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Tables 1 and 2 are available in the Supplementary Files section.

**Integrated GIS, APCS-MLR, and MixSIAR for Groundwater Pollution Source
Apportionment: A Case Study of a Multi-Source Contaminated Area in Rural China**

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Abstract

Accurate apportionment of groundwater contamination sources is essential for effective pollution control. This study integrated GIS mapping, absolute principal component scores-multiple linear regression (APCS-MLR), and the MixSIAR model (incorporating $\delta^{15}\text{N-NO}_3^-$ and $\delta^{18}\text{O-NO}_3^-$ isotopes) to quantitatively apportion groundwater pollution sources in a multi-source contaminated area in rural China. Results indicate that fishery ponds are the dominant point sources of NH_4^+ , COD_{mn} , and TP, contributing 65.76%, 36.09%, and 37.67% in the dry season, and 63.94%, 49.51%, and 52.89% in the wet season, respectively. Landfill leachate is the primary contributor to Cl^- and TDS, accounting for 58.44% and 40.61% in the dry season, and 63.20% and 41.38% in the wet season. Combined agricultural and domestic sources (manure, fertilizer, and sewage) contributed 81.8% and 84.1% to nitrate in the dry and wet seasons, respectively, with manure identified as the predominant contributor (48.1% and 54.4%, respectively). These findings highlight the critical role of agricultural activities, particularly manure management, in groundwater nitrate contamination.

Keywords: Groundwater; Source apportionment; GIS mapping; APCS-MLR; MixSIAR

1 Introduction

Groundwater serves as the primary terrestrial freshwater reservoir, is indispensable for global irrigation and drinking water security (Alley et al., 2002; De Graaf et al., 2019; Kuang et al., 2024; Macallister, 2024). However, widespread nitrogen contamination increasingly threatens groundwater quality (Hinton et al., 2024; Liu et al., 2023), arising from the complex interplay of natural geogenic processes and diverse anthropogenic activities, such as

agricultural fertilization, livestock farming, domestic sewage discharging, and landfill leaching (Han et al., 2020; Islam, 2025; Oh et al., 2021; Rajan et al., 2024). In multi-source contaminated regions, the co-occurrence of organic matter and nitrogen species complicates the hydrochemical environment. Consequently, accurate pollution source apportionment is a prerequisite for effective groundwater management; yet, it remains a formidable challenge. This difficulty is primarily attributed to the overlapping source profiles of multiple sources, further compounded by complex biogeochemical transformations (e.g., nitrification and denitrification) that alter pollutant's speciation and concentration during migration (Xin et al., 2021; Zhao et al., 2025).

To achieve accurate source apportionment, various methodologies have been developed. The prevailing methods include GIS mapping, hydrochemical analysis, multivariate statistical analysis, and stable isotope techniques (Carrey et al., 2021; Machiwal and Jha, 2015; Nas and Berktaş, 2010; Sun, 2014). GIS mapping can rapidly identify potential source areas and provide visual evidence, yet it cannot quantify specific contribution ratios (Huang et al., 2015; Nas and Berktaş, 2010). Hydrochemical analysis provides qualitative assessments, but its reliability is often compromised by the diverse origins of chemical constituents (Gemail and Abd-Elaty, 2023; Romshoo et al., 2017; Wang et al., 2023). Multivariate statistical methods, such as Principal Component Analysis (PCA) and Positive Matrix Factorization (PMF), have been widely adopted (Gong et al., 2024; Machiwal and Jha, 2015). While PMF offers quantitative insights, it is computationally intensive and highly sensitive to initial parameters such as the number of factors and weights (Hopke, 2016; Jahan et al., 2025). In contrast, the Absolute

Principal Component Scores-Multiple Linear Regression (APCS-MLR) method is characterized by simpler operation and the avoidance of complex iterative processes, making it a practical tool for quantitative apportionment (Chen et al., 2023a; Chen et al., 2023b; Li et al., 2021). Notably, these statistical methods often overlook the reactive transport and biogeochemical transformations of pollutants during migration, leading to potential uncertainties in apportionment results.

Stable isotope analysis has been extensively applied to address the limitations of chemical tracers, as different nitrate sources exhibit distinct $\delta^{15}\text{N}\text{-NO}_3^-$ and $\delta^{18}\text{O}\text{-NO}_3^-$ signatures (Carrey et al., 2021). Nitrate from different sources exhibits distinct $\delta^{15}\text{N}\text{-NO}_3^-$ ratios, allowing $\delta^{15}\text{N}\text{-NO}_3^-$ to serve as a single tracer for identifying nitrate sources in groundwater (Doncila, 2022). While single-isotope approaches may suffer from overlapping isotopic ranges, the dual-isotope approach significantly improves resolution by leveraging complementary information (Ren et al., 2022). Furthermore, the Bayesian mixing model (MixSIAR) has emerged as a mainstream tool, as it can explicitly account for fractionation effects and uncertainty in complex systems (Wang, 2023; Zhang et al., 2025). Despite these advancements, a robust framework that integrates spatial visualization, statistical quantification, and isotopic fingerprinting—while explicitly accounting for nitrogen transformation—is still lacking for multi-source contaminated sites. The integration of APCS-MLR and MixSIAR creates a synergistic effect by combining broad-spectrum hydrochemical screening with high-precision isotopic fingerprinting, thereby enabling cross-validation of source contributions and reducing the inherent uncertainties associated with single-method approaches.

Given these limitations, this study aims to enhance the operability of source apportionment in complex groundwater systems. Taking a site co-polluted by agricultural, domestic, and landfill sources as a case study, a novel integrated approach combining GIS, APCS-MLR, and MixSIAR is proposed to: (i) characterize the spatial distribution of pollutants using GIS mapping; (ii) perform qualitative and quantitative apportionment of bulk groundwater pollutants via APCS-MLR; and (iii) precisely determine the sources and contribution proportions of NO_3^- using the dual-isotope MixSIAR model. This integrated framework will assist decision-makers in developing targeted interventions for sustainable groundwater management.

2 Materials and methods

2.1 Study area and sampling

2.1.1 Study area

The study area is located in the red beds region of Sichuan Province in rural China (Fig. 1), where the land use is predominantly forest (68%), followed by farmland (24%), residential land (5%), and fishery ponds (2%). Furthermore, an operational municipal solid waste landfill is situated within the area, with a disposal capacity of 200 t/d and a leachate production rate of 70 m³/d. Consequently, potential anthropogenic groundwater pollution sources include agricultural fertilization, domestic sewage, fishery pond leakage, and landfill leachate.

Groundwater in the region is dominated by weathered fissure water, with the underlying red beds consisting of thick mudstone formations. Shallow wells typically yield 10–30 m³/d; however, the aquifer is prone to rapid depletion during pumping due to limited water retention

capacity. The depth to groundwater varies markedly between seasons, ranging from 3.5–6.0 m (dry season) to 1.0–1.5 m (wet season). Groundwater recharge occurs primarily through the vertical infiltration of atmospheric precipitation via fissures in the red beds. The groundwater flows along fractures and dissolution cavities, ultimately discharging into surface ditches or as gravity springs.

The study area features a denudational hilly terrain interspersed with valley depressions, with a mean annual precipitation of 1009.4 mm. Precipitation peaks in July to August, whereas the driest months are December to January.

2.1.2 Sampling

Based on the distribution of pollution sources and land use, groundwater samples were collected during both the dry season (January, n=15) and the wet season (September, n=11). Considering the distribution of anthropogenic activities in the study area, four types of potential pollution source samples were collected: (i) farm irrigation water (FIW), (ii) fishery pond water (FPW), (iii) domestic sewage (DS), and (iv) landfill leachate (LL). Additionally, a background well was established in an upstream forested area. All samples were collected and preserved in strict accordance with the Technical Specifications for Environmental Monitoring of Groundwater (HJ/T 164, China) and subsequently transported to the laboratory for comprehensive analysis. Detailed methodology regarding sample point optimization and placement was provided in a previous study (Han et al., 2020).

2.2 Analytical methods

2.2.1 Physicochemical analysis

Temperature, total dissolved solids (TDS), electrical conductivity (EC), pH, and oxidation-reduction potential (ORP) were measured in situ using portable water quality analyzers (Hanna HI98129 and CT-8022). Nitrate and chloride were determined using ion chromatography (861 Advanced Compact IC). The permanganate index (COD_{mn}) was determined by the acidic potassium permanganate method (GB/T 11892, China), total hardness (TH) by the EDTA titration method (GB/T 7477, China), ammonium levels by Nessler's reagent spectrophotometry (HJ 535, China), total phosphorus (TP) by ammonium molybdate spectrophotometry (HJ 670, China), and total nitrogen (TN) by the alkaline potassium persulfate digestion UV spectrophotometric method (HJ 636, China).

2.2.2 Stable isotope testing method

The isotopic compositions of $\delta^{15}\text{N}\text{-NO}_3^-$ and $\delta^{18}\text{O}\text{-NO}_3^-$ were determined via the denitrifier method using a stable isotope ratio mass spectrometer (IRMS; Isoprime100, Elementar, UK) at the Environmental Stable Isotope Laboratory, Institute of Agricultural Environment and Sustainable Development, Chinese Academy of Agricultural Sciences. Isotopic ratios were calibrated against international reference materials, including USGS32 ($\delta^{15}\text{N} = +180.0\text{‰}$; $\delta^{18}\text{O} = +25.7\text{‰}$), USGS34 ($\delta^{15}\text{N} = -1.8\text{‰}$; $\delta^{18}\text{O} = -27.9\text{‰}$), and USGS35 ($\delta^{15}\text{N} = +2.7\text{‰}$; $\delta^{18}\text{O} = +57.5\text{‰}$). Specifically, USGS32 and USGS34 were employed for $\delta^{15}\text{N}$ calibration, while USGS34 and USGS35 were used for $\delta^{18}\text{O}$ calibration (Bell and Sickman, 2014; Rock and Ellert, 2007).

Nitrate in the samples was quantitatively converted to N₂O by the denitrifying bacterium *Pseudomonas aureofaciens* (ATCC 13985), and the resulting N₂O was subsequently introduced into an automated trace gas extraction system (Precon, Thermo Fisher, USA) via an autosampler for extraction, purification, and trapping. The nitrogen and oxygen isotopic compositions were then measured by the IRMS. The analytical precision for $\delta^{15}\text{N-NO}_3^-$ and $\delta^{18}\text{O-NO}_3^-$ was better than $\pm 0.25\text{‰}$ and $\pm 0.50\text{‰}$, respectively.

2.3 Statistical analysis

Experimental data were compiled using Microsoft Excel 2021. Multivariate statistical analysis, including APCS-MLR, was performed using IBM SPSS Statistics 26.0. The Wilcoxon signed-rank test was employed to identify significant differences in groundwater quality between the dry and wet seasons at a significance level of $p < 0.05$. Spatial distributions of groundwater pollutants were characterized using Inverse Distance Weighting (IDW) interpolation in ArcGIS 10.8. MixSIAR modeling was implemented in R 4.5.1 (using the JAGS 4.3.1 engine) to quantify nitrate source contributions. All graphical representations, including concentration profiles and correlation matrices, were generated using OriginPro 2024.

2.3.1 GIS Mapping–Inverse Distance Weighting (IDW)

IDW interpolation estimates the unknown value of $\hat{Z}$ at the point x_0 using the values of a given number of observation points x_i (or by a given radius of search neighborhood), weighted by an inverse function of the distance between the unknown point and the observation (Paul L et al., 2023):

$$Z(x_0) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (1)$$

Where λ_i represents the weight function assigned to each observation point x_i and $Z(x_i)$ is the measured value at x_i . The weights are determined as:

$$\lambda_i = \frac{d_i^{-p}}{\sum_{i=1}^n d_i^{-p}} \quad (2)$$

Where d_i is the Euclidean distance between the predicted point x_0 and the observation point x_i , n is the total number of observation points used in the interpolation of x_0 , and the exponent p decides how the weight decreases as the distance increases.

For inverse distance weighting (IDW) interpolation, the power exponent was specified as 2. A variable search radius was adopted, with the maximum number of neighboring points set to 8.

2.3.2 Absolute principal component scores - multiple linear regression (APCS-MLR)

After principal component analysis (PCA) of groundwater samples, the APCS-MLR receptor model was applied to quantify the contribution rates of various groundwater pollution sources. The main calculation steps of APCS-MLR are as follows (Wang, 2023):

Step 1: Standardize the concentrations of groundwater quality indicators and derive normalized factor scores from PCA.

Step 2: Introduce an artificial sample with zero concentrations for all groundwater quality indicators and compute its factor scores.

Step 3: Subtract the factor scores of the zero-concentration sample from those of each actual sample to obtain the APCS for each groundwater quality indicator.

Step 4: Perform MLR using the concentrations of groundwater quality indicators as the dependent variables and the APCS values as the independent variables. The calculation formula

180 is as follows:

$$181 \quad C_i = b_i + \sum_{m=1}^n (APCS_{im} \times a_{im}) \quad (3)$$

182 Step 5: The product of a_i and $\overline{APCS_{im}}$ represents the contribution of identified pollution
183 sources to groundwater quality indicators, while b_i is interpreted as the contribution from
184 unidentified sources (other sources). The contribution rates of individual pollution sources are
185 calculated using the following formula:

$$186 \quad PC_{im} = \frac{|a_{im} \times \overline{APCS_{im}}|}{|b_i| + \sum_{m=1}^n |a_{im} \times \overline{APCS_{im}}|} \quad (4)$$
$$PC_{im} = \frac{|b_i|}{|b_i| + \sum_{m=1}^n |a_{im} \times \overline{APCS_{im}}|}$$

187 In the formula 3–4, C_i represents the measured concentration of groundwater quality factor
188 i ; a_{im} denotes the regression coefficient of pollution source m for i ; $APCS_{im}$ is the APCS value
189 of i across all samples; b_i is a constant term; PC_{im} stands for the contribution rate of m to i ; and
190 $\overline{APCS_{im}}$ is the average value of the APCS of i across all samples.

191 2.3.3 Mixing Models in R (MixSIAR)

192 Bayesian mixing models represent an advancement over simpler linear mixing models, as
193 they explicitly account for uncertainty in source values, categorical and continuous covariates,
194 as well as prior information (Ward et al., 2010). MixSIAR incorporates years of developments
195 in Bayesian mixing model theory. The MixSIAR can be expressed as follows (Ling et al., 2023;
196 Parnell et al., 2010; Ren et al., 2022):

$$\begin{aligned}
X_{ij} &= \sum_{k=1}^k p_k (S_{jk} + c_{jk}) + \varepsilon_{ij} \\
S_{jk} &\sim N(\mu_{jk}, \omega_{jk}^2) \\
c_{jk} &\sim N(\lambda_{jk}, \tau_{jk}^2) \\
\varepsilon_{jk} &\sim N(0, \sigma_{jk}^2)
\end{aligned} \tag{5}$$

Where X_{ij} is the isotope value j of the mixture i ($i=1, 2, 3, \dots, N$ and $j=1, 2, 3, \dots, J$); S_{jk} represents the source value k on isotope j ($k=1, 2, 3, \dots, K$) and is normally distributed with mean μ_{jk} and standard deviation (SD) ω_{jk} ; p_k indicates the proportional contribution of source k , which needs to be estimated by the SIAR model; c_{jk} is the fractionation factor for isotope j on source k and is normally distributed with mean λ_{jk} and SD τ_{jk} ; finally, ε_{ij} is the residual error representing the additional unquantified variation between individual mixtures and is normally distributed with mean zero and SD σ_j .

The MixSIAR was applied to quantify source contributions. The isotopic endmembers of five sources (Sewage, fertilizer, Manure, rainfall, soil N) were characterized by the mean and standard deviation of $\delta^{15}\text{N}$ and $\delta^{18}\text{O}$. The $\delta^{15}\text{N}$ means were 13.45, -0.2, 22.2, 0.89, and 3.98 (SD: 3.24, 0.4, 2.2, 2.12, 1.95), while the $\delta^{18}\text{O}$ means were 4.87, 22.1, -2.1, 57.59, and 2.51 (SD: 1.87, 2.8, 0.6, 12.47, 1.41) (Li et al., 2025; Udeshani et al., 2025a).

3 Results and discussion

3.1 Spatiotemporal analysis of groundwater pollutants

3.1.1 Statistical analysis of pollutants

Groundwater in the study area was weakly alkaline, with pH values ranging from 6.67 to 7.82. The concentrations of TN, NO_3^- , NH_4^+ , TP, and TDS were 10.63 ± 8.70 , 8.16 ± 8.30 , 0.22 ± 0.32 , 0.10 ± 0.19 , and 402.85 ± 128.84 mg/L in the dry season, and 10.74 ± 9.77 , 8.68 ± 8.22 ,

0.24 ± 0.26, 0.12 ± 0.17, and 363.88 ± 110.37 mg/L in the wet season, respectively (Fig. 2a). No significant seasonal variations were observed for these parameters ($P > 0.05$). In contrast, Cl^- concentrations were significantly higher in the dry season (57.44 ± 99.61 mg/L) than in the wet season (28.28 ± 43.71 mg/L) ($P = 0.041$), while COD_{mn} concentrations were significantly lower in the dry season (1.81 ± 1.82 mg/L) compared to the wet season (3.90 ± 3.23 mg/L) ($P = 0.006$). Reduced rainfall during the dry season decreases groundwater recharge and aquifer volume, leading to elevated Cl^- concentrations due to the "concentration effect" (Li et al., 2020a). Additionally, substantial rainfall during the wet season facilitates the leaching of surface organic matter—including organic acids, hydrocarbons, and organic nitrogen from agricultural fertilization in spring and summer, as well as other easily oxidizable organic substances in surface soils—into the groundwater (Gan et al., 2025; Mei et al., 2024).

3.1.2 Spatial distribution of pollutants

The spatial distribution of groundwater pollutants in the study area, determined via Inverse Distance Weighting (IDW) interpolation, is presented in Fig. 2b. High-concentration zones of TN and NO_3^- were predominantly distributed in residential and agricultural areas, indicating that domestic sewage and agricultural non-point sources are the primary anthropogenic contributors. Furthermore, elevated concentrations of NH_4^+ , COD_{mn} , and TP were generally clustered near fishery ponds. Notably, NH_4^+ and COD_{mn} concentrations were also relatively high in the vicinity of the landfill, while TP concentrations exhibited higher levels in residential areas during the wet season. These patterns suggest that fishery ponds (acting as point sources) are the most significant anthropogenic contributors of NH_4^+ , COD_{mn} , and TP. Additionally, the

landfill represents a notable point source for NH_4^+ and COD_{mn} , while domestic non-point sources contribute to TP enrichment during the wet season. The overlapping high-concentration plumes of Cl^- and TDS near the landfill further confirm its role as a major point source for these pollutants.

3.2 Quantitative analysis of groundwater pollution sources

3.2.1 Pearson correlation analysis

Pearson correlation analysis revealed that the investigated pollutants could be categorized into three distinct groups during both the dry and wet seasons: NH_4^+ - COD_{mn} -TP, NO_3^- -TN, and Cl^- -TDS (Fig. 3a and b). Significant positive correlations ($P < 0.05$) were observed among pollutants within the same group, with correlation coefficients (r) exceeding 0.65. In contrast, correlations between pollutants from different groups were generally weak, with the exception of COD_{mn} and Cl^- during the dry season. These strong intra-group correlations indicate the presence of common contamination sources (Ma et al., 2023), while the lack of inter-group correlations suggests that these three groups of substances originate from distinct sources (Pacheco Castro et al., 2018).

3.2.2 Principal component analysis (PCA)

The KMO (the KMO values were 0.592 and 0.554) and Bartlett's test results (the approximate chi - square values from Bartlett's test of sphericity were 76.453 and 115.367, with corresponding significance levels of 3.13E-8 and 3.96E-10) confirmed the suitability of Principal Component Analysis (PCA) for both the dry and wet seasons (Table 1) (Kazakis et al., 2017). Based on normalized data, Kaiser's varimax orthogonal rotation revealed three

factors with eigenvalues ranging from 1.24 to 4.01. These factors collectively accounted for 95.61% and 93.97% of the total variance in the dry and wet seasons, respectively, with communalities for all pollutants ranging from 0.91 to 0.99 (Table 1). This indicates that the extracted factors provide high adequacy in representing the dataset (Belkhiri and Narany, 2015).

Integrating the spatiotemporal distribution of pollutants with the PCA results, the following source identifications are inferred: (1) Factor 1 primarily represents fishery pond discharge, characterized by high loadings of NH_4^+ , COD_{mn} , and TP. The TP and total organic matter (TOM) contents in pond sediments can exceed 4 mg/g and 100 mg/g, respectively (Xu et al., 2023). Inadequate anti-seepage measures in these ponds have led to the continuous seepage of ammonia and organic matter into the underlying aquifer. (2) Factor 2 represents landfill leachate, identified as the primary source of Cl^- and TDS. High concentrations of Cl^- (5233.79 mg/L) and TDS (16420 mg/L) in the leachate migrate into the groundwater due to liner leakage, resulting in elevated Cl^- (400.39 mg/L) and TDS (778.00 mg/L) levels in monitoring wells. Although NH_4^+ and COD_{mn} in the leachate reach 1677.65 mg/L and 814.85 mg/L, respectively, the red bed soils possess a strong adsorption capacity for ammonium nitrogen and organic matter, effectively attenuating their downward migration (Li et al., 2022; Zhao et al., 2025). (3) Factor 3 represents domestic and agricultural sources, which are the predominant contributors of NO_3^- and TN. The discharge of untreated rural domestic sewage, leaching from unregulated waste dumping, and the application of manure and chemical fertilizers all contribute to nitrogen enrichment. In the study area, fertilization relies heavily on

manure; organic nitrogen and NH_4^+ (5.44 mg/L) from domestic sewage are readily converted to nitrate under aerobic conditions. Furthermore, the limited adsorption capacity of red bed soils for NO_3^- facilitates its infiltration, leading to elevated nitrate levels in the groundwater (Li et al., 2022).

3.2.3 Quantitative apportionment of groundwater pollution sources

The coefficients of determination (R^2) for the regression models of various groundwater pollutants ranged from 0.87 to 0.99 (Table 2). The total contribution rates of identified sources ranged from 43.07% to 98.66% in the dry season and from 51.57% to 96.83% in the wet season (Fig. 3c and d). Specifically, fishery pond discharge contributed 65.76%, 36.09%, and 37.67% to NH_4^+ , COD_{mn} , and TP in the dry season, and 63.94%, 49.51%, and 52.89% in the wet season, respectively. The landfill leachate accounted for 58.44% and 40.61% of Cl^- and TDS in the dry season, and 63.20% and 41.38% in the wet season. Domestic and agricultural sources contributed 69.17% to TN and 82.65% to NO_3^- in the dry season, with these contributions increasing to 86.91% and 80.68% in the wet season. The relatively lower contributions of fishery ponds (to COD_{mn} and TP) and domestic/agricultural sources (to TN) during the dry season can be attributed to reduced precipitation. Decreased rainfall limits surface runoff, reduces fishery pond overflow, and diminishes agricultural fertilizer leaching, thereby decreasing the input intensity of these pollutants (Ariadi et al., 2023; Halbach et al., 2021; Qiu et al., 2022).

Furthermore, unidentified sources were found to contribute 48.43%–56.93% to TDS. Based on its spatial distribution, this "missing source" is likely attributable to geogenic

processes. The study area is situated in a red bed region enriched with iron oxides, clay minerals (e.g., montmorillonite and illite), and soluble minerals such as halite and gypsum (Li et al., 2022; Li et al., 2020b). The dissolution of these minerals and subsequent cation-exchange processes within the red bed soils contribute to elevated Cl^- and TDS levels. Additionally, regional lithological variations influencing ion release (Subba Rao and Surya Rao, 2010), alongside hydrogeological features such as faults, fractures, and groundwater depth, may further modulate TDS transport pathways and input dynamics (Moore and Walsh, 2021; Williams et al., 2014).

While GIS mapping and APCS-MLR provided a quantitative framework for source apportionment, their reliance on concentration-based data presents limitations. Specifically, NH_4^+ from fishery ponds and landfill leachate can undergo nitrification into NO_3^- in the groundwater, potentially introducing uncertainties in the quantitative nitrate source apportionment. Concentration-based methods are inherently limited in tracing the origins of biogeochemically reactive nitrogen species. In contrast, stable isotope analysis offers a more robust approach for identifying the sources of such dynamically evolving groundwater pollutants.

3.3 Identification of NO_3^- sources in groundwater based on $\delta^{15}\text{N}-\text{NO}_3^-$ and $\delta^{18}\text{O}-\text{NO}_3^-$ dual-isotope

3.3.1 Characteristic values of $\delta^{15}\text{N}-\text{NO}_3^-$ and $\delta^{18}\text{O}-\text{NO}_3^-$

The potential sources of NO_3^- in groundwater within the study area were categorized into atmospheric deposition, soil nitrogen (soil N), synthetic fertilizer, manure, and sewage, each

characterized by distinct isotopic signatures (Husic et al., 2020; Kendall et al., 2007; Ren et al., 2022; Udeshani et al., 2025b). The $\delta^{15}\text{N-NO}_3^-$ values exhibit a wide range of variation, reflecting diverse nitrate origins. The dual-isotope plot of $\delta^{15}\text{N-NO}_3^-$ and $\delta^{18}\text{O-NO}_3^-$ showed that the groundwater samples predominantly clustered within the characteristic ranges of manure, sewage, and soil N (Fig. 4a). This distribution suggests that groundwater nitrate is primarily derived from agricultural manure, with secondary contributions from domestic sewage and soil organic nitrogen.

The $\delta^{18}\text{O-NO}_3^-$ values in groundwater remained relatively stable across seasons, with averages of $6.97 \pm 5.02\text{‰}$ in the dry season and $5.86 \pm 5.83\text{‰}$ in the wet season. In contrast, $\delta^{15}\text{N-NO}_3^-$ values were significantly higher in the dry season ($20.21 \pm 7.60\text{‰}$) compared to the wet season ($8.82 \pm 7.17\text{‰}$) (Fig. 4a). This seasonal depletion of $\delta^{15}\text{N-NO}_3^-$ during the wet season may be attributed to the enhanced leaching of soil-derived nitrogen and the infiltration of rainfall (atmospheric deposition), both of which typically possess lower $\delta^{15}\text{N}$ values than manure or sewage sources (Wei et al., 2024).

3.3.2 Quantitative analysis of NO_3^- sources

Nitrate transformation processes can significantly fractionate $\delta^{15}\text{N-NO}_3^-$ and $\delta^{18}\text{O-NO}_3^-$ signatures. Compared to nitrification and denitrification, the effects of adsorption, mineralization, and assimilation on these isotopic values are generally considered negligible (Ahmed Mahmoud and Mohamed, 2025; Udeshani et al., 2025a). During the wet season, groundwater in the study area was characterized by an aerobic environment (ORP = 150.0–196.1 mV), with 50% of the samples exhibiting $\delta^{15}\text{N-NO}_3^-$ values between -10‰ and 10‰ . In

contrast, less 25% of the samples fell within this range during the dry season. Consequently, a nitrification fractionation effect (-30‰) was incorporated into the MixSIAR model for the wet season but excluded for the dry season (Yang et al., 2026). Notably, the observed $\delta^{15}\text{N-NO}_3^-/\delta^{18}\text{O-NO}_3^-$ slope was 2.05, which deviates from the characteristic denitrification confidence interval (1.3–2.0). Furthermore, linear regression analysis showed no significant correlation between $\delta^{15}\text{N-NO}_3^-$ and NO_3^- concentration or $\text{Ln}(\text{NO}_3^-)$ ($R^2 = 0.038\text{--}0.155$, $P > 0.05$) (Fig. 4b and c). These lines of evidence collectively demonstrate that no significant denitrification occurred in the groundwater, thereby minimizing potential bias in the source apportionment results (Adebowale et al., 2019).

The MixSIAR model (via the JAGS interface) was configured with $n.chains = 3$, $n.adapt = 2000$, $n.iter = 50000$, and $thin = 50$. The Gelman-Rubin statistic ranged from 1.000 to 1.016, confirming excellent model convergence (Vats and Knudson, 2021). Quantitative results identified manure as the primary nitrate contributor, accounting for 48.1% in the dry season and 54.4% in the wet season, followed by sewage (24.7% and 22.3%, respectively) (Fig. 4d). Combined agricultural and domestic sources (manure, fertilizer, and sewage) contributed 81.8% in the dry season and 84.1% in the wet season. Significantly, these isotopic findings are consistent with the APCS-MLR results. The complementary application of a receptor model (APCS-MLR) and a Bayesian mixing model (MixSIAR) strengthens the reliability of source apportionment, confirming that agricultural and domestic activities—particularly manure management—are the predominant drivers of groundwater nitrate contamination. In this rural setting, unregulated manure application directly exacerbates groundwater degradation,

highlighting the urgent need for targeted nitrogen management strategies.

4 Conclusion

This study integrated GIS, APCS-MLR, and MixSIAR models to address the challenges of operational complexity and source identification uncertainty in multiple pollution sources regions. The spatiotemporal distribution and source contributions of groundwater pollutants were quantified using GIS mapping and APCS-MLR. Results indicated that fishery ponds were the primary sources of NH_4^+ , COD_{mn} , and TP, contributing 65.76%, 36.09%, and 37.67% in the dry season, and 63.94%, 49.51%, and 52.89% in the wet season, respectively. Landfill leachate was the predominant source of Cl^- and TDS, with contribution rates of 58.44% and 40.61% in the dry season, and 63.20% and 41.38% in the wet season. Domestic and agricultural activities were the major contributors to NO_3^- and TN, accounting for 82.65% and 69.17% in the dry season, and 86.91% and 80.68% in the wet season. Furthermore, the MixSIAR model, incorporating $\delta^{15}\text{N}-\text{NO}_3^-$ and $\delta^{18}\text{O}-\text{NO}_3^-$, was employed to quantify nitrate sources while considering nitrogen transformation processes. The isotopic evidence identified manure as the primary nitrate contributor (48.1% in the dry season and 54.4% in the wet season). The integrated findings from both APCS-MLR and MixSIAR consistently identified agricultural and domestic sources as the principal drivers of groundwater nitrate contamination. However, due to the isotopic overlap and detection limitations of landfill leachate, its specific contribution to nitrate could not be independently resolved using dual isotopes alone. These findings provide a scientific basis for groundwater management.

CRedit authorship contribution statement

Ziliang Zhao: Investigation, Data curation, Methodology, Software, Validation, Formal analysis, Visualization, Writing – original draft. **Hao Zhu:** Methodology, Formal analysis, Visualization, Writing – review & editing. **Yongqiang Fei:** Investigation, Data curation. **Jionghuang Chen:** Writing – original draft. **Mengting He:** Writing – original draft. **Zhiyong Han:** Conceptualization, Funding acquisition, Methodology, Supervision, Project administration, Resources, Visualization, Writing – review & 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.

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Data Availability Statement

Data will be made available on request.

References

- Adebowale, T., Surapaneni, A., Faulkner, D., McCance, W., Wang, S. and Currell, M. 2019. Delineation of contaminant sources and denitrification using isotopes of nitrate near a wastewater treatment plant in peri-urban settings. *Science of the Total Environment* 651, 2701-2711. <https://doi.org/10.1016/j.scitotenv.2018.10.146>.
- Ahmed Mahmoud, A.O. and Mohamed, S. 2025. Global Applications of Stable Isotopes for Identifying Nitrate Pollution Sources in Groundwater: A Comprehensive Review. *Frontiers in Water* 7, 1666498. <https://doi.org/10.3389/frwa.2025.1666498>.

- Alley, W.M., Healy, R.W., LaBaugh, J.W. and Reilly, T.E. 2002. Hydrology - Flow and storage in groundwater systems. *Science* 296(5575), 1985-1990.
<https://doi.org/10.1126/science.1067123>.
- Ariadi, H., Azril, M. and Mujtahidah, T. 2023. Water Quality Fluctuations in Shrimp Ponds During Dry and Rainy Seasons. *Croatian Journal of Fisheries* 81(3).
<https://doi.org/10.2478/cjf-2023-0014>.
- Belkhir, L. and Narany, T.S. 2015. Using multivariate statistical analysis, geostatistical techniques and structural equation modeling to identify spatial variability of groundwater quality. *Water Resources Management* 29(6), 2073-2089. <https://doi.org/10.1007/s11269-015-0929-7>.
- Bell, M.D. and Sickman, J.O. 2014. Correcting for background nitrate contamination in KCl - extracted samples during isotopic analysis of oxygen and nitrogen by the denitrifier method. *Rapid Communications in Mass Spectrometry* 28(5), 520-526.
<https://doi.org/10.1002/rcm.6824>.
- Carrey, R., Ballesté, E., Blanch, A.R., Lucena, F., Pons, P., López, J.M., Rull, M., Solà, J., Micola, N. and Fraile, J. 2021. Combining multi-isotopic and molecular source tracking methods to identify nitrate pollution sources in surface and groundwater. *Water Research* 188, 116537. <https://doi.org/10.1016/j.watres.2020.116537>.
- Chen, Y., Zhao, J., Chen, X. and Zheng, L. 2023a. Analysis of the source apportionment and pathways of heavy metals in soil in a coal mining area based on machine learning and an APCS-MLR model. *Minerals* 14(1), 54. <https://doi.org/10.3390/min14010054>.
- Chen, Z., Zhou, Q., Lv, J., Jiang, Y., Yang, H., Yang, H., Mei, S., Jia, Z., Zhang, H. and Jin, Y. 2023b. Assessment of groundwater quality using APCS-MLR model: a case study in the pilot promoter region of Yangtze river Delta integration demonstration zone, China. *Water* 15(2), 225. <https://doi.org/10.3390/w15020225>.
- De Graaf, I.E.M., Gleeson, T., Van Beek, L.P.H., Sutanudjaja, E.H. and Bierkens, M.F.P. 2019. Environmental flow limits to global groundwater pumping. *Nature* 574(7776), 90-+. <https://doi.org/10.1038/s41586-019-1594-4>.
- Doncila, A. (2022) Nitrogen cycling in the warming Arctic Ocean, University of Edinburgh.
- Gan, C., Jiang, Y., Wang, Y., Lin, S., Luo, Y., Li, H., Li, Y., Tang, N., Fei, Y. and Hu, R. 2025. Organic fertilizer application reduce ammonia volatilization in an acidic soil. *Agriculture, Ecosystems & Environment* 383, 109510.
<https://doi.org/10.1016/j.agee.2025.109510>.
- Gemail, K.S. and Abd-Elaty, I. 2023. Unveiling the hidden depths: A review for

- understanding and managing groundwater contamination in arid regions. *Groundwater Quality and Geochemistry in Arid and Semi-Arid Regions* 126, 3-35.
https://doi.org/10.1007/698_2023_1049.
- Gong, C., Xia, X., Lan, M., Shi, Y., Lu, H., Wang, S. and Chen, Y. 2024. Source identification and driving factor apportionment for soil potentially toxic elements via combining APCS-MLR, UNMIX, PMF and GDM. *Scientific Reports* 14(1), 10918.
<https://doi.org/10.1038/s41598-024-58673-9>.
- Halbach, K., Möder, M., Schrader, S., Liebmann, L., Schäfer, R.B., Schneeweiss, A., Schreiner, V.C., Vormeier, P., Weisner, O. and Liess, M. 2021. Small streams—large concentrations? Pesticide monitoring in small agricultural streams in Germany during dry weather and rainfall. *Water Research* 203, 117535.
<https://doi.org/10.1016/j.watres.2021.117535>.
- Han, Z., Wang, S., Zhao, J., Hu, X., Fei, Y. and Xu, M. 2020. Identification of nitrogen-sources in an aquifer beneath a municipal solid waste landfill in the vicinity of multiple pollutant sources. *Journal of Environmental Management* 268, 110661.
<https://doi.org/10.1016/j.jenvman.2020.110661>.
- Hinton, R.G.K., Kalin, R.M., Kanjaye, M.B., Mleta, P., Macleod, C.J.A. and Troldborg, M. 2024. Spatial model of groundwater contamination risks from pit-latrines in a low-income country. *Water Research* 267. <https://doi.org/10.1016/j.watres.2024.122734>.
- Hopke, P.K. 2016. Review of receptor modeling methods for source apportionment. *Journal of the Air & Waste Management Association* 66(3), 237-259.
<https://doi.org/10.1080/10962247.2016.1140693>.
- Huang, Y., Li, T., Wu, C., He, Z., Japenga, J., Deng, M. and Yang, X. 2015. An integrated approach to assess heavy metal source apportionment in peri-urban agricultural soils. *Journal of Hazardous materials* 299, 540-549.
<https://doi.org/10.1016/j.jhazmat.2015.07.041>.
- Husic, A., Fox, J., Mahoney, T., Gerlitz, M., Pollock, E. and Backus, J. 2020. Optimal Transport for Assessing Nitrate Source - Pathway Connectivity. *Water Resources Research* 56(10). <https://doi.org/10.1029/2020wr027446>.
- Islam, F.S. 2025. Groundwater pollution and contamination: Sources, impacts, management, and the integration of AI/ML for future solutions. *Research Journal in Civil, Industrial and Mechanical Engineering* 2(2), 01-52.
<https://doi.org/10.61424/rjcime.v2i2.307>.
- Jahan, A., Rai, N. and Khan, M.U. 2025. Groundwater contamination characterization and

source apportionment of heavy metals and associated source-specific health risk appraisal using Monte Carlo simulation coupled with PCA-MLR and PMF models in the middle Gangetic Basin, India. *Exposure and Health*, 1-32.
<https://doi.org/10.1007/s12403-025-00693-5>.

Kazakis, N., Mattas, C., Pavlou, A., Patrikaki, O. and Voudouris, K. 2017. Multivariate statistical analysis for the assessment of groundwater quality under different hydrogeological regimes. *Environmental Earth Sciences* 76(9), 349.
<https://doi.org/10.1007/s12665-017-6665-y>.

Kendall, C., Elliott, E.M. and Wankel, S.D. (2007) *Tracing anthropogenic inputs of nitrogen to ecosystems*, Blackwell Publishing, Malden, MA, USA.
<https://doi.org/10.1002/9780470691854.ch12>.

Kuang, X.X., Liu, J.G., Scanlon, B.R., Jiao, J.J., Jasechko, S., Lancia, M., Biskaborn, B.K., Wada, Y., Li, H.L., Zeng, Z.Z., Guo, Z.L., Yao, Y.Y., Gleeson, T., Nicot, J.P., Luo, X., Zou, Y.G. and Zheng, C.M. 2024. The changing nature of groundwater in the global water cycle. *Science* 383(6686), 14. <https://doi.org/10.1126/science.adf0630>.

Li, C., Gao, X., Li, S. and Bundschuh, J. 2020a. A review of the distribution, sources, genesis, and environmental concerns of salinity in groundwater. *Environmental Science and Pollution Research* 27(33), 41157-41174. <https://doi.org/10.1007/s11356-020-10354-6>.

Li, J., Sun, Q. and Lei, K. 2025. Multiple isotopes reveal the nitrate sources in Aojiang River Basin, Eastern China. *Bulletin of Environmental Contamination and Toxicology* 114(4), 1-7. <https://doi.org/10.1007/s00128-025-04026-9>.

Li, M., Liu, Z., Zhang, M. and Chen, Y. 2021. A workflow for spatio-seasonal hydro-chemical analysis using multivariate statistical techniques. *Water Research* 188, 116550. <https://doi.org/10.1016/j.watres.2020.116550>.

Li, N., Han, Z., Ren, Y., Wang, S., Hu, X. and Zeng, Z. 2022. Retarding performance of the vadose zone for nitrogen pollutants derived from municipal solid waste landfills in the red bed zone. *Journal of Environmental Management* 306.
<https://doi.org/10.1016/j.jenvman.2021.114406>.

Li, N., Han, Z., Wang, S., Li, L., Huang, J. and Zhao, J. 2020b. Impacts of different pollution sources on the microbial community in groundwater at municipal solid waste landfill sites. *China Environmental Science* 40(11), 4900-4910.
<https://doi.org/10.19674/j.cnki.issn1000-6923.20200918.002>.

Ling, J.h., Zhang, Y.z., Cao, Y.j., Li, X. and Zhao, G.l. 2023. An analysis of nitrate sources

in Nansi Lake based on nitrogen and oxygen isotopes. *China Environmental Science* 43(6), 3100-3106. <https://doi.org/10.19674/j.cnki.issn1000-6923.20230106.009>.

Liu, S., Zheng, T., Li, Y. and Zheng, X. 2023. A critical review of the central role of microbial regulation in the nitrogen biogeochemical process: New insights for controlling groundwater nitrogen contamination. *Journal of Environmental Management* 328. <https://doi.org/10.1016/j.jenvman.2022.116959>.

Ma, N., Gao, L., Ge, Z. and Li, M. 2023. Hydrochemical characteristics of groundwater in a plain river network region: Establishing linkages between source and water quality variables. *Chemosphere* 331, 138809. <https://doi.org/10.1016/j.chemosphere.2023.138809>.

Macallister, D.J. 2024. Groundwater decline is global but not universal. *Nature* 625(7996), 668-670. <https://doi.org/10.1038/d41586-024-00070-3>.

Machiwal, D. and Jha, M.K. 2015. Identifying sources of groundwater contamination in a hard-rock aquifer system using multivariate statistical analyses and GIS-based geostatistical modeling techniques. *Journal of Hydrology: Regional Studies* 4, 80-110. <https://doi.org/10.1016/j.ejrh.2014.11.005>.

Mei, S., Tong, T., Zhang, S., Ying, C., Tang, M., Zhang, M., Cai, T., Ma, Y. and Wang, Q. 2024. Optimization study of soil organic matter mapping model in complex terrain areas: A case study of mingguang city, China. *Sustainability* 16(10), 4312. <https://doi.org/10.3390/su16104312>.

Moore, J. and Walsh, J. 2021. Quantitative analysis of Cenozoic faults and fractures and their impact on groundwater flow in the bedrock aquifers of Ireland. *Hydrogeology Journal* 29(8), 2613-2632. <https://doi.org/10.1007/s10040-021-02395-z>.

Nas, B. and Berktaş, A. 2010. Groundwater quality mapping in urban groundwater using GIS. *Environmental monitoring and assessment* 160(1), 215-227. <https://doi.org/10.1007/s10661-008-0689-4>.

Oh, J., Kim, H.-R., Yu, S., Kim, K.-H. and Yun, S.-T. 2021. Delineating the impacts of poultry burial leachate on shallow groundwater in a reclaimed agro-livestock farming area, using multivariate statistical analysis of hydrochemical data. *Environmental science and pollution research* 28(7), 7742-7755. <https://doi.org/10.1007/s11356-020-08178-5>.

Pacheco Castro, R., Pacheco Avila, J., Ye, M. and Cabrera Sansores, A. 2018. Groundwater quality: analysis of its temporal and spatial variability in a karst aquifer. *Groundwater* 56(1), 62-72. <https://doi.org/10.1111/gwat.12546>.

Parnell, A.C., Inger, R., Bearhop, S. and Jackson, A.L. 2010. Source partitioning using

- stable isotopes: coping with too much variation. PLoS One 5(3), e9672.
<https://doi.org/10.1371/journal.pone.0009672>.
- Paul L, O., Martin, B. and Lutz, B. 2023. Accuracy assessment of inverse distance weighting interpolation of groundwater nitrate concentrations in Bavaria (Germany). Environmental Science and Pollution Research 30(4), 9445-9455.
<https://doi.org/10.1007/s11356-022-22670-0>.
- Qiu, W., Ma, X., Cao, H., Huang, T., She, X., Huang, M., Wang, Z. and Liu, J. 2022. Improving wheat yield by optimizing seeding and fertilizer rates based on precipitation in the summer fallow season in drylands of the Loess Plateau. Agricultural Water Management 264, 107489. <https://doi.org/10.1016/j.agwat.2022.107489>.
- Rajan, M., Karunanidhi, D., Jaya, J., Preethi, B., Subramani, T. and Aravinthasamy, P. 2024. A comprehensive review on human health hazards due to groundwater contamination: A global perspective. Physics and Chemistry of the Earth, Parts A/B/C 135, 103637. <https://doi.org/10.1016/j.pce.2024.103637>.
- Ren, K., Pan, X., Yuan, D., Zeng, J., Liang, J. and Peng, C. 2022. Nitrate sources and nitrogen dynamics in a karst aquifer with mixed nitrogen inputs (Southwest China): Revealed by multiple stable isotopic and hydro-chemical proxies. Water Research 210, 118000. <https://doi.org/10.1016/j.watres.2021.118000>.
- Rock, L. and Ellert, B.H. 2007. Nitrogen - 15 and oxygen - 18 natural abundance of potassium chloride extractable soil nitrate using the denitrifier method. Soil Science Society of America Journal 71(2), 355-361. <https://doi.org/10.2136/sssaj2006.0266>.
- Romshoo, S.A., Dar, R.A., Murtaza, K.O., Rashid, I. and Dar, F.A. 2017. Hydrochemical characterization and pollution assessment of groundwater in Jammu Siwaliks, India. Environmental monitoring and assessment 189(3), 122. <https://doi.org/10.1007/s10661-017-5860-3>.
- Subba Rao, N. and Surya Rao, P. 2010. Major ion chemistry of groundwater in a river basin: a study from India. Environmental Earth Sciences 61(4), 757-775. <https://doi.org/10.1007/s12665-009-0389-6>.
- Sun, L. 2014. Statistical analysis of hydrochemistry of groundwater and its implications for water source identification: a case study. Arabian Journal of Geosciences 7(9), 3417-3425. <https://doi.org/10.1007/s12517-013-1061-8>.
- Udeshani, C., Yue, F.J., Gong, Y.Q., Li, S.L. and Chandrajith, R. 2025a. Sources and dynamics of nitrate in groundwater in a crystalline terrain of tropical Sri Lanka based on a dual isotope approach. Water Research 282.

<https://doi.org/10.1016/j.watres.2025.123914>.

Udeshani, C., Yue, F.J., Gong, Y.Q., Li, S.L. and Chandrajith, R. 2025b. Sources and dynamics of nitrate in groundwater in a crystalline terrain of tropical Sri Lanka based on a dual isotope approach. *Water Research* 282, 123914.

<https://doi.org/10.1016/j.watres.2025.123914>.

Vats, D. and Knudson, C. 2021. Revisiting the gelman–rubin diagnostic. *Statistical Science* 36(4), 518-529. <https://doi.org/stable/27286459>.

Wang, M. 2023. Source Analysis of Heavy Metals in Typical Farmland Soils Based on PCA-APCS-MLR and Geostatistics. *Environmental Science* 44(4), 3509-3519. <https://doi.org/10.13227/j.hjlx.202208002>.

Wang, Y., Yuan, S., Shi, J., Ma, T., Xie, X., Deng, Y., Du, Y., Gan, Y., Guo, Z. and Dong, Y. 2023. Groundwater quality and health: making the invisible visible. *Environmental Science & Technology* 57(13), 5125-5136. <https://doi.org/10.1021/acs.est.2c08061>.

Ward, E.J., Semmens, B.X. and Schindler, D.E. 2010. Including source uncertainty and prior information in the analysis of stable isotope mixing models. *Environmental Science & Technology* 44(12), 4645-4650. <https://doi.org/10.1021/es100053v>.

Wei, X., Zhou, Y., Ran, L., Chen, M., Zou, J., Fan, Z. and Fu, Y. 2024. Sources and transformation of nitrate in shallow groundwater in the Three Gorges Reservoir Area: Hydrogeochemistry and isotopes. *Water* 16(22), 3299. <https://doi.org/10.3390/w16223299>

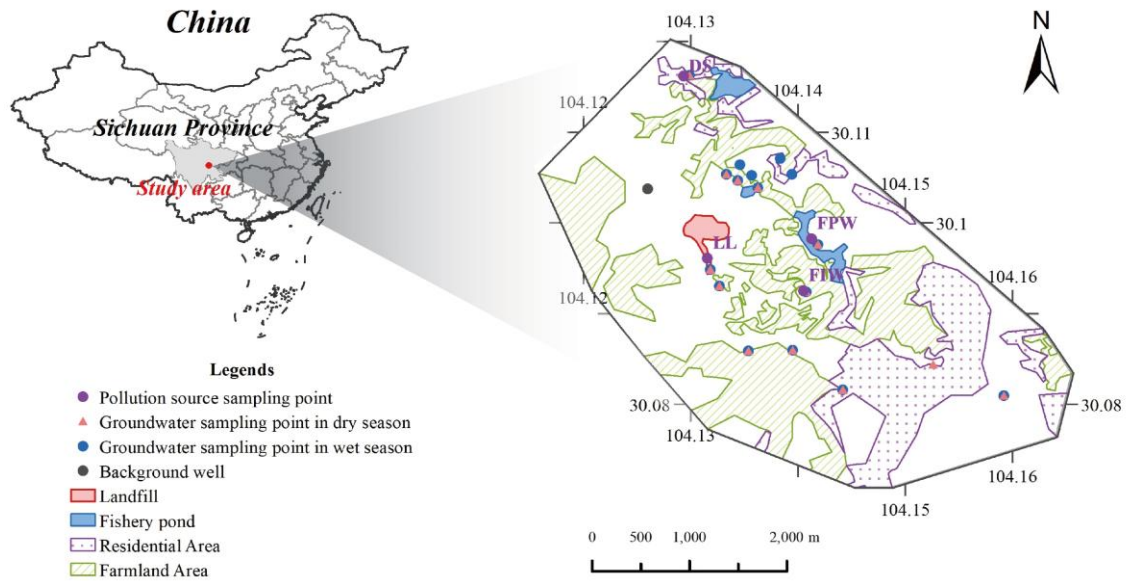
Williams, M.R., Buda, A.R., Elliott, H.A., Hamlett, J., Boyer, E.W. and Schmidt, J.P. 2014. Groundwater flow path dynamics and nitrogen transport potential in the riparian zone of an agricultural headwater catchment. *Journal of Hydrology* 511, 870-879. <https://doi.org/10.1016/j.jhydrol.2014.02.033>.

Xin, L., Rui, Z., Jinsheng, W., Zhukun, H. and Qiao, L. 2021. Advances in researches on ammonia, nitrite and nitrate on migration and transformation in the groundwater level fluctuation zone. *Hydrogeology & Engineering Geology* 48(2), 27-36. <https://doi.org/10.16030/j.cnki.issn.1000-3665.202007033>.

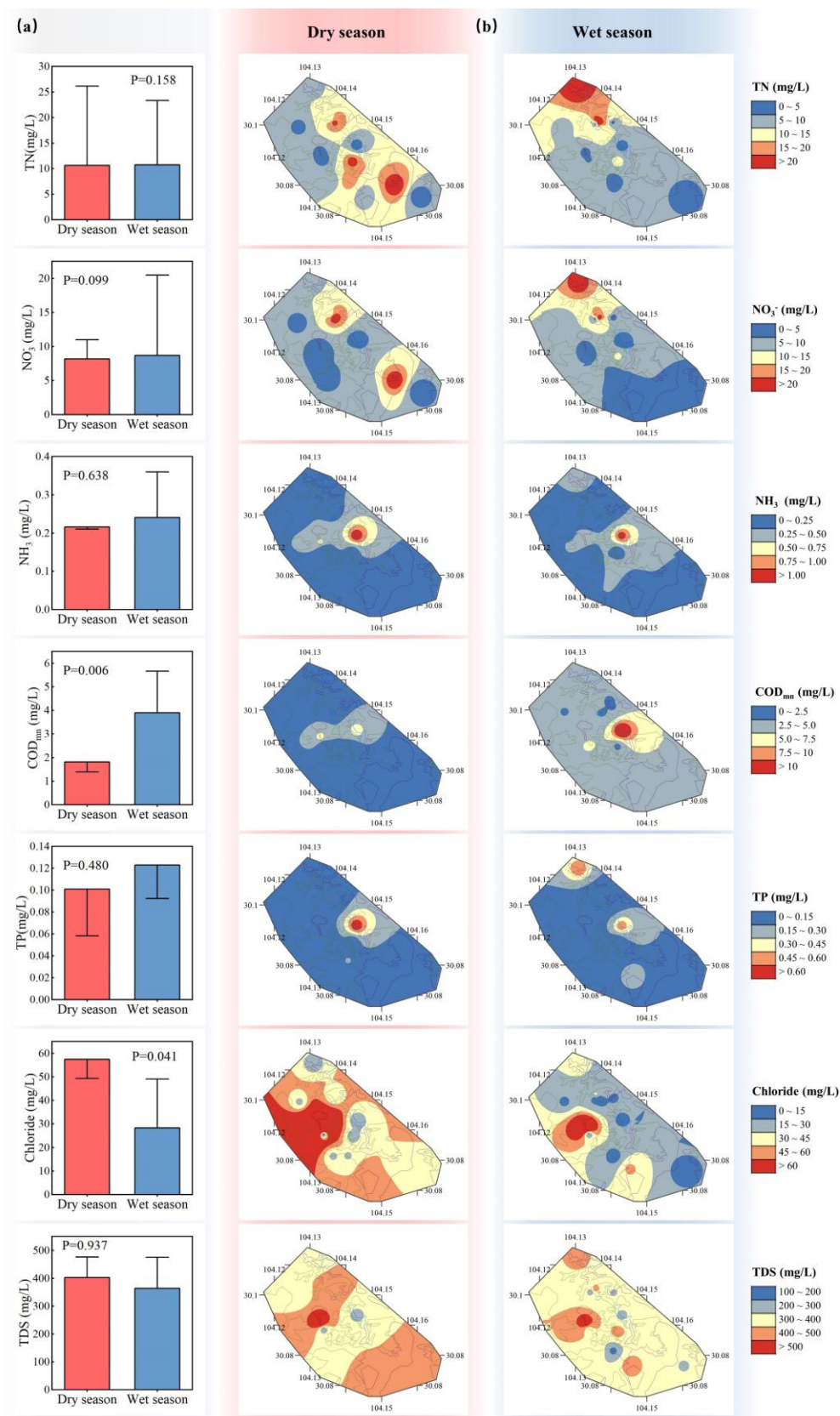
Xu, J., Wang, J., Lin, S., Hou, L., Ma, S., Lv, Y., Chen, R., He, X. and Hou, J. 2023. The effect of novel aquaculture mode on phosphorus sorption-release in pond sediment. *Science of The Total Environment* 905, 167019. <https://doi.org/10.1016/j.scitotenv.2023.167019>.

Yang, Z., Yang, Y., Wen, Y., Gao, C., Zheng, C., Teng, X. and La, Y. 2026. Using Hydrochemistry, Multi-Isotope, and MixSIAR Model to Analyze Nitrate Sources of

612 Groundwater: A Case Study of the Yongning River Banks. *Hydrology* 13(3), 84.
613 <https://doi.org/10.3390/hydrology13030084>
614 Zhang, S., Han, G., Gao, X., Liu, J. and Qiao, N. 2025. Megacity river as a critical
615 anthropogenic source of strontium release in global Sr cycle: Insights from Bayesian
616 mixing model and Sr isotope. *Water Research* 278, 123402.
617 <https://doi.org/10.1016/j.watres.2025.123402>.
618 Zhao, Z.-L., Zhu, H., Chen, X., Feng, S.-J., Salam, M., He, S., Du, Y.-P., Chen, J.-K., Lan, Z.-
619 X. and Zhou, Y.-J. 2025. Influence of iron and manganese on nitrogen
620 biotransformation in the vadose zone of red beds following landfill leachate leakage.
621 *Science of The Total Environment* 997, 180168.
622 <https://doi.org/10.1016/j.scitotenv.2025.180168>.
623

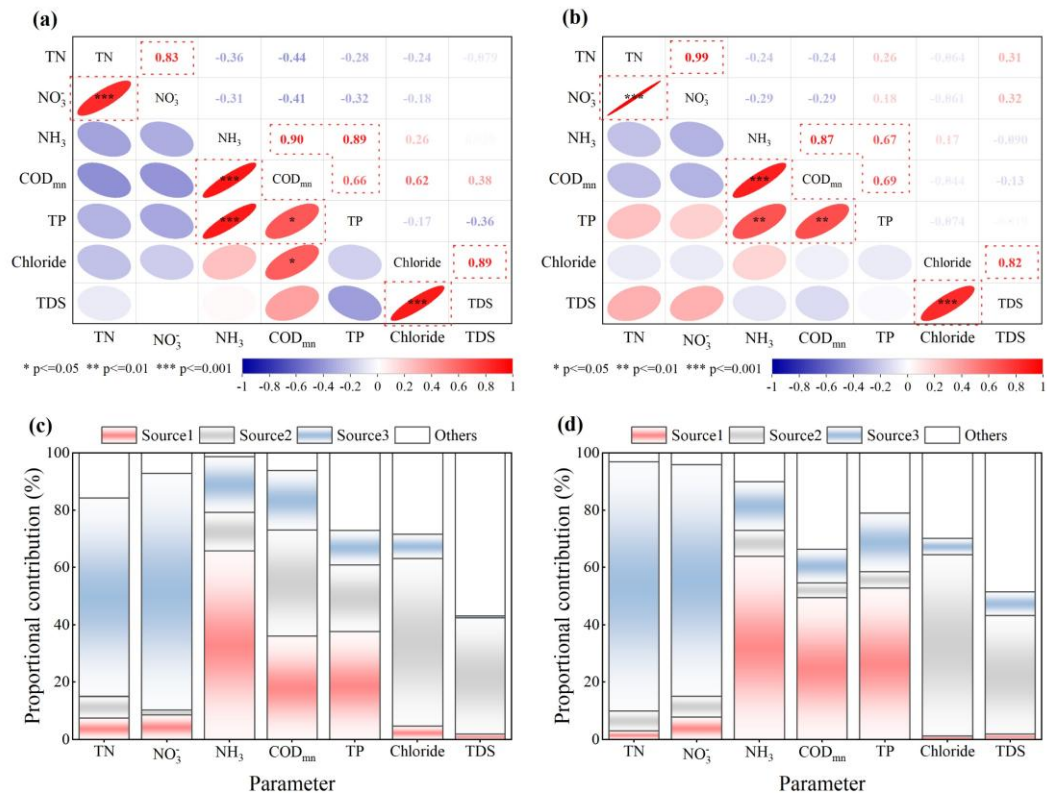


1 Fig. 1. Location of the study area in the red beds of Sichuan Province in rural China, showing
 2 sampling locations and different land use types within the study area.



3 Fig. 2. Concentrations of pollutants and their significant differences between the dry and wet

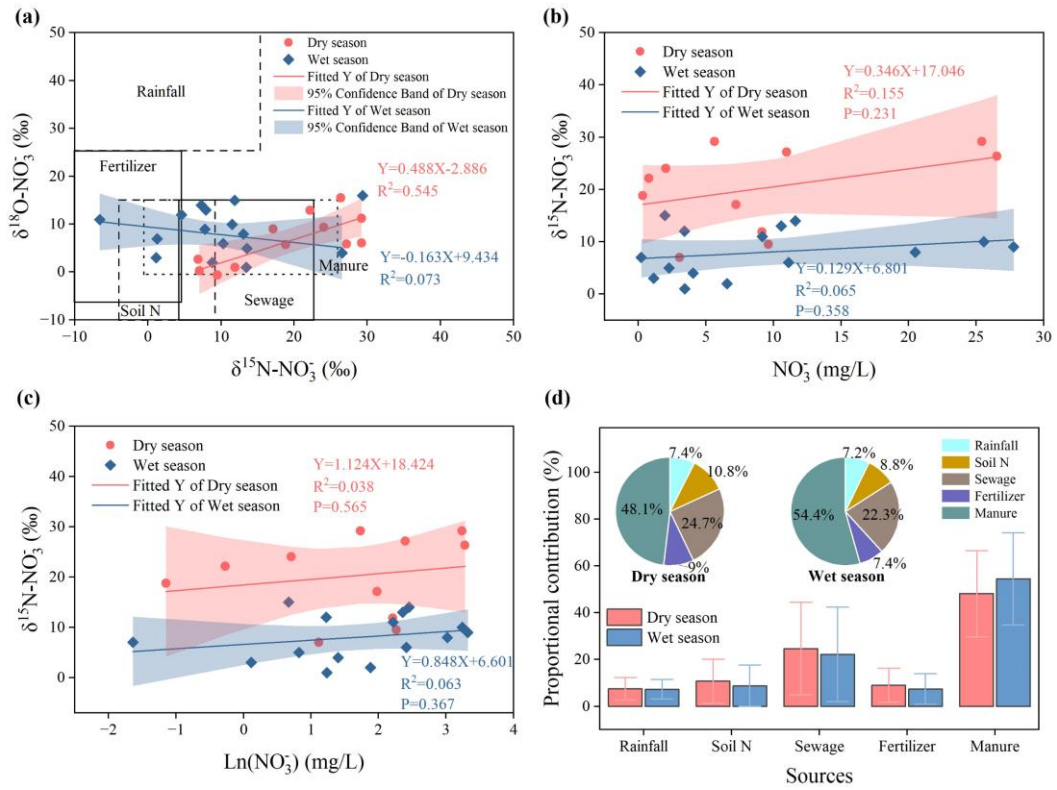
4 seasons (a); spatial distribution of pollutant concentrations in the dry and wet seasons (b).



5 Fig. 3. Correlation matrix of groundwater pollutants in the dry season (a) and wet season (b);

6 proportional contribution of different sources to groundwater pollutants based on APCS-MLR

7 in the dry season (c) and wet season (d).



8 Fig. 4. Distribution characteristics of $\delta^{18}\text{O-NO}_3^-$ and $\delta^{15}\text{N-NO}_3^-$ values in groundwater (a);
9 relationship between $\delta^{15}\text{N-NO}_3^-$ and NO_3^- concentration (b); relationship between $\delta^{15}\text{N-NO}_3^-$
10 and $\text{Ln}(\text{NO}_3^-)$ (c); proportional contribution of different sources to nitrate contamination in
11 groundwater based on MixSIAR (d).

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