3.3 Relationship between Temperature and Land Use/Land Cover

A significant positive correlation (Table 5) was observed between bare surfaces and water temperature (0.427, p = 0.033), suggesting that exposed land increases thermal absorption, which subsequently raises water temperature. This aligns with previous studies indicating that deforested or degraded landscapes experience higher temperatures due to direct exposure to solar radiation (APHA, 2017). Additionally, water body cover had a negative correlation (-0.424, p = 0.035), reinforcing the moderating effect of water bodies in absorbing and regulating temperature fluctuations.

Table 5: Spearman's Correlation Coefficients between Temp (°C) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with Temp (°C)	Sig. (2-tailed)
Water Body	.-0.424	0.035
Built-up Area	-0.081	0.699
Vegetation	0.264	0.202
Agricultural land	-0.301	0.144
Bare Surface	0.427*	0.033

**. Correlation is significant at the 0.05 level (2-tailed).*

***. Correlation is significant at the 0.01 level (2-tailed).*

The regression analysis (Table 6) revealed that bare surface had a statistically significant positive effect on temperature (β = 0.385, p = 0.025). This indicates that landscapes with greater proportions of exposed soil or surfaces lacking vegetation are associated with higher water temperature. This observation is supported by recent research showing that changes in land cover alter surface thermal dynamics: removal of vegetation increases solar radiation reaching water bodies, which raises water temperature and affects aquatic thermal regimes (Gani et al., 2023). Vegetation typically moderates these thermal effects through shading and evapotranspiration, reducing direct heating of surface waters and helping maintain cooler and more stable temperature conditions. The significant positive association between bare surfaces and temperature in this study aligns with these findings, reflecting the broader consensus that vegetative cover plays a key role in buffering thermal stress in freshwater systems.

Table 6: Regression Analysis of Temperature (Temp) and Land Use/Land Cover

Predictor Variable (%)	B (Unstandardized Coefficient)	Std. Error	Beta (Standardized Coefficient)	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	-0.025	0.065	-0.084	-0.379	0.708	
Built-up Area	-0.012	0.020	-0.124	-0.595	0.558	
Vegetation	0.009	0.024	0.080	0.366	0.072	
Bare Surface	0.026	0.016	0.385	1.654	0.025	
Agricultural Land	0.572	0.014	0.080	0.937	0.890	
Model Summary	R = 0.463	R^2 = 0.214	Adj. R^2 = 0.057	Std. Error = 0.864		Regression = 0.080
ANOVA (Residual)						Residual =0.960
ANOVA (Total)						Total = 1.040

3.4 Relationship between Chloride (Cl) and Land Use/Land Cover

Chloride is an essential ion in water, but excessive concentrations may indicate anthropogenic pollution sources such as agricultural runoff, wastewater discharge, or urbanization (Edokpayi et al., 2017). The correlation analysis (Table 7) did not reveal significant relationships between chloride and any LU/LC type, indicating that chloride levels in the study area are relatively stable and not strongly influenced by land use changes. Similarly, the regression analysis (Table 8) showed no significant predictors of chloride concentration, with agricultural land, vegetation, and built-up areas having negligible effects. These results contrast with previous studies in highly urbanized areas, where chloride levels often increase due to road salt application, industrial discharge, and intensive irrigation (Mathews et al., 2020).

Table 7: Spearman's Correlation Coefficients between Cl (mg/l) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with Cl (mg/l)	Sig. (2-tailed)
Water Body	0.081	0.700
Built-up Area	0.146	0.485
Vegetation	-0.122	0.562
Agricultural land	-0.105	0.618
Bare Surface	0.011	0.959

**. Correlation is significant at the 0.05 level (2-tailed).*

***. Correlation is significant at the 0.01 level (2-tailed).*

The findings suggest that chloride sources in the study area may be primarily natural, with minimal anthropogenic influence. However, continuous monitoring is recommended to assess potential future increases due to expanding agricultural or urban activities.

Table 8: Regression Analysis of Chloride (Cl) and Land Use/Land Cover

Predictor Variable (%)	B (Unstandardized Coefficient)	Std. Error	Beta (Standardized Coefficient)	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	0.016	0.035	0.115	0.470	0.644	
Built-up Area	0.007	0.010	0.155	0.672	0.509	
Vegetation	-0.005	0.013	-0.097	-0.405	0.690	
Bare Surface	0.004	0.008	0.117	0.454	0.655	
Agricultural Land	-0.524	0.019	-0.611	0.017	0.514	
Model Summary	R = 0.213	R^2 = 0.045	Adj. R^2 = 0.145	Std. Error = 0.462		Regression = 0.204
ANOVA (Residual)						Residual = 0.276
ANOVA (Total)						Total = 0.480

3.5 Relationship between Chemical Oxygen Demand (COD) and Land Use/Land Cover

Chemical Oxygen Demand (COD) measures the total oxygen required for the oxidation of both organic and inorganic matter in water, making it an important indicator of water pollution (WHO, 2017). The correlation analysis (Table 9) did not reveal significant relationships between COD and any LU/LC type, suggesting that chemical pollution sources in the study area are relatively uniform and not strongly influenced by land use patterns.

Table 9: Spearman's Correlation Coefficients between COD (mg/l) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with COD (mg/l)	Sig. (2-tailed)
Water Body	-0.049	0.818
Built-up Area	-0.034	0.872
Vegetation	0.152	0.468
Agricultural land	-0.169	0.419
Bare Surface	0.307	0.136

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

The regression results for COD (Table 10) showed low explanatory power (R^2 = 0.123) and no significant predictors among the LU/LC variables. This suggests that COD, which represents organic chemical load, may be less directly tied to broad land cover patterns in the study area or may be influenced by sources not captured by simple land cover percentages, such as point-source pollution or in-stream biological processes. Although many watersheds studies link land use to water quality degradation, the strength of those relationships varies widely with geographic context and local sources of organic inputs (Gani et al., 2023). The weak statistical associations observed here underscore that COD variability may be more sensitive to localized inflows and organic pollution sources than to broad land cover composition alone.

Table 10: Regression Analysis of Chemical Oxygen Demand (COD) and Land Use/Land Cover

Predictor Variable (%)	B (Unstandardized Coefficient)	Std. Error	Beta (Standardized Coefficient)	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	0.017	0.028	0.138	0.591	0.561	
Built-up Area	-0.006	0.009	-0.151	-0.686	0.501	
Vegetation	-0.007	0.010	-0.147	-0.639	0.530	
Bare Surface	0.011	0.007	0.392	1.594	0.127	
Agricultural Land	0.866	0.003	0.282	0.215	0.282	
Model Summary	R = 0.351	R^2 = 0.123	Adj. R^2 = -0.052	Std. Error = 0.37781		Regression = 0.402
ANOVA (Residual)						Residual = 0.855
ANOVA (Total)						Total = 1.257

3.6 Relationship between Total Nitrogen (TN) and Land Use/Land Cover

Total Nitrogen (TN) is a key nutrient influencing water quality, with excessive levels contributing to eutrophication and declining aquatic health (Mathews et al., 2020). The correlation analysis (Table 11) revealed a significant positive relationship between agricultural land (0.427, p = 0.029) and TN, indicating that increased farming activities contribute to nitrogen enrichment in surface water. This finding aligns with previous studies, such as those by Adekunle et al. (2007), which showed that nitrogen-based fertilizers and livestock waste are major sources of nitrogen pollution in agricultural watersheds.

Table 11: Spearman's Correlation coefficients between TN (mg/l) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with TN (mg/l)	Sig. (2-tailed)
Water Body	0.309	0.133
Built-up Area	-0.041	0.848
Vegetation	0.261	0.207
Agricultural land	0.427*	0.029
Bare Surface	0.055	0.793

**. Correlation is significant at the 0.05 level (2-tailed).*

***. Correlation is significant at the 0.01 level (2-tailed).*

The regression model (Table 12) for total nitrogen (TN) revealed that agricultural land had a significant positive relationship with TN levels (β = 0.208, p = 0.029), explaining a substantial proportion of variation (R^2 = 0.025). This finding is strongly supported by recent studies demonstrating that agricultural land use increases nitrogen concentrations in water bodies through nutrient runoff from fertilizers and soil processes (Pakoksung et al., 2025). For example, seasonal redundancy analysis in Thailand showed that agricultural land is positively correlated with nitrate and ammonia nitrogen due to runoff, especially during periods of heavy precipitation (Pakoksung et al., 2025). The positive association observed in this study reinforces the understanding that increased agricultural activity contributes to elevated nitrogen pollution, a concern for eutrophication and aquatic ecosystem health.

Table 12: Regression Analysis of Total Nitrogen (TN) and Land Use/Land Cover

Predictor Variable (%)	Unstandardized Coefficient	Std. Error	Standardized Coefficient	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	0.011	0.042	0.068	0.274	0.787	
Built-up Area	-0.005	0.013	-0.096	-0.411	0.686	
Vegetation	0.005	0.015	0.079	0.328	0.747	
Bare Surface	0.002	0.010	0.043	0.164	0.871	
Agricultural Land	0.114		0.302	0.208	0.029	
Model Summary	R = 0.16	R^2 = 0.025	Adj. R^2 = -0.17	Std. E = 0.55		Regression = 0.161
ANOVA (Residual)						Residual = 0.153
ANOVA (Total)						Total = 0.314

3.7 Relationship between Total Phosphorus (TP) and Land Use/Land Cover

Total Phosphorus (TP) is another critical nutrient affecting water quality, often associated with agricultural runoff and soil erosion (Chapman, 1996). However, the correlation analysis (Table 13) did not reveal significant relationships between TP and any LU/LC type, suggesting that phosphorus levels in the study area are relatively stable and not strongly influenced by land use patterns.

Table 13: Spearman's Correlation Coefficients between TP (mg/l) and Land Use/Land Cover

LU/LC Type (%)	Spearman Correlation with TP (mg/l)	Sig. (2-tailed)
Water Body	-0.026	0.903
Built-up Area	-0.093	0.659
Vegetation	0.205	0.325
Agricultural land	-0.182	0.384
Bare Surface	0.238	0.251

**. Correlation is significant at the 0.05 level (2-tailed).*

***. Correlation is significant at the 0.01 level (2-tailed).*

The regression analysis (Table 14) for total phosphorus (TP) indicated low explanatory power ($R^2 = 0.163$) and no significant predictors among LU/LC categories. This suggests that broad land use proportions did not have a detectable impact on phosphorus levels in this dataset. Recent research also shows that phosphorus dynamics are complex and can depend on specific soil characteristics, hydrological connectivity, and management practices, making linear associations with broad land cover difficult to detect (Gani et al., 2023). Additionally, phosphorus may be retained or mobilized differently than nitrogen due to differences in soil binding and runoff processes, leading to weaker or more context-dependent relationships with land use. The lack of significant TP predictors in this study highlights the need for more detailed assessments of phosphorus sources and transport pathways to understand its variation in aquatic systems.

Table 14: Regression Analysis of Total Phosphorus (TP) and Land Use/Land Cover

Predictor Variable (%)	B (Unstandardized Coefficient)	Std. Error	Beta (Standardized Coefficient)	t-value	Sig. (p-value)	ANOVA (Sum of Squares)
Water Body	-0.001	0.001	-0.251	-1.099	0.285	
Built-up Area	0.000	0.000	-0.096	-0.443	0.662	
Vegetation	0.000	0.000	0.232	1.033	0.314	
Bare Surface	0.000069	0.000	0.069	0.286	0.778	
Agricultural Land	-0.937	0.001	-0.414	0.684	0.213	
Model Summary	R = 0.404	R^2 = 0.163	Adj. R^2 = -0.004	Std. Error = 0.01336		Regression = 0.001
ANOVA (Residual)						Residual =0.004
ANOVA (Total)						Total = 0.005

4 Conclusion

This study confirms that land use and land cover (LU/LC) patterns are significant determinants of surface water quality in Southern Yobe State. The integration of geospatial analysis (Thiessen polygon interpolation) with correlation and regression techniques provided clear evidence that agricultural land and bare surfaces are the dominant landscape features influencing water quality variability across the sampled villages.

Agricultural land demonstrated a statistically significant positive association with electrical conductivity (EC) and total nitrogen (TN), indicating nutrient enrichment and increased dissolved ion concentrations linked to fertilizer application, soil disturbance, and runoff processes. Bare surfaces showed a significant positive relationship with water temperature and contributed to increased electrical conductivity (EC), reflecting enhanced solar radiation exposure and sediment transport from erosion-prone areas. In contrast, vegetation cover exhibited a significant negative relationship with EC, confirming its buffering capacity in reducing dissolved ions, stabilizing soils, and moderating hydrological and thermal processes.

Parameters such as chloride (Cl) and chemical oxygen demand (COD) showed weak and statistically non-significant relationships with LU/LC variables, suggesting that, under current land use intensity, these indicators remain relatively stable and may be influenced more by localized or natural factors than by broad land cover composition. The study concluded that the sustainability of surface water resources in Southern Yobe is closely tied to land management practices, particularly agricultural expansion, vegetation loss, and soil erosion.

i. Given the significant contribution of agricultural land to EC and TN levels, farmers should adopt controlled fertilizer application, precision farming, integrated nutrient management, and organic soil amendments. Agricultural extension services should strengthen awareness programs on nutrient runoff reduction and best management practices.

ii. The strong relationship between bare surfaces and increased temperature highlights the need for erosion control strategies. Afforestation, reforestation, mulching, contour farming, and community-based soil conservation initiatives should be implemented to minimize sediment yield and regulate surface thermal conditions.

iii. Since vegetation demonstrated a protective effect on water quality, land restoration programs should prioritize riparian buffer establishment, greenbelt development, and community woodlots. Protecting and expanding vegetative cover will enhance pollutant filtration, reduce runoff velocity, and improve overall watershed resilience.

iv. Although built-up areas currently exert limited statistical influence, expanding settlements may increase pollution risks. Local planning authorities should integrate stormwater drainage systems, wastewater treatment measures, and solid waste management frameworks to prevent future contamination.

v. Policymakers at state and local government levels should adopt integrated watershed management approaches that align land use planning with water resource protection. Coordinated strategies linking agriculture, environmental conservation, and rural development are essential for long-term water security in semi-arid environments such as Southern Yobe.

vi. Even though chloride and COD showed weak associations with LU/LC, periodic monitoring is necessary to detect early signs of degradation as land use intensifies. Establishing a routine, community-supported monitoring framework will support evidence-based decision-making and adaptive management.

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