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Relationship between land use and water quality in a tropical urban catchment of the Congo Basin: A case study of N'Djili River catchment

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ABSTRACT

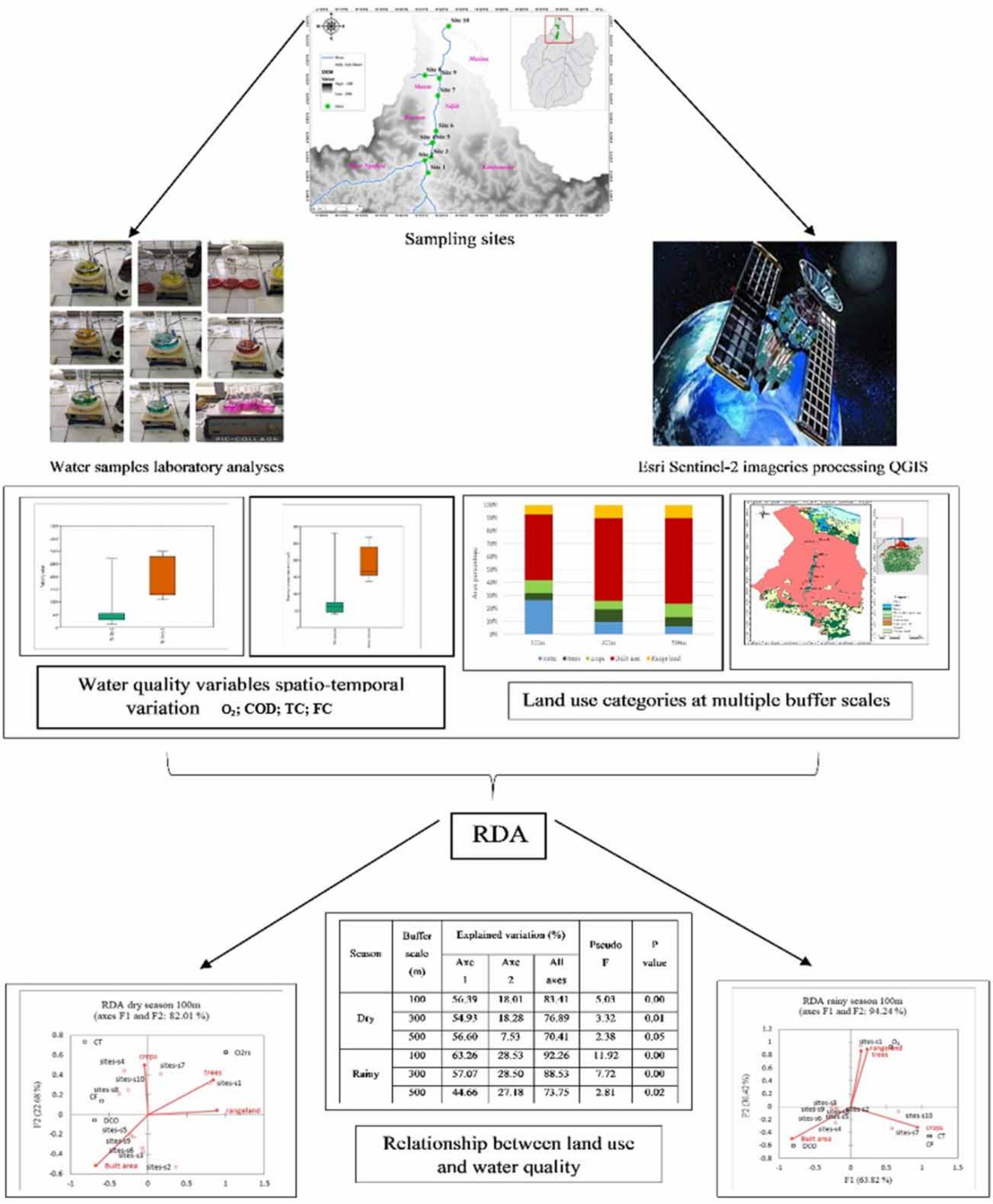
This study focuses on N'Djili River catchment, a vital water source in Kinshasa that undergoes anthropogenic pressure and land use changes. The lower course of the river is particularly affected by uncontrolled urbanization, informal settlements, improper waste management practices, and vegetation degradation. The aim of this study is to determine the relationship between land use and river water quality in this catchment. Water samples were collected for physico-chemical and bacteriological analysis from 10 sampling sites along the river course. Land use categories were determined using Sentinel-2 land cover imageries and buffer scaling techniques. A redundancy analysis (RDA) was conducted to determine the relationship between land use categories and water quality variables. The laboratory analysis revealed physical, chemical, and biological pollution of the river waters. The RDA results showed that 70% of water quality parameters were explained by the studied land use categories. The urbanized area was the most significant explanatory variable at all buffer scales, negatively impacting water quality parameters. Conversely, trees and range lands had a positive impact on water quality. The study concludes that further research is needed to assess the extent of water pollution and develop integrated management strategies for minimizing pollution in this catchment.

Key words: anthropogenic activities, buffer scale, freshwater, N'Djili River catchment, water pollution, water quality

HIGHLIGHTS

- N'Djili River water quality is affected by point and non-point pollution sources.
- Esri-Sentinel-2 10 m resolution land cover imageries were used to generate land use categories.
- Buffer zone approach and redundancy analysis were used to determine the relationship between land use and water quality.
- Land use indicators at multiple scales were related to water quality.

GRAPHICAL ABSTRACT



Season	Buffer scale (m)	Explained variation (%) Axe 1	Axe 2	All axes	Pseudo F	P value
Dry	100	56.39	18.01	83.41	5.03	0.00
	300	54.93	18.28	76.89	3.32	0.01
	500	56.60	7.53	70.41	2.38	0.05
Rainy	100	63.26	28.53	92.26	11.92	0.00
	300	57.07	28.50	88.53	7.72	0.00
	500	44.66	27.18	73.75	2.81	0.02

1. INTRODUCTION

Rivers are abundant ecosystems and vital sources of life and livelihoods, serving multiple purposes to sustain both natural and human systems (Chan 2012). Water quality is a key factor that significantly influences socioeconomic, agricultural, public health, and industrial domains (Shi *et al.* 2017; Zhang *et al.* 2021). Assessing and monitoring water quality is hence very critical in protecting natural ecosystems whose degradation is driven by human activities (Mohammadpour *et al.* 2015; Ding *et al.* 2016; Wang *et al.* 2023).

Water quality assessment and understanding its impacts are important elements in the safeguarding processes of water resources (Mohammadpour *et al.* 2016). The main difficulty in preserving water quality arises from the presence of both point source and non-point source pollution (Fan *et al.* 2012). Point sources include the discharge from sewage treatment facilities, industrial wastewater, and non-point sources include runoff from urban and agricultural areas (Sliva & Dudley 2001). The unequal distribution of regional NPS pollution is exacerbated by intensive human activities and the intricate interplay between rainfall and landscape features, thereby amplifying the challenges associated with identifying these pollutants (Liu *et al.* 2016; Shi *et al.* 2017; Zhang *et al.* 2021). Land use is a major factor contributing to NPS pollution; numerous studies have employed land use types (LUTs) to model and evaluate NPS pollution (Prakash Basnyat *et al.* 2000; Xiao & Ji 2007; Maillard & Nádia 2008; Shen *et al.* 2013; Abdulkareem *et al.* 2018; Wang *et al.* 2021). Land use refers to the way in which land is utilized by humans for various purposes such as residential, commercial, industrial, agricultural, and recreational activities. It plays a significant role in water quality (Tu 2011, 2013).

The influences of LUT on water quality parameters can vary greatly depending on the scale at which they are examined (Shi *et al.* 2017). At a local scale, the type of land use adjacent to a water body can have a significant impact on water quality, whereas at a larger scale, the impacts of land use on water quality can become more complex and interrelated (Ding *et al.* 2016; Zhang *et al.* 2019). The buffer zone approach has often been applied at catchment, riparian, and site scales (Zhang *et al.* 2021; Wang *et al.* 2023).

Due to the multiple sources of water pollution and geographical characteristics combined with highly dynamic aquatic ecosystems in a river basin, the impact of LUTs on water quality parameters may vary from one area to another. In recent years, human activities have significantly degraded water resources ecosystems (Odume 2020; Brontowiyono *et al.* 2022).

The current study focused on the N'Djili River catchment system which is one of the Congo River tributaries (Tshimanga *et al.* 2021). In its lower course, N'Djili River crosses Kinshasa, the capital city of the Democratic Republic of the Congo. It is a very important source of water supply, satisfying almost 60% of the water demand of the city (Kimfuta 2013). However, there is a lot of pressure on the river due to the increasing human and livestock populations, watershed degradation from agricultural practices, informal settlements, and vegetation degradation. Despite the fact that there have been previous studies reporting water pollution in this catchment (Muteba 2002; Kimfuta 2013; Kakundika *et al.* 2022), none of these studies has found a concrete solution face to its water quality degradation. This study is the first in the study area to consider both satellite imagery and field observations to determine the relationship between land use and water quality. Hence, assessing the relationship between land use and water quality parameters becomes critical in trying to understand the impact of human activities on the river's ecosystem. This will further enhance the scientific capacity needed to develop effective strategies for its restoration and conservation.

Thus, the main objective of this study is to determine the relationship between land use and water quality variables in the N'Djili River catchment lower course. The physico-chemical and bacteriological quality of N'Djili river waters were first assessed. The water samples were collected both during the rainy and dry seasons. The study followed a source-to-sink approach, starting from an upstream point (Lemba Imbu – less populated) and moving downstream towards the sink (Masina – most populated).

The land use categories were determined at different sites based on buffer scaling using the Sentinel-2 land use/land cover data product (Karra *et al.* 2021). Furthermore, the study focused on field data collection to find out the different anthropogenic activities taking place in the surrounding areas. Finally, a redundancy analysis (RDA) was performed in view to determine the relationship between land use categories and water quality variables (Zhao *et al.* 2015; Ding *et al.* 2016; Batbayar *et al.* 2019; Zhang *et al.* 2019).

This study is the first step towards the development of the N'Djili River catchment water resource-integrated management approach. By applying the buffer scaling method, the study provides a comprehensive understanding of the relation between land use categories and water quality variables. But some questions need to be asked: what kind of relation can it be, which land use categories influence the water quality the most; and where exactly is the influence situated along the river. The study was able to find out the specific sources of pollution and their extent, thereby allowing for targeted interventions to reduce pollution and improve water quality in this catchment.

2. METHODS

2.1. Study area description

N'Djili River catchment extends from the province of Kongo-Central to the city of Kinshasa over a land area of about 2,000 km^2 between 15°9′ and 15°39′ East longitude and 4°22′ and 4°59′ South latitude (Figure 1). It is a

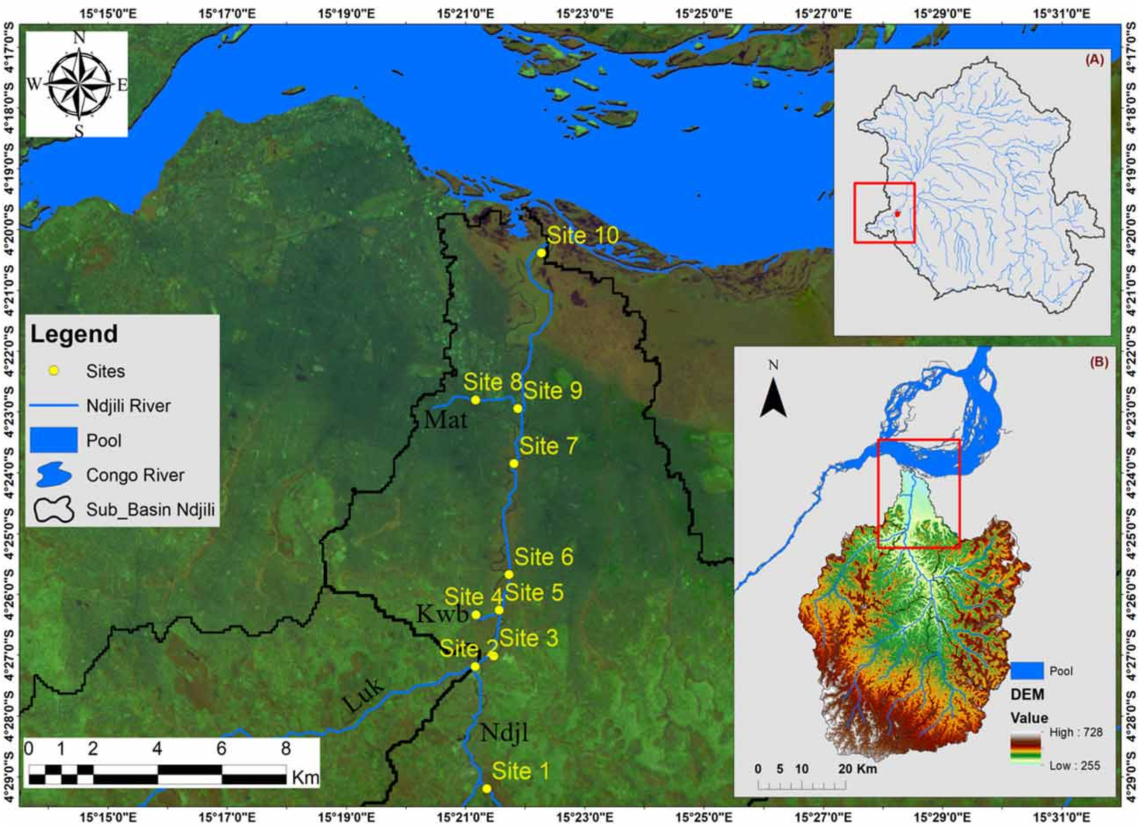


Figure 1 | Map of the study area. (a) The Congo River Basin and the location of N'Djili River catchment and (b) the N'Djili River catchment geographical elevation, and the study area is the lower part of the catchment (Digital Elevation Model (DEM) Yamazaki *et al.* 2017). Ndjl, N'Djili River; Luk, Lukaya; Kwb, Kwambila; Mat, Matete.

complex system comprising two clearly distinct courses, i.e. the upper course (rural part), which includes the territories of Madimba and Kasangulu located in the province of Kongo-Central, and the lower course (urban part) located in the city of Kinshasa and which extends between 15°9′ and 15°18′ East longitude and 4°22′ and 4°37′ South latitude, covering an area of approximately 625 km^2 (nearly 31.2% of the entire catchment area) (Muteba 2002). This urban part of N'Djili River catchment, located in the city of Kinshasa, is under strong anthropogenic pressure; hence, we are interested in it. The catchment is characterized by a hot and humid tropical climate; the rainy season covers 8 months, while the dry season covers 4. More than 90% of the annual precipitation is received during the rainy season. The precipitation annual average is about 1,470 mm (Ndolo *et al.* 2015). With 22 m^3/s flow, N'Djili River is one of the most important tributaries of the Congo River. It is about 30 km long and takes its source in the hills of Kongo-central, flows from south to north through the city of Kinshasa, and empties into the Congo River via the Malebo pool. Figure 1 shows the location of the study area and the different rivers that were selected for sampling, especially N'Djili River and three of its major tributaries (Lukaya, Kwambila, and Matete River). N'Djili River catchment's average maximum and minimum elevations are 428, 728 (southeastern, upper part) and 255 m (basin outlet, lower part), respectively. The slope average maximum and minimum are 16, 148 and 0%, respectively (Ndolo *et al.* 2015).

For the purposes of this study, a perimeter within the lower course of the N'Djili River catchment was delineated. The perimeter starts from the least populated area upstream (Site 1), extending to a highly populated area downstream (Site 10) (Figure 1). The sampling points were identified based on the potential sources of pollution along the river within the defined boundary. Ten study sites were selected. The sites were located using the Garmin brand global positioning system to obtain the geographical coordinates (Figure 1, Table 1, and see Supplementary Materials). The QGIS 3.10 software was used to create a map. Each site was carefully chosen to demonstrate the source-to-sink approach. Criteria such as accessibility, hydrographic distribution, and proximity to potential sources of pollution (e.g. sparsely populated areas, densely populated areas, presence of household waste, sandpits, farming area, and pig breeding) were considered when selecting the sites.

2.2. Water quality sampling and measurement procedures

Four sampling campaigns were carried out throughout the rainy and dry seasons for the assessment of seasonal water quality variability. A total of 80 water samples were collected from 10 sampling sites. The water samples were later taken in PET bottles for physico-chemical analyses and in labelled glass bottles previously sterilized for the collection of bacteriological samples. All samples were taken according to the procedures described in the water analysis manual by Rodier & Coll (2009). Five parameters were measured *in situ*, i.e. pH (using a pH meter HANNA) and temperature (T^0), dissolved oxygen (O_2) with a WTW oximeter, and electrical conductivity (EC) with a conductivity meter HANNA and turbidity using a turbid meter HANNA. Tree physico-chemical (chemical oxygen demand (COD), nitrate (NO_3^-), and phosphate (PO_4^{3-}) and two bacteriological parameters (total coliforms (TCs) and faecal coliforms (FC)) were measured in the laboratory (Table 2 Supplementary Materials).

2.3. Land use data

Land use classification and water resources management have greatly benefited from the use of remote sensing imagery data (Catherine *et al.* 2013; Liu *et al.* 2022). The study area land use data were obtained from global land use/land cover with ESA Sentinel-2 imagery at 10 m resolution. These satellite imageries allow visualization and analysis of land use/land cover data, providing insights into specific areas and their composition (Karra *et al.* 2021). They were downloaded via Esri-Sentinel-2 Land Cover Explorer site and processed using QGIS 3.10 software by following seven technical land cover classification steps: automatic conversion to surface reflectance; clipping the data; defining the band set and creation of the training input file; creation of the Region-of-Interests (ROIs); creation of the classification preview; assessment of the spectral signatures; and creation of the classification output. Eight LUTs were found at the end of this procedure: water, trees, flooded vegetation, crops, urbanized areas, bare ground, clouds, and rangelands (Figure 2). Each land use description is presented in Table 3 Supplementary Materials.

Esri-Sentinel-2 land cover explorer 2022 imageries were used (Karra *et al.* 2021). Eight land use categories were found.

2.3.1. Site multiple buffer scale

The site buffer scale approach was used in this study because of the data gaps in hydrological information on the Congo Basin in general (Tshimanga & Hughes 2014) and water quality historical data in particular. This challenge necessitates the exploration of potential strategies to bridge the information gaps. Many studies linking land use and water quality based on the buffer scaling approach have been done (Sliva & Dudley 2001; Ding *et al.* 2016; Liu *et al.* 2016; Shi *et al.* 2017; Zhang *et al.* 2019, 2021; Wang *et al.* 2023). The advantage of using this approach is that it allows the capture of spatial heterogeneity, accounting for the variability in land use patterns and their impact on water quality across different distances from the site (Wang *et al.* 2014). This approach helps in assessing cumulative effects by evaluating the combined impact of land use practices at different distances and also enhances research accuracy by reducing potential bias caused by using a single buffer scale. Furthermore, it aids in identifying critical zones where land use has a significant influence on water quality and supports decision-making processes for land use management and water quality protection. To assess the correlation between land use categories and water quality parameters, buffers were created at three spatial scales of 100, 300, and 500 m (Figure 3). The area percentage of each land use category was later calculated at the three buffer scales for each sampling site as the land use indicator. QGIS 3.10 and Excel software were used to perform these spatial calculations.

Three buffer scales were fixed around each site, at 100, 300, and 500 m. A total of 100 m was considered as the minimal distance at which river waters are directly impacted by its surrounding environment. We stopped at 500 m because at this distance all site's buffer scales start overlapping.

2.4. Statistical analyses

Water quality was evaluated based on the guide to assessing the status of inland surface waters (François *et al.* 2019). The Shapiro–Wilk data normality test was used to check if water quality parameters were in conformity with statistical normal distribution (Haidary *et al.* 2013). The Kruskal–Wallis test was used to find out if there are seasonal significant differences among the different water quality parameters (Woldeab et al. 2019). The XLSTAT life sciences 2023.2.0 software was used in these calculations (Lumivero 2023). A detrended

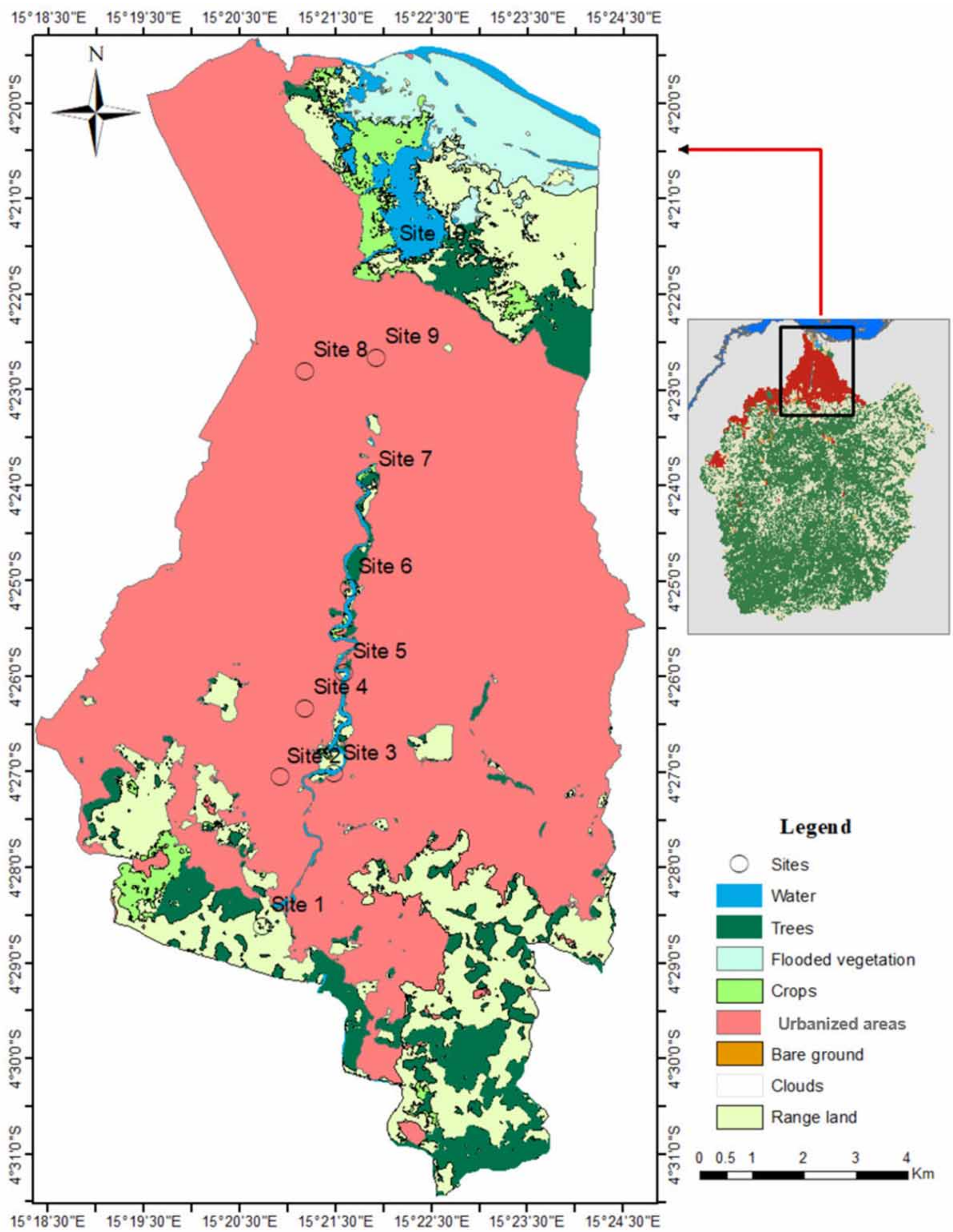


Figure 2 | Map of the study area showing the land use categories spatial distribution.

correspondence analysis was performed to determine the type of model in which both land use indicators and water quality parameters were analysed (Zhao *et al.* 2015; Ding *et al.* 2016; Batbayar *et al.* 2019; Zhang *et al.* 2019, 2021). The RDA was carried out to achieve two objectives: firstly, to create ordination diagrams, known as biplots, to visualize the correlation between land use categories and water quality parameters and secondly, to determine the percentage of variation in water quality parameters that could be explained by several land use indicators. XLSTAT Life Sciences 2023.2.0 software was used to perform the RDA (Lumivero 2023).

3. RESULTS AND DISCUSSION

3.1. Water quality parameters spatio-temporal variation

Statistical analyses were used to compute various descriptive measures such as the mean, median, standard deviation, skewness, kurtosis, and coefficient of variation (Table 1). Shapiro–Wilk and Kruskal–Wallis tests were also

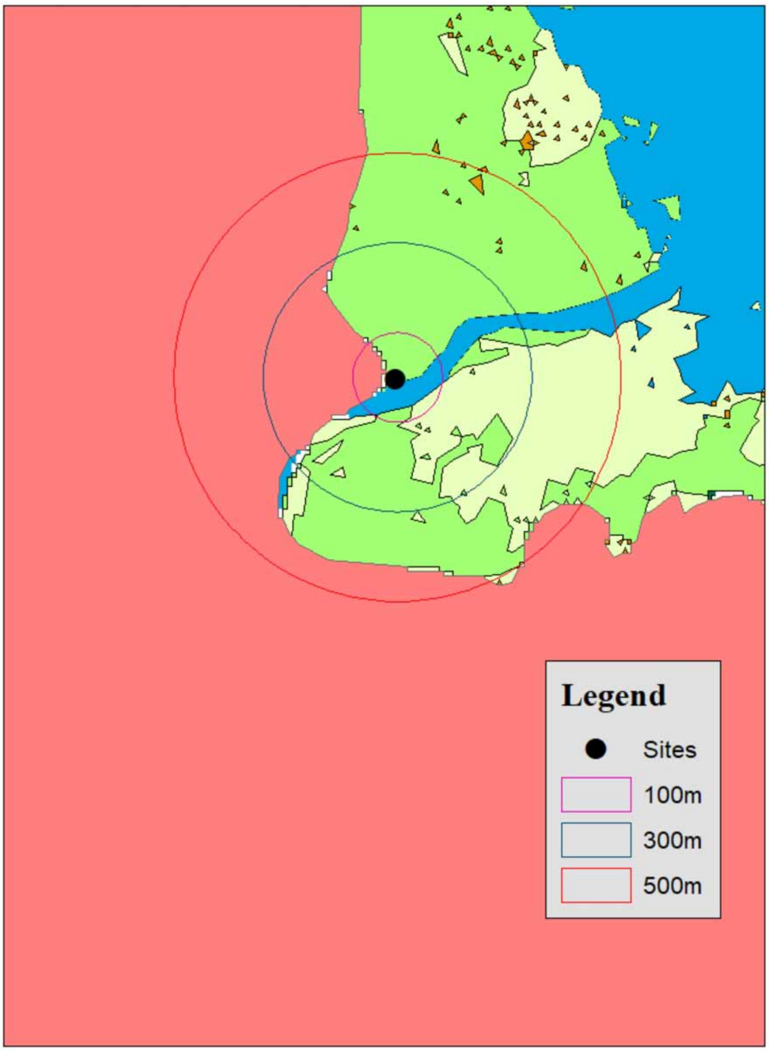


Figure 3 | Illustration of the site buffer scale.

computed. During the dry season, concentrations of dissolved oxygen were higher (0.5 mgO_2/l) compared to the rainy season (0.2 mgO_2/l), while COD, total/FC, temperature, and turbidity showed higher levels in the rainy season with 134.5 mgO_2/l), 93,240 UFC/100 ml, 24,940 UFC/100 ml, 28.42 °C, and 177.19 NTU, respectively, compared to the dry season (Figure 4 and Table 1). A positive skewness was recorded for both dry and rainy seasons except for the pH and COD which recorded negative skewness values, respectively, −0.06 and −0.42. Dry season O_2, EC, T^0, Tb, and PO_4^{3-} kurtosis values were greater than 3, while COD, TC total coliform and FC fecal coliform, pH, and NO_3^- values were lesser than 3 (Table 1). Rainy season O_2, COD, TC, FC, pH, Tb, and PO_4^{3-} kurtosis values were greater than 3, while EC, T^0, and NO_3^- values were lesser than 3 (Table 1). The computed normality test applied to all parameters shows that p values inferior to 0.05 ($p < 0.05$), except for TC and the pH which recorded values greater than 0.05. The Kruskal–Wallis test p values were also inferior to 0.05 with some exceptions for the pH, EC, $NO_{3,}^-$ and PO_4^{3-} (Table 1). The O_2, $NO_{3,}^-$ and PO_4^{3-} levels are lesser than the recommended international value. COD chemical oxygen demand, TC, FC, and Tb levels are greater than the international limit.

Table 1 shows the summary statistics of studied water quality parameters for both dry and rainy seasons, such as dissolved oxygen (O_2), chemical demand of oxygen (COD), TC, FC, pH, conductivity (EC), temperature (T^0), turbidity (Tb), nitrate (NO_3^-), and phosphate (PO_4^{3-}).

It also shows the p values of Shapiro–Wilk test ($p < 0.05$, data are not normally distributed) and Kruskal–Wallis test ($p < 0.05$, there is a significant seasonal difference between dry and rainy season data) for each parameter. Results were also compared to international standards, namely, the guide for assessing the status of inland surface waters (François *et al.* 2019).

Table 1 | Summary statistics for the water quality parameters on seasonal variations

Test / Variables	Summary statistics: Mean		Median		SD		Skewness		Kurtosis		Coeff. Var		Shapiro–Wilk test		Kruskal–Wallis test		Intl. standards
	DS	RS	DS	RS	DS	RS	DS	RS	DS	RS	DS	RS	P_{DS}	P_{RS}	H	P	
O_2 (mgO_2/l)	0.5	0.2	0.3	0.15	0.7	0.21	2	1.18	3.1	0.47	1.31	0.81	**0.006**	**0.008**	11.12	**0.000**	>4
COD (mgO_2/l)	108	134,5	95	140	63.9	56.98	0.12	−0.42	−1.22	−0.45	0.59	0.42	**0.000**	0.087	9.15	**0.002**	≤30
TC (UFC/100 ml)	1,771	93,240	1,700	38,250	1,033.5	1,248.2	0.2	1.47	−1.6	0.72	0.58	1.33	0.168	**0.000**	14.29	**0.000**	–
FC (UFC/100 ml)	381.2	24,940	118.5	4,900	483.1	3,828.9	1.4	1.58	0.5	0.91	1.26	1.53	**0.00**	**0.00**	10.08	**0.00**	<101
pH	7.2	7.17	7.2	7.08	0.2	0.23	−0.06	0.55	−1.61	−1.29	0.04	0.03	0.44	0.15	1.12	0.28	pH > 6.5 pH < 9.5
EC (μs/cm)	28.9	27.79	19.9	21.4	25.05	19.84	2.05	2.47	4.09	6.73	0.86	0.71	**0.00**	**0.00**	0.28	0.59	–
T^0 (^{0}C)	26.3	28.42	26	27.7	1.4	2.14	1.7	1.99	3.9	4.79	0.05	0.07	**0.02**	**0.00**	6.82	**0.00**	25
Tb (NTU)	61.3	177.19	35.5	134.1	76	77.49	2.8	1	8.2	−1.13	1.24	0.43	**0.00**	**0.00**	10.57	**0.00**	<5
NO_3^- (mg NO_3^-/l)	2.38	2.95	0	0.15	4.9	5.46	1.8	2.55	1.9	7.02	2.07	1.85	**0.00**	**0.00**	0.28	0.59	<50
PO_4^{3-} (mg PO_4^{3-}/l)	0.3	0.15	0.1	0.06	0.5	0.21	3.09	1.62	9.7	1.48	1.77	1.35	**0.00**	**0.00**	1.46	0.22	<0.5

Bold values in table 1 are Shapiro-Wilk and Kruskal-Wallis test *P* values that are inferior to 0.05. Bold values = P<0.05.

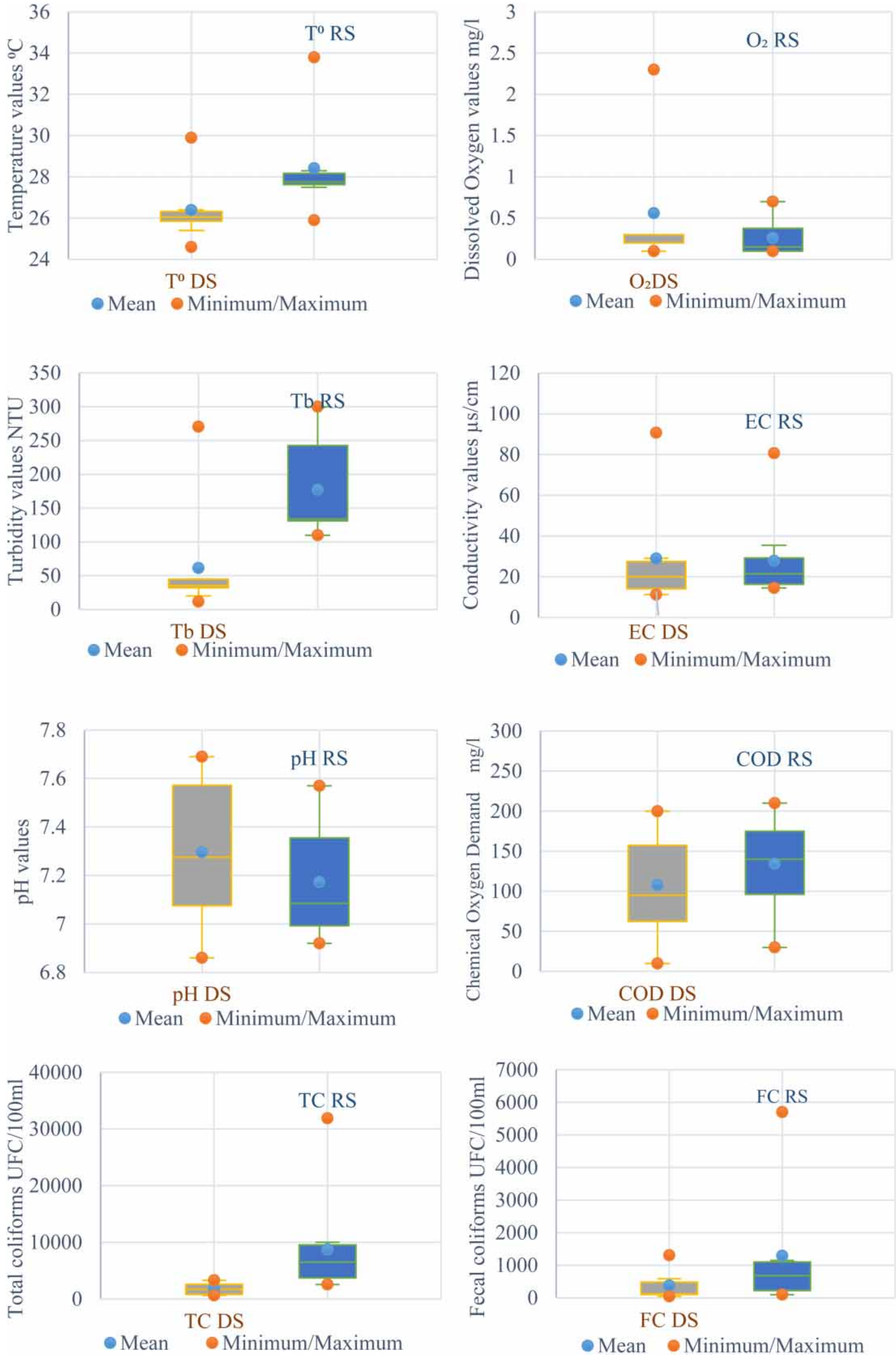


Figure 4 | Comparison between dry season (DS) and rainy season (RS) data: seasonal boxplots for water quality parameters of the N'Djili River.

Dry and rainy season data from the 10 sampling sites were used to make the boxplots. Each boxplot represents the mean, minimum, and maximum values of measured parameters during dry and rainy seasons.

3.2. Land use categories distribution

Urbanized areas are the major LUTs at all buffer scales from 51.06% (at 100 m buffer scale) to 69.75% (at 500 m buffer scale), followed by water at 26.54% (100 m buffer scale), rangelands at 10.24%, trees at 9.64% (300 m buffer scale), and crops at 10.67% (500 m buffer scale) (Figure 5 and Table 2).

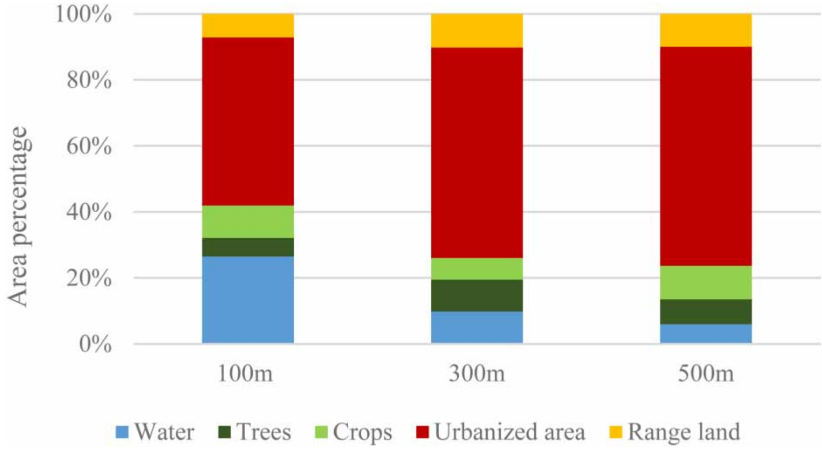


Figure 5 | Land use categories at each buffer scale.

Table 2 | Land use categories in the whole study area and buffer scales

		Mean ± SD		
Land use (%)	**Whole study area**	**100 m buffer**	**300 m buffer**	**500 m buffer**
Water	2.44	26.54 ± 16.97	9.80 ± 6.27	6.26 ± 4.47
Trees	7.41	5.66 ± 11.66	9.64 ± 20.38	7.90 ± 17.86
Flooded vegetation	4.29	–	0.00 ± 0.01	0.06 ± 0.20
Crops	2.55	9.85 ± 19.59	6.51 ± 15.47	10.67 ± 17.36
Urbanized area	67.01	51.06 ± 33.89	63.60 ± 32.88	69.75 ± 30.22
Bare ground	0.07	0.07 ± 0.14	0.02 ± 0.03	0.06 ± 0.08
Clouds	0.00	0.19 ± 0.56	0.09 ± 0.20	0.04 ± 0.09
Rangeland	16.21	7.18 ± 11.20	10.24 ± 11.47	10.50 ± 11.67

Percentage of land use categories inside the three fixed buffer scales. QGIS 3.10 and Excel software were used to perform these spatial calculations. Built area is the major land use category at each scale. Table 2 shows the percentages of land use indicators at the whole study area scale but also at each buffer scale. For each buffer scale, the mean and standard deviation values were given using the 10 sampling sites' percentages values of land use indicators.

Urbanized areas accounted for 67.01%, rangelands 16.21%, trees 7.41%, crops 2.55%, and water 2.44%, and the total was about 95%. Considering the whole study area's spatial scale, some other smaller land uses occupied the remaining proportion (5%). These remaining land uses were excluded from our statistical analyses. As the spatial scale increased, built-up areas and range land proportions increased too, while the proportion of water as land use decreased. The crop land proportion decreased and then increased, while trees area increased and later decreased.

Site 1 has very little urbanized area land and is mostly covered by trees and rangelands. It is the control site for this study. The percentage of trees and rangeland is highest at this site. As the spatial scale increased, urbanized areas and range land proportions increased too, while the proportion of water as a land use decreased. The crop land proportion decreased and then increased, while trees area increased and later decreased (Figure 6).

Percentages of land use indicators over the sampling sites per scale. QGIS 3.10 and Excel software were used to perform these spatial calculations. The proportion of urbanized area land increases from site 2 and decreases at site 10. Sites 8 and 9 are completely covered by urbanized area land. Crops land is present at sites 7 and 10 at 100 m buffer scale, with 46.98 and 41.66% coverage, respectively. Crops land also extends to site 6 at 300 m buffer scale and to site 3 at 500 m buffer scale (Figure 6).

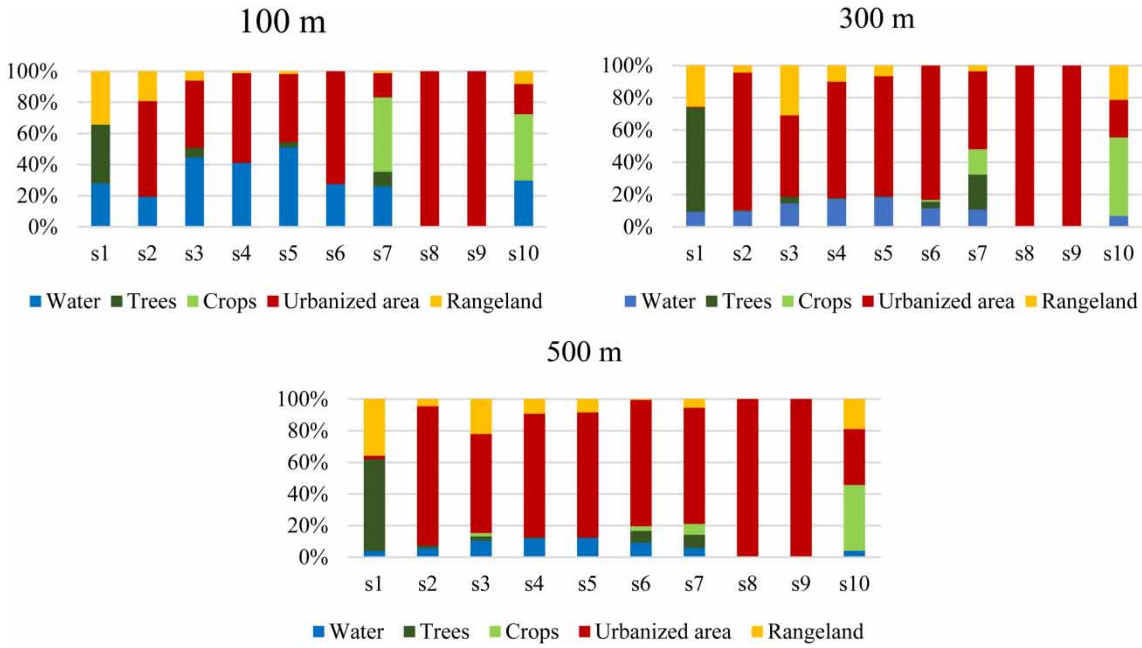


Figure 6 | Land use categories per site at each buffer scale.

3.3. Relationship between land use and water quality (RDA)

RDA was used to analyse the relationship between land use categories and water quality parameters. Table 3 shows the results of the RDA test. Details of the constrained inertia carried by each RDA axis are provided in the table as their cumulative value percentage. It also shows the pseudo *F* and *p* values of the permutation test. The permutation test is a statistical method used to determine if there is a linear relationship between the response and explanatory variables. In this case, the *p*-value obtained from the test is significantly smaller than the predetermined risk threshold alpha 0.05. Therefore, we can confidently reject the null hypothesis, while still maintaining a very low risk of making an incorrect decision. Overall, 80% of the four water quality parameters for dry and rainy seasons were explained by the four land use indicators under investigation. The RDA analysis shows that land use indicators' impact on water quality parameters has significant seasonal variation. The water quality parameters show that the variation recorded in all the axes during the rainy season is much higher (about 10%) than the percentage recorded during the dry season. The explained variation decreases in both the dry and rainy seasons (Table 3).

Table 3 | RDA results, percentages of water quality parameters explained by land use categories

		Explained variation (%)				
Season	**Buffer scale (m)**	**Axis 1**	**Axis 2**	**All axes**	**Pseudo *F***	***p*-Value**
Dry	100	56.39	18.01	83.41	5.03	0.00
	300	54.93	18.28	76.89	3.32	0.01
	500	56.60	7.53	70.41	2.38	0.05
Rainy	100	63.26	28.53	92.26	11.92	0.00
	300	57.07	28.50	88.53	7.72	0.00
	500	44.66	27.18	73.75	2.81	0.02

The first explanatory land use variable at all buffer scales is the urbanized area (51.06–69.75%). The second explanatory variable is water (26.54%) at a 100 m buffer scale, then rangeland (10.24%) at a 300 m buffer, and finally, crops (10.67%) at a 500 m buffer (Table 4 Supplementary materials). Dry and rainy season water quality parameters values and land use category percentages for each of the 10 sampling sites were used to make the RDA seasonal boxplots (Figure 7). Land use indicators were used as independent variables and water quality parameters as dependent variables.

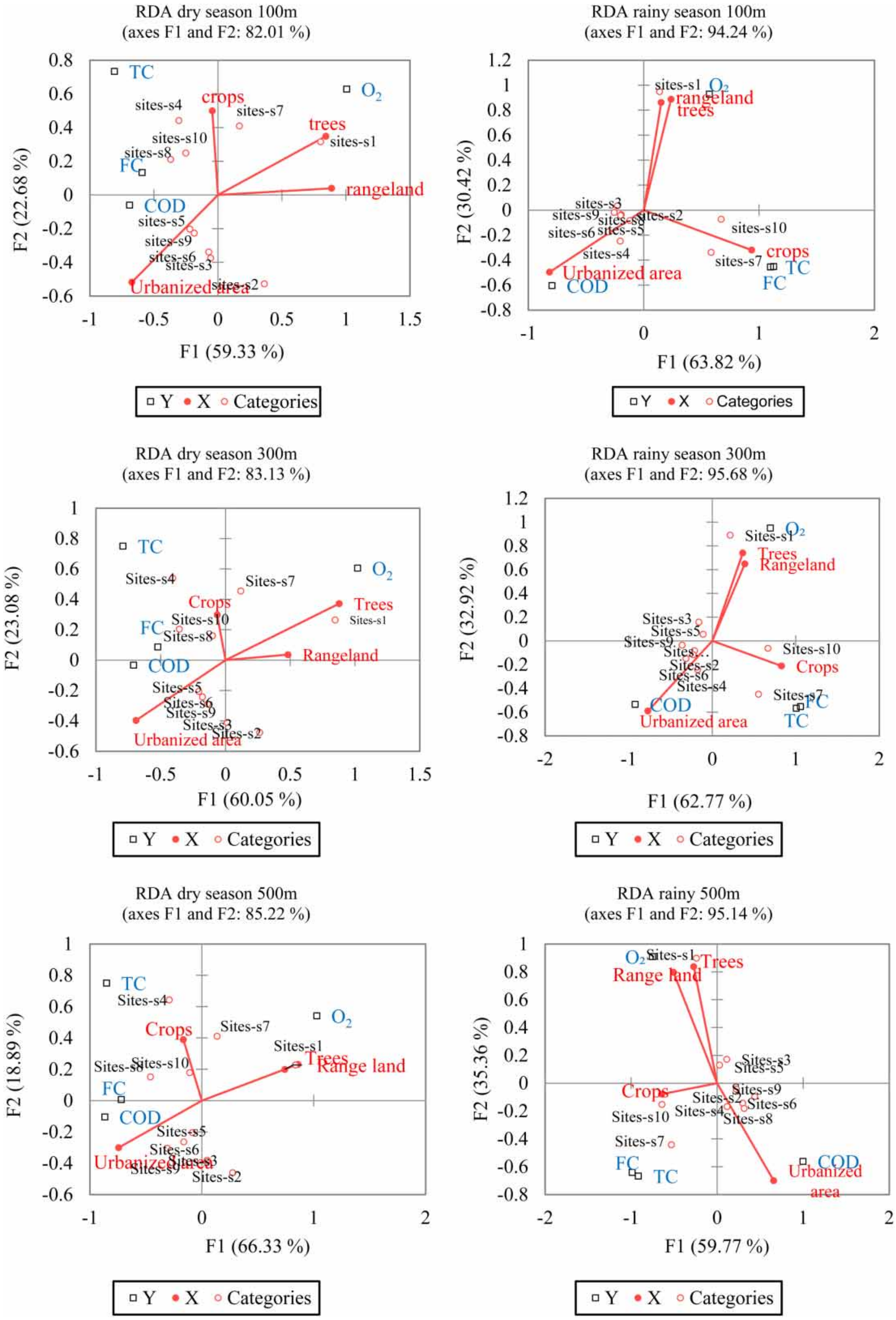


Figure 7 | RDA results seasonal boxplots at multiple buffer scales.

During the drying season, the first axis F1 showed a pollution concentration gradient (COD, FC, and TC decrease along the axis) and that it is positively correlated with urbanized area land use category and negatively correlated with trees and rangeland categories (Figure 7). At all buffer scales, dissolved oxygen (O_2) and urbanized area are negatively correlated, while O_2 is positively correlated with trees and rangeland use types. Site 1 is positively correlated with O_2, trees, and rangeland use, while sites 3, 5, 6, and 9 are positively correlated with urbanized area, COD, FC, and TC. Sites 4, 8, and 10 are strongly correlated with crop land, TC, and FC (Figure 7).

During the rainy season, O_2, trees, and rangeland are well represented on axis F2. On axis F1, crops are positively correlated with FC and TC, while negatively correlated with urbanized areas and COD, which are also positively correlated. At all buffer scales, dissolved oxygen (O_2) and urbanized areas are negatively correlated, while O_2 is positively correlated with trees and rangeland use types (Figure 7). Site 1 is positively correlated with O_2, trees, and rangeland use, while sites 7 and 10 are positively correlated with crops land FC and TC. Sites 2, 3, 4, 5, 6, and 9 are positively correlated with urbanized areas and COD. The correlation between land use indicators and water quality variables is greater during the rainy season than in the dry season (Figure 7).

Four land use indicators were used, namely, urbanized area, crops, trees, and rangeland. Four water quality parameters were used, namely, dissolved oxygen (O_2), chemical demand for oxygen (COD), TC, and FC (TF). XLSTAT Life Sciences 2023.2.0 software was used to perform the RDA (Lumivero 2023).

3.4. Discussion

The mean represents the average value, while the median identifies the middle value in an ordered sequence or positional average. Skewness indicates the symmetry of the data distribution, while kurtosis measures the degree of flatness around the mode of a frequency curve. The coefficient of variation provides a relative measure of variability within the sample (Parmar & Bhardwaj 2014). In addition, the Shapiro–Wilk and Kruskal–Wallis tests are utilized for assessing normality and seasonal differences, respectively (Table 1). During the dry season, higher dissolved oxygen levels may be attributed to reduced organic matter decomposition and increased oxygen solubility due to lower temperatures (Rajendiran *et al.* 2023). Conversely, the elevated COD levels (134.5 mgO_2/l) in the rainy season could be linked to intensified runoff carrying pollutants (Maulud *et al.* 2021), while the increased microbial load (TC and FC) may result from enhanced faecal inputs and nutrient transport during precipitation events (Zhang *et al.* 2020). The higher temperatures in the rainy season can accelerate biochemical reactions and microbial activity, influencing pollutant concentrations according to (Englert *et al.* 2015). Furthermore, heightened turbidity (177.19 NTU) during the rainy season may be associated with increased sedimentation and suspended solids carried by runoff (Nukapothula *et al.* 2022; Singh *et al.* 2024). The observed deviations from a normal distribution and significant differences (Table 1) indicated by the Kruskal–Wallis test across various environmental parameters, including dissolved oxygen (O_2), COD, TC, FC, temperature (T^0), and turbidity (Tb), suggest a notable seasonal variation in water quality. Both dry and rainy seasons exhibit positive skewness for most parameters, indicating that the distribution of these parameters is skewed towards higher values (skewed to the right). However, pH and COD show negative skewness values, which suggest that their distributions are skewed towards lower values (skewed to the left). Kurtosis values greater than 3 indicate leptokurtic distributions, which means the distribution has heavy tails and is more peaked than a normal distribution. For the dry season, O_2, EC, T^0, Tb, and PO_4^{3-} exhibit leptokurtic distributions, indicating that they have heavier tails and are more peaked than a normal distribution. On the other hand, COD, TC, FC, pH, and NO_3^- have kurtosis values less than 3, suggesting they have lighter tails and are less peaked than a normal distribution (platykurtic curve).

The RDA results have shown that trees and rangeland had a positive impact on water quality parameters, and urbanized areas had a negative impact on them (Figure 7 and Tables 3 and 4 Supplementary Material). Urbanized areas have a positive impact on COD, FC, and TC. These results are similar to many of the previous studies. Dou *et al.* 2022 have recently worked on the spatial scale effects of landscape structure on water quality in the Yellow River. They found that the deterioration of river water quality is directly correlated with the expansion of urban areas and agricultural lands. Numerous studies have been conducted on the impact of land use change resulting from anthropogenic and socioeconomic activities on river water quality. All of these studies demonstrate that landscape categories associated with urban development and agricultural lands have a significant impact on changes in water quality. Furthermore, these studies confirm the negative influence of anthropogenic activities and land use change on river water quality (Wang *et al.* 2014; Schreiber *et al.* 2015; Xiao *et al.* 2016; Camara *et al.* 2019; Yadav *et al.* 2019; Tahiru *et al.* 2020; Brontowiyono *et al.* 2022; Chen *et al.* 2022).

This study is the first in N'Djili River catchment to consider both satellite imagery and field observations to determine the relationship between land use and water quality. As most sites were positively correlated to the urbanized area, site 1 as the control site was negatively correlated to this area (Figure 7). Most of these sites were densely populated and recorded high COD, FC, and TC levels. In 2022, Chen *et al.* evaluated the impact of urbanization on the water quality of four typical urban rivers in Tanzania and found that there is a strong correlation between large cities and the high pollution level of water bodies, suggesting that as the population rapidly increases, the pollution levels also tend to rise. Urbanized areas are the major source of water pollution in the N'Djili River catchment. Sewage, waste, and garbage are dumped into the river in their raw state without prior treatment (Joseph *et al.* 2023).

Vegetation plays a crucial role in reducing water pollution (Mohammadpour *et al.* 2014), and areas with trees or rangeland cover tend to have better water quality due to reduced runoff and soil erosion (Xiao *et al.* 2016). Site 1 was positively correlated to trees and rangeland, and this site recorded a low level of pollutants. Crop lands are positively correlated with FC and TC. Sites 7 and 10 are positively correlated with crop lands. While conducting the field survey at these sites, it was observed that activities such as pig farming, substantial agricultural operations utilizing chemical fertilizers, as well as the use of poultry and cattle droppings as manure were taking place. The contamination of rivers with microbes is significantly influenced by the runoff from the catchment area. The most significant levels of microbial contamination were found in downstream sites (most populated) and areas where intensive agricultural practices were being carried. These results are similar to those of Schreiber *et al.* (2015), who have worked on the impact of land use on microbial surface water pollution.

The RDA results show that water quality parameters are better explained during the rainy season than during the dry season (Table 3). Indeed, large and small businesses, gas stations, garages, slaughter houses, and storm water runoff create additional pollution risks, and these results are similar to those of Xiao *et al.* 2016 who have made a multi-scale analysis of the relationship between landscape patterns and urban river water quality in different seasons and found that some water quality parameters such as COD are influenced by seasonality. From site 1 (source) towards site 10 (Sink), urbanized areas increasingly negatively impact water quality (Figures 6 and 7).

The rapid growth of Kinshasa city has led to more paved surfaces, which are impermeable and hence prevent rainwater from infiltrating into the ground; this leads to an increase in the runoff amount. This runoff carries pollutants along the way from buildings such as sewage and waste into the river, resulting in more pollutants, bacteria, heavy metals, and other contaminant levels in the N'Djili river waters, posing risks to aquatic life and human health (Kakundika *et al.* 2022).

The scale plays a crucial role in understanding the relationship between land use indicators and water quality. As the scale increases, the impact of various land use categories on water quality decreases (see Table 3, the percentage of explained variation in all axes decreases from 100 to 500 m scale for both seasons). Specifically, the influence of land use indicators on water quality is more pronounced at a 100 m scale compared to a 500 m scale. This suggests that the immediate surrounding environment has a more direct impact on river waters. In light of this, when developing strategies for water quality management in this region, it may not be necessary to consider a larger spatial scale, as the finer scale assessments appear to be more relevant and informative.

At all scales, urbanized areas were more closely related to water quality because the study area is situated in a highly urbanized area. At the higher scale of 500 m buffer, after urbanized areas, crop land had relatively negative effects on water quality; this is due to the fact that at this scale, crop land extended from sites 7 and 10 to other sites, including sites 6 and 3 (Figure 6).

This study demonstrates innovation by strategically employing the site buffer scale approach to overcome substantial data gaps in hydrological information across the Congo Basin, particularly in the context of limited historical water quality data. The method effectively captures spatial heterogeneity, considering variations in land use patterns and their impact on water quality at multiple distances from the site. By creating buffers at various spatial scales, the research enhances accuracy and provides a nuanced understanding of the correlation between land use categories and water quality parameters. This approach not only addresses data gaps but also aids in identifying critical zones influencing water quality, supporting informed decision-making for land use management and water quality protection.

The present study is the first work to provide a relationship between land use and water quality, using high spatial resolution (10 m) and a buffer zone approach in a River catchment of the Congo Basin. This study is fundamental for the establishment of integrated water resources management strategies in the study area. However, a limitation arises as the study does not fully consider the temporal fluctuations introduced by rainfall patterns, overlooking potential influences on runoff, sediment transport, pollutant wash-off, and some externals events (Wang *et al.* 2013; Luo *et al.* 2020; Zhang *et al.* 2020, 2022; Sent *et al.* 2021). Hydrological uncertainty also, driven by factors like precipitation variations, land use shifts, and climate fluctuations, significantly impacts the length and variability of water quality samples, posing challenges in environmental monitoring. This uncertainty leads to unpredictable changes in water flow patterns and contaminant transport, complicating sample collection due to erratic temporal and spatial pollutant distributions. As elucidated by Dimitriadis *et al.* (2021), this behaviour underscores the need for extensive and high-resolution sampling to accurately quantify variability on daily, seasonal, and annual scales. According to them, longer sampling durations may be needed to encompass diverse hydrological conditions, resulting in increased variability in water quality parameters. Consequently, accurately characterizing water quality becomes inherently challenging, demanding adaptable monitoring strategies to address the impacts of hydrological uncertainty and maintain the reliability of environmental assessments. Future research should incorporate temporal rainfall patterns perspective and streamflow to comprehensively assess the impact of extreme weather events on water quality dynamics in river catchments. Also, as the redundancy analyses are based on linear correlations, which creates some difficulties in small or medium data lengths, such as statistical bias and standardization error, it is recommended for future studies to look at the so-called cross-climacogram (Koutsoyiannis 2019), which is a tool proven to have smaller bias and error compared to the linear-(auto) correlation (Dimitriadis & Koutsoyiannis 2015).

4. CONCLUSION

This study was about the spatio-temporal impacts of land use categories on river water quality parameters in an urban catchment. The study found that water quality parameters were affected by land use to a certain degree. In particular, the high influence of urbanized areas was significant. In fact, multiple factors affected water quality and these included seasonality, scaling, and land use indicators. Land use categories' effects on water quality parameters were more significant during the rainy season than the dry season. The total variation explained by land use indicators on water quality parameters was higher at the 100 m buffer scale than at the 500 m scale. The study indicated that urbanized areas had negative effects on water quality parameters, while trees and rangelands had a positive impact. Scale plays a crucial role in understanding the relationship between land use indicators and water quality. As the scale increases, the impact of various land use categories on water quality decreases (see Table 3, the percentage of explained variation in all axes decreases from 100 to 500 m scale for both seasons). Specifically, the influence of land use indicators on water quality is more pronounced at a 100 m scale compared to a 500 m scale. This suggests that the immediate surrounding environment has a more direct impact on river waters. In light of this, when developing strategies for water quality management in this region, it may not be necessary to consider a larger spatial scale, as the finer scale assessments appear to be more relevant and informative. These results provide key insights into the multiple-scale impact of major land use categories on the N'Djili River catchment's lower course water quality, thus allowing for targeted interventions to reduce pollution and improve water quality in this part of the Congo River basin. It takes into consideration the effective impact of land use on water quality, thereby providing a valuable and concrete reference for the development of an integrated management strategies plan for this river's water resources. A systematic analysis of the sources and nature of pollution and their interactions with N'Djili River waters should be conducted to determine the extent of its water pollution so as to develop a water resources integrated management strategy for minimizing pollution in this area.

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AUTHOR CONTRIBUTIONS

Zouera Sani: writing – original draft, methodology, analysis; Pr. Haddy Mbuyi, Pr. Raphael Tshimanga, Pr. Twaha Basamba, and Pr. Nelson Odume: Supervision – writing – review and editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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