

Seasonal Spatial Variability of Groundwater and Surface Water Quality Using WQI and Cross-Validated Kriging in Lamurde, Jalingo, Nigeria

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Abstract

Seasonal spatial variability of groundwater and River Lamurde was assessed using laboratory measurements, weighted arithmetic water quality index (WQI) and cross-validated kriging. Thirty groundwater and thirty surface water locations were monitored in wet and dry seasons. Eight common physicochemical parameters formed WQI; nitrate, total chromium and *Escherichia coli* were retained as independent warnings. Mean groundwater WQI was 69.79 dry and 45.00 wet, while surface water WQI was 50.67 and 360.39. Wet season nitrate exceeded 50 mg/L at 30/30 groundwater and 21/30 surface water locations; chromium exceeded 0.05 mg/L at 1/30 and 28/30, while *E. coli* occurred throughout both networks. LOOCV selected Gaussian kriging for dry groundwater and spherical kriging for wet groundwater and surface water seasons. R^2 values were 0.876/0.115 and 0.980/0.882, demonstrating seasonal differences in spatial prediction reliability.

Keywords: Groundwater; River Lamurde; weighted arithmetic WQI; seasonal variability; ordinary kriging; LOOCV

1. Introduction

Drinking water quality is a major concern for human health and wellbeing. Contaminants in water can affect human health to varying degrees, including death. The deterioration in drinking water quality results from the entry of chemicals into freshwater bodies and the water supply system through natural and anthropogenic activities [13]. The natural contamination of water is governed by the presence and concentration of various chemical constituents, which are mostly derived from the geological formation of the particular region, while anthropogenic contamination mainly occurs through the use of pesticides and herbicides in agriculture, leaching of poisonous toxins, septic tank waste disposal, coal mining and petroleum refining, etc.

Physiochemical and microbiological parameters are important determinants for assessing industrial, irrigation, and domestic water quality. Therefore, water quality management in rapidly growing urban and peri-urban settings requires information on both the chemical condition of available sources and how that condition changes in space and time. Groundwater and surface water respond differently to recharge, runoff, mineral reactions, drainage inputs and local land use pressures, making seasonal assessment particularly important in Lamurde because households depend on multiple water sources. Drinking water interpretation must also distinguish between composite water quality condition and individual parameters that can independently restrict untreated use [21], [19].

Water Quality Index methods condense multivariable physicochemical data into a common scale for comparison across locations and seasons. The weighted arithmetic approach is useful where concentrations are interpreted against adopted standards and the contribution of each parameter is explicit. A composite index, however, is not a complete statement of drinking water safety because aggregation can mask an important exceedance and low numerical standards can give individual parameters disproportionate influence.[8] identified parameter selection and weighting as recurring weaknesses in adapted WQI applications. [21] likewise showed that WQI classification can be sensitive to model structure and uncertainty.

Water quality indices provide a practical means of reducing multiple physicochemical measurements to an interpretable numerical scale. The weighted arithmetic water quality index (WAWQI) is widely used because it is transparent, standards-referenced and suitable for comparing water quality conditions across locations [5]. However, composite

indices are mathematically compensatory: highly favourable values for some parameters can offset unfavourable values for others. Recent work has therefore emphasised the need to report index uncertainty and parameter-specific evidence alongside the aggregate score [8]. Masood et al. [2] demonstrated the usefulness of combining WQI with GIS and geostatistical techniques for groundwater assessment, while Khan et al. [9] showed that ordinary and universal kriging can support spatial interpretation of WQI when model performance is evaluated.

Within Jalingo and neighbouring parts of Taraba State, previous studies have examined treated public water, groundwater seasonal quality, faecal contamination of shallow wells and pollution in River Lamurde as largely separate problems [4]–[5]. These studies establish that water quality concerns occur in the area, but they do not provide a paired seasonal comparison of groundwater and River Lamurde under a common WQI structure combined with explicit validation of the interpolation models. This is important because an apparently smooth water quality map may still have weak predictive support at omitted monitoring locations.

This paper therefore evaluates the seasonal spatial variability of groundwater and surface water quality in Lamurde, Jalingo. The specific aims were to: (i) characterise wet and dry season water quality conditions; (ii) compare groundwater and surface water WQI under a common eight parameter framework; (iii) retain nitrate, total chromium and E. coli as independent untreated-use warnings; and (iv) map seasonal WQI using interpolation models selected and evaluated by leave-one-out cross-validation (LOOCV).

2. Materials and Methods

2.1 Study Area

Lamurde Area is located within Jalingo, Taraba State, north eastern Nigeria, approximately between latitudes 8°53'–8°54' N and longitudes 11°20'–11°22' E. The mapped study boundary covers about 3.885 km² and contains residential development, shallow groundwater sources, drainage corridors and River Lamurde. The area experiences a tropical continental climate with a wet season generally extending from April to October and a dry season from November to March. Mean annual rainfall of about 958 mm and a mean annual temperature of approximately 27.9 °C have been reported for Jalingo [4].

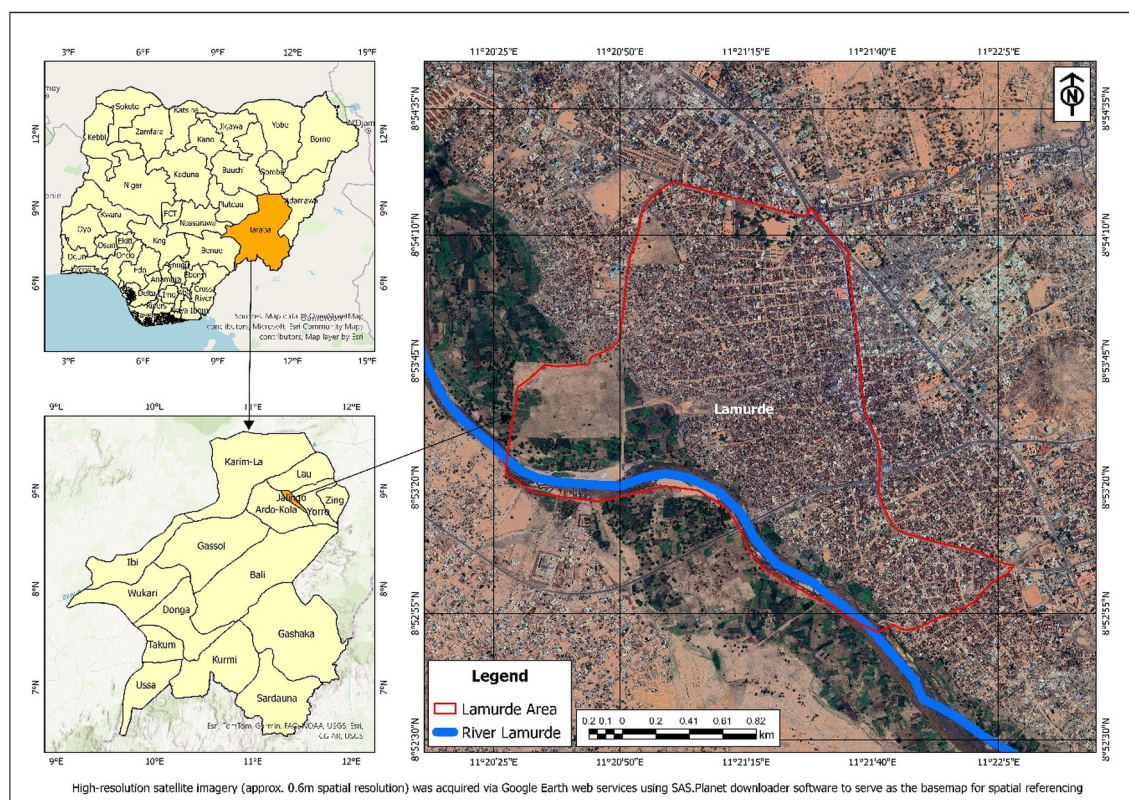


Fig. 1 Location and mapped extent of Lamurde Area within Jalingo, Taraba State, Nigeria.

2.2 Sampling Design and Laboratory Analysis

A reconnaissance network of 122 georeferenced water source locations was screened for identity, coordinate consistency, analytical completeness and spatial coverage. The final analytical network comprised 30 groundwater sources denoted (G1–G30; which comprised 24 hand-dug wells and six boreholes) and 30 fixed River Lamurde monitoring locations denoted (S1–S30). The same locations were retained in both seasons. Wet season sampling was

conducted in July, August and September 2025, while dry season sampling was conducted in November and December 2025 and January 2026. Three monthly observations contributed to each seasonal location value. The location, was the inferential unit, giving 30 paired seasonal groundwater values and 30 paired seasonal surface water values. The sampling design followed the monitoring objective principles of ISO 5667-1:2023 [6].

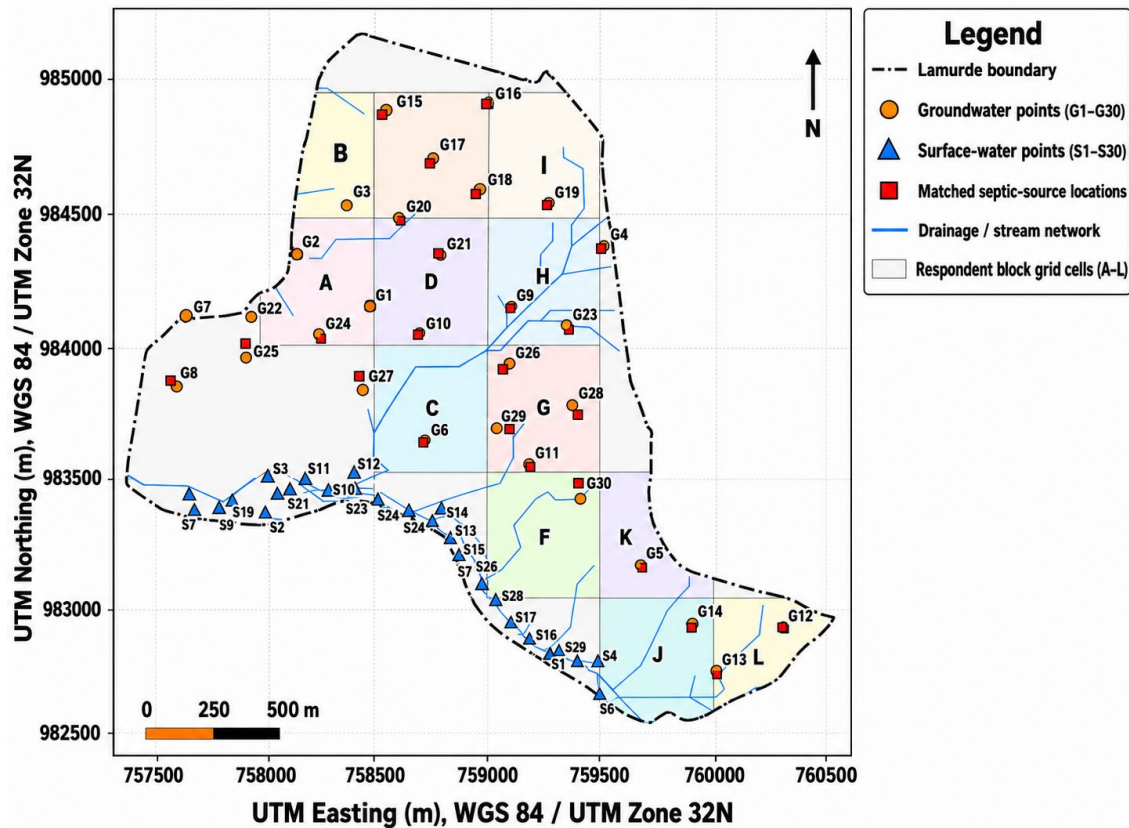


Fig. 2 Final groundwater (G1-G30) and River Lamurde (S1-S30) monitoring network.

Samples were collected in pre-cleaned containers, labelled by source and sampling period, cooled at approximately 4 °C and transported for analysis. Laboratory procedures followed Standard Methods [3]. Groundwater measurements retained pH, turbidity, total dissolved solids (TDS), electrical conductivity (EC), nitrate, iron, zinc, total chromium, dissolved oxygen (DO), biochemical oxygen demand (BOD₅) and E. coli. Surface water assessment used the same set except DO. The common WQI core comprised pH, turbidity, TDS, EC, nitrate, iron, zinc and total chromium. Nitrate and total chromium were compared with 50 mg/L and 0.05 mg/L, respectively, while E. coli was interpreted against non-detection in 100 mL [21], [19].

2.3 Weighted Arithmetic Water Quality Index

The Weighted Arithmetic Water Quality Index (WAWQI) method was adopted to integrate multiple physicochemical parameters into a single dimensionless index that represents relative composite physicochemical condition in groundwater and surface water. The method was originally developed by [12] and has been widely used in hydrochemical investigations for its simplicity and suitability for water quality classification.

The WAWQI approach was selected because it provides a transparent standards-referenced weighting structure for comparing the common eight parameter physicochemical core across sources and seasons. The computation comprised four stages: (a) quality rating determination; (b) unit weight assignment; (c) sub-index computation; and (d) overall index aggregation.

(a) Quality rating determination

The quality rating for each parameter was computed using Equation 1:

$$q_n = \frac{(V_n - V_0)}{(S_n - V_0)} \times 100$$

Where:

qn = quality rating of the nth parameter

Vn = measured concentration of the nth parameter

Sn = permissible standard value of the parameter

V_o = ideal value of the parameter in pure water

The ideal value (V_o) was set to 0 for all parameters except pH, for which $V_o = 7.0$. Dissolved oxygen was not included in the final GWQI/SWQI computation.

(b) Unit weight assignment

The unit weight assigned to each parameter was determined using Equation 2:

$$W_n = \frac{K}{S_n} \quad 2$$

Where:

W_n = unit weight of the nth parameter

S_n = standard permissible limit

K = proportionality constant = 0.041654 for the eight selected parameters

The proportionality constant was calculated using Equation 3:

$$K = \frac{1}{\sum \left(\frac{1}{S_n} \right)} \quad 3$$

Parameters with lower adopted standards received larger reciprocal weights as a mathematical consequence of $W_n = K/S_n$; these weights were not interpreted as direct measures of toxicological importance.

(c) Sub-index computation

The subindex for each parameter was computed using Equation 4:

$$SI_n = W_n \times q_n \quad 4$$

Where:

SI_n = subindex of parameter n;

W_n = unit weight; and

q_n = quality rating.

(d) Overall index aggregation. The same equations were used to generate GWQI and SWQI from the common eight parameter.

The overall groundwater and surface water quality index was computed using Equation 5:

$$WQI = \frac{\sum SI_n}{\sum W_n} \quad 5$$

2.4 Statistical Analysis

Descriptive statistics included means, standard deviations, ranges and criterion-conformity counts. For wet-dry comparisons, normality of paired differences was assessed with the Shapiro Wilk test. Normally distributed differences were analysed using paired t-tests with Cohen's d_z , while non-normal differences were analysed using Wilcoxon signed rank tests with matched pairs rank biserial effect size. Benjamini Hochberg false discovery rate adjustment was applied separately to the 11 groundwater indicators and 10 surface water indicators. Groundwater and surface water WQI distributions were compared by Mann-Whitney U tests for each season.

2.5 Spatial Modelling and Cross-Validation

Inverse distance weighting and ordinary kriging models were evaluated separately for dry and wet groundwater and surface water WQI. LOOCV omitted each monitoring location in turn and predicted its value from the remaining 29 observations. Model comparison used mean error (ME), mean absolute error (MAE), root mean square error (RMSE) and observed predicted R^2 , with RMSE as the principal selection criterion. Groundwater surfaces were generated within the Lamurde boundary at 30 m resolution. Surface water interpolation was restricted to a 150 m analytical corridor around the DEM-derived River Lamurde centreline to avoid unsupported extrapolation across the wider land surface. The corridor is an interpolation support mask and does not represent river width or contaminant transport distance.

3. Results and Discussion

3.1 Seasonal Variability of Water Quality Parameters

Groundwater and surface water displayed contrasting seasonal responses. In groundwater, mean pH declined from 6.85 to 6.59, turbidity increased from 2.40 to 8.40 NTU and nitrate increased from 24.79 to 82.14 mg/L. E. coli remained detectable at every groundwater location and the mean increased from 19.00 to 24.78 CFU/100 mL. By contrast, zinc declined from 0.772 to 0.306 mg/L and total chromium from 0.034 to 0.022 mg/L. These results show that the wet season did not produce a uniform deterioration or improvement; the parameters most relevant to untreated-use restriction worsened even while selected metals became lower.

River Lamurde showed much stronger wet season deterioration. Mean turbidity increased from 14.52 to 80.62 NTU, nitrate from 28.51 to 61.96 mg/L, iron from 0.404 to 0.806 mg/L, zinc from 0.305 to 1.024 mg/L, total chromium from 0.017 to 0.186 mg/L and BOD₅ from 2.19 to 39.49 mg/L. Mean E. coli declined from 23.50 to 10.01 CFU/100 mL, but every location remained positive in both seasons. The wet season increases in turbidity, nitrate and BOD₅ are consistent in direction with rainfall associated deterioration reported for the Lower River Benue [21], while the metal response is comparable with recent seasonal observations in Nigerian surface water systems [14].

Table 1: Seasonal mean water quality values for groundwater and River Lamurde

Parameter	GW Dry	GW Wet	SW Dry	SW Wet	Adopted value
pH	6.85	6.59	8.51	6.72	6.5-8.5
Turbidity (NTU)	2.40	8.40	14.52	80.62	≤5
TDS (mg/L)	554.42	589.88	106.67	131.69	≤500
EC (μS/cm)	889.67	983.64	143.80	169.68	≤1,000
NO ₃ ⁻ (mg/L)	24.79	82.14	28.51	61.96	≤50
Fe (mg/L)	0.255	0.163	0.404	0.806	≤0.30
Zn (mg/L)	0.772	0.306	0.305	1.024	≤3.0
Total Cr (mg/L)	0.034	0.022	0.017	0.186	≤0.05
DO (mg/L)	7.03	7.26	-	-	-
BOD ₅ (mg/L)	7.63	9.41	2.19	39.49	Operational†
E. coli (CFU/100 mL)	19.00	24.78	23.50	10.01	0

† BOD₅ was retained as an operational organic loading indicator and not as a drinking water health limit.

The groundwater pH response agrees with studies from Ado-Ekiti and Enugu that reported lower wet season groundwater pH [11], [16], although the magnitude and absolute acidity differ among hydrogeological settings. The universal groundwater E. coli detection is also consistent with evidence of faecal contamination in shallow wells within the wider Taraba environment [5]. These comparisons support the importance of retaining source-specific and parameter-specific interpretation of water quality indicators.

3.2 Seasonal WQI Condition and Source Comparison

Mean GWQI declined from 69.79 in the dry season to 45.00 in the wet season. The dry season groundwater distribution comprised 2 Excellent, 10 Good, 9 Fair, 3 Poor and 6 Unsuitable locations. The wet season distribution comprised 7 Excellent, 15 Good, 5 Fair, 2 Poor and 1 Unsuitable. This numerical improvement in the composite groundwater index was restricted from presenting the the water quality as safe for consumption because nitrate and microbiological results simultaneously became more severe across all sampling points.

River Lamurde showed the opposite and much larger seasonal response. Mean SWQI increased from 50.67 in the dry season to 360.39 in the wet season. Dry season classes comprised 15 Good, 11 Fair and 4 Poor locations, whereas the wet season contained 1 Poor and 29 Unsuitable locations. Groundwater and surface water WQI distributions were not significantly different in the dry season ($U = 534$, $p = 0.217$), but differed strongly in the wet season ($U = 3$, $p < 0.001$). The wet season mean SWQI was approximately eight times the mean GWQI.

Table 2: Seasonal WQI summary and class distribution

Source	Season	Mean	Range	Excellent	Good	Fair	Poor	Unsuitable
Groundwater	Dry	69.79	10.38-179.88	2	10	9	3	6
Groundwater	Wet	45.00	10.04-120.56	7	15	5	2	1
Surface water	Dry	50.67	29.30-85.72	0	15	11	4	0
Surface water	Wet	360.39	75.48-546.13	0	0	0	1	29

The apparently improved wet season GWQI arises partly from the reciprocal weighting framework. Total chromium accounted for 83.308% of the index weight and iron for 13.885%, whereas nitrate contributed only 0.083%. Consequently, lower wet season groundwater chromium and iron exerted strong downward pressure on GWQI even though nitrate and E. coli conditions were unfavourable. This demonstrates the type of structural sensitivity highlighted in broader WQI uncertainty research [8]. The index therefore represents a measure of relative composite physicochemical condition when critical warnings are reported independently.

3.3 Independent Nitrate, Chromium and E. coli Warnings

The warning analysis confirms why the WQI should not be interpreted as a standalone safety classification. No groundwater location exceeded 50 mg/L nitrate in the dry season, but all 30 exceeded the limit in the wet season. Groundwater total chromium warnings occurred at six locations in the dry season and one in the wet season. E. coli warnings occurred at all 30 groundwater locations in both seasons. For River Lamurde, no dry season nitrate or chromium warning occurred, whereas wet season nitrate and chromium warnings occurred at 21 and 28 locations, respectively; E. coli was detected at every surface water location in both seasons.

Table 3: Independent warning prevalence by source and season

Source	NO ₃ Dry	NO ₃ Wet	Cr Dry	Cr Wet	E. coli Dry	E. coli Wet
Groundwater	0/30	30/30	6/30	1/30	30/30	30/30
Surface water	0/30	21/30	0/30	28/30	30/30	30/30

The warning patterns identify different seasonal constraints in the two source domains. Groundwater was dominated by wet season nitrate and persistent microbiological restriction, while the River Lamurde experienced widespread wet

season nitrate, chromium, turbidity and organic loading problems. The finding that *E. coli* persisted even where mean surface water counts declined, illustrating that a lower seasonal concentration does not imply microbiological suitability for untreated use.

3.4 Spatial Variability and Cross-Validated Kriging

For groundwater, Gaussian ordinary kriging produced the lowest dry season RMSE (16.127) and a cross-validated R^2 of 0.876. The wet season groundwater surface was better represented by spherical ordinary kriging than by the IDW model, but predictive support remained weak (RMSE = 22.518; R^2 = 0.115). The retained wet season map therefore represent broad regional context between sampled sources.

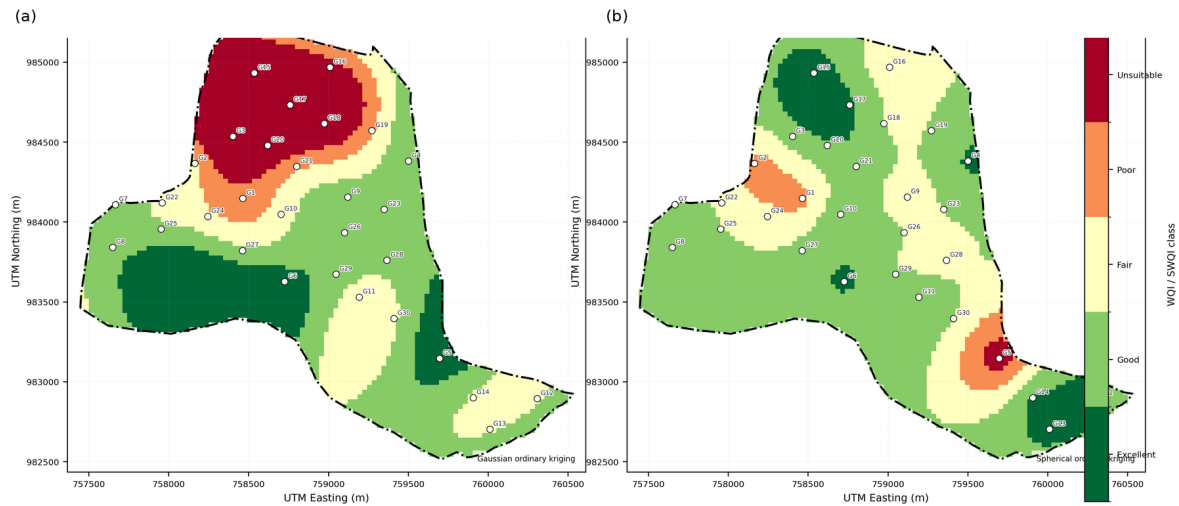


Fig. 3 Seasonal groundwater WQI surfaces: (a) dryseason Gaussian ordinary kriging and (b) wet season spherical ordinary kriging.

Surface water prediction was considerably stronger. Spherical ordinary kriging produced the lowest RMSE in both seasons. Dry season SWQI achieved RMSE = 2.506 and R^2 = 0.980, while wet season SWQI achieved RMSE = 49.884 and R^2 = 0.882. The larger wet season RMSE reflects the much wider SWQI range, while the high R^2 shows that relative spatial structure remained strongly reproduced. Restricting interpolation to the River Lamurde corridor preserved the linear hydrological support of the S1-S30 observations.

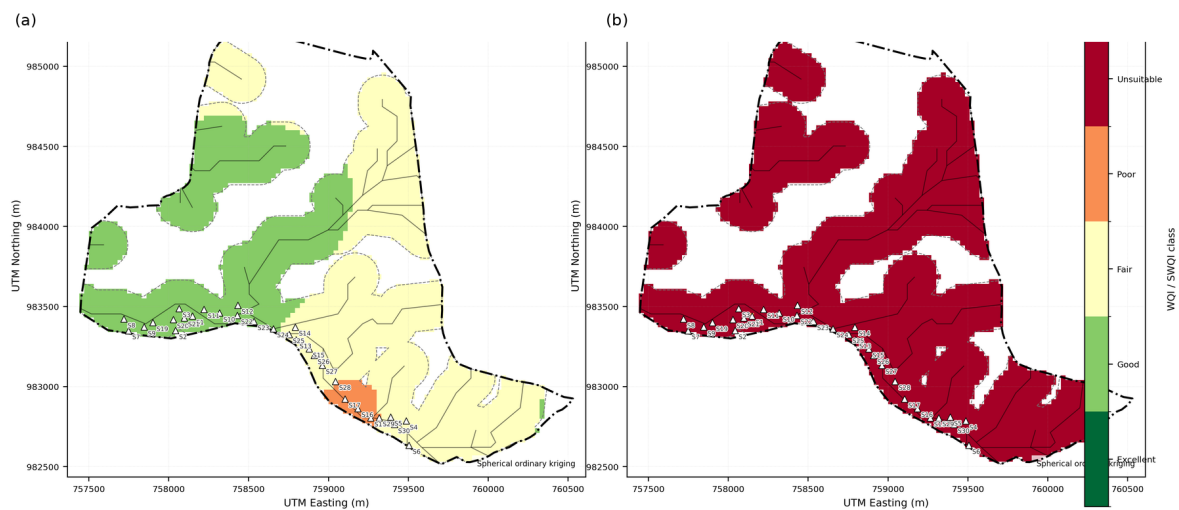


Fig. 4 Seasonal River Lamurde SWQI corridor surfaces: (a) dry season and (b) wet season, both using spherical ordinary kriging.

Table 4: Cross-validation performance of retained ordinary kriging models

Source	Season	Variogram	ME	MAE	RMSE	R^2	Decision
Groundwater	Dry	Gaussian	3.241	11.942	16.127	0.876	Retained
Groundwater	Wet	Spherical	-0.216	16.202	22.518	0.115	Retained with caution
Surface water	Dry	Spherical	-0.072	1.822	2.506	0.980	Retained
Surface water	Wet	Spherical	-1.228	28.138	49.884	0.882	Retained

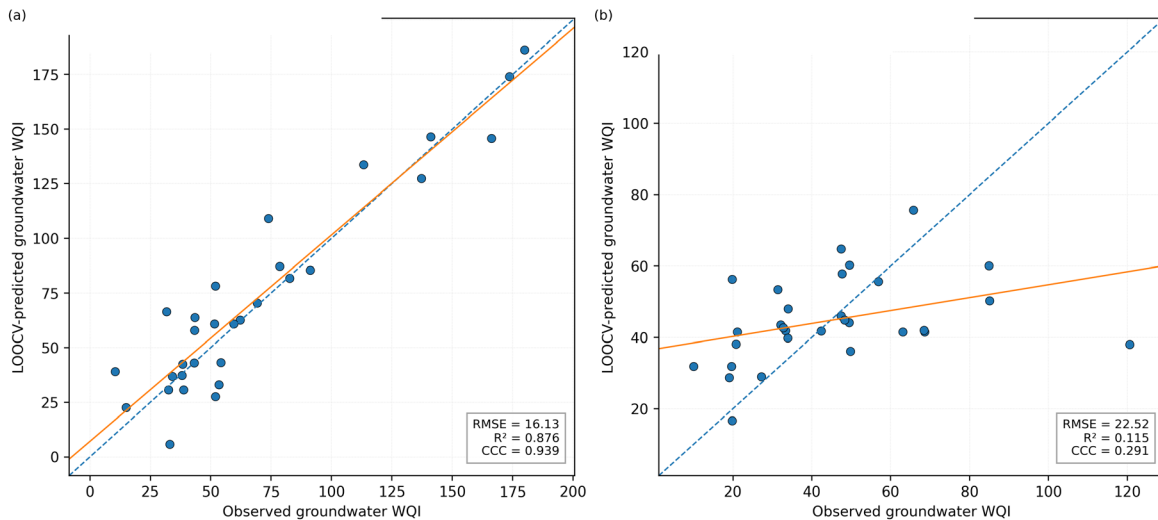


Fig. 5 Observed versus leave-one-out cross-validated groundwater WQI predictions for the dry and wet seasons.

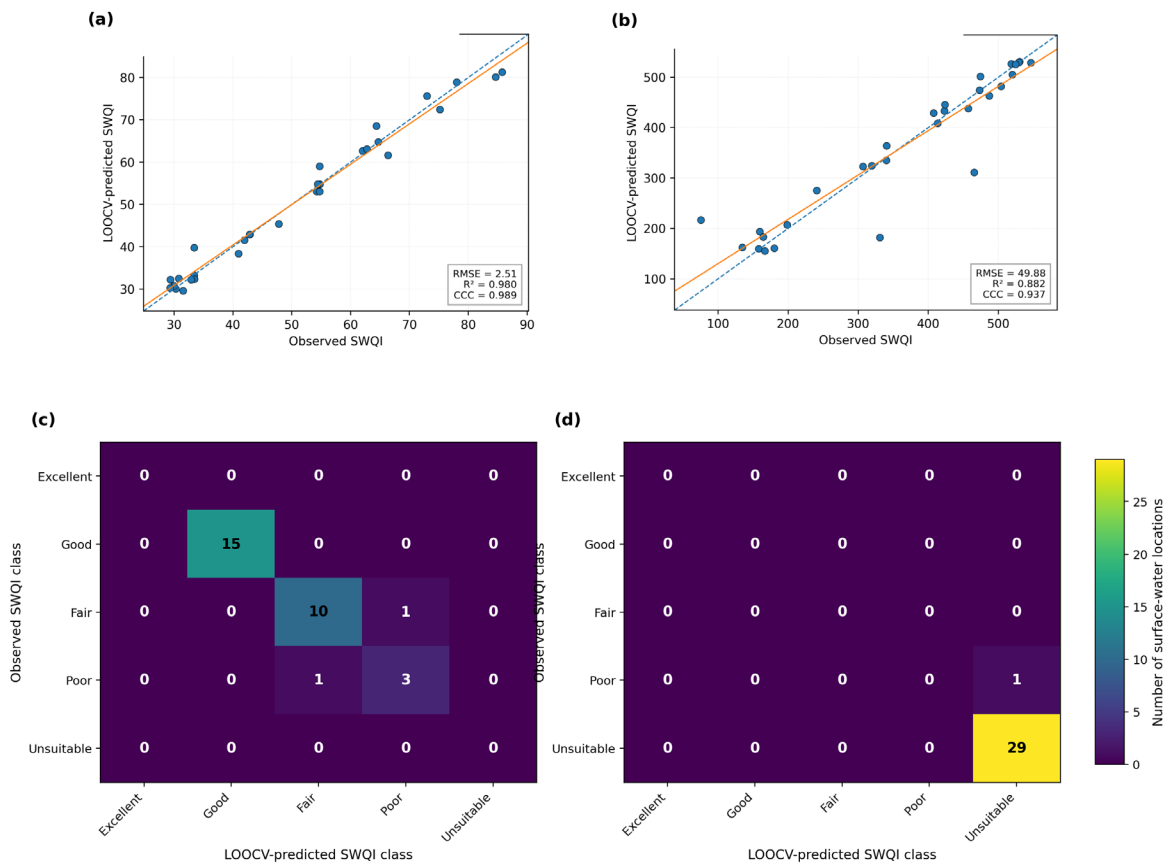


Fig. 6 Numerical and thematic LOOCV performance for River Lamurde SWQI in the dry and wet seasons.

These results reinforce the value of cross-validation in water quality mapping. Kriging can produce visually continuous surfaces even when omitted location prediction is weak. [2] and [9] demonstrate the usefulness of geostatistical mapping for WQI, but the Lamurde results show that model reliability can differ substantially by source domain and season. The weak wet groundwater R^2 is therefore showed that source monitoring and measurement should be used in defining the water quality of the study area.

3.5 Management implications and Study Limitations

The combined results indicate that untreated-use management should not rely on composite WQI class alone. Groundwater may appear numerically more favourable in the wet season while all monitored sources simultaneously fail the nitrate criterion and remain microbiologically contaminated. River Lamurde shows a clearer composite deterioration, with the wet season WQI and the independent nitrate, chromium and E. coli warnings pointing in the

same adverse direction. For practical management, monitoring and treatment prioritisation should therefore retain the index, the warning parameters and the reliability of the spatial surface as distinct pieces of evidence.

The study is bounded by one monitored wet season and one monitored dry season, and the final network was selected for analytical completeness and spatial coverage and not as a probability sample. LOOCV is an internal prediction test based on the same 30 location networks used for model development and does not replace geographically independent external validation. Surface water interpolation is valid only within the monitored River Lamurde corridor, while the weak wet groundwater prediction limits confidence in local unsampled class boundaries. These limitations should remain explicit when the maps are used for source screening or follow-up sampling.

4. Conclusions

Groundwater and River Lamurde displayed distinct seasonal water quality behaviour. Groundwater WQI changed from a mean of 69.79 in the dry season to 45.00 in the wet season, but this numerical improvement did not represent improved untreated-use safety because all groundwater locations exceeded 50 mg/L nitrate in the wet season and *E. coli* was detected throughout both seasons. River Lamurde deteriorated markedly, with mean SWQI changing from 50.67 to 360.39 and 29 of 30 locations becoming Unsuitable in the wet season.

Cross-validated kriging showed that spatial prediction reliability also varied by source and season. Dry groundwater and both surface water surfaces had useful predictive support, while wet groundwater interpolation was weak and is treated as broad regional context. The study therefore supports a water quality mapping framework in which WQI, independent health related warnings and cross-validation are interpreted together. Continued seasonal monitoring and independent external validation are recommended before extending spatial predictions beyond the monitored network.

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