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Original Research

Spatio-Temporal Dynamics and Source Apportionment of Nutrient Loading in a High-Altitude Fragile River: A Case Study of the Niyang River, Qinghai-Tibet Plateau

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Abstract

This study addresses the critical knowledge gap in nutrient dynamics within high-altitude fragile ecosystems by investigating the Niyang River, a primary tributary of the Yarlung Zangbo River. A multi-dimensional diagnostic framework was developed by coupling the Comprehensive Pollution Index (CPI) with a refined Output Coefficient Model (OCM) and stoichiometric correlation analysis, bridging the gap between ambient concentration-based risk profiling and land-use-driven pollution flux calculation. Through systematic monitoring of nine representative sections during contrasting hydrological seasons, the spatio-temporal evolution of Chemical Oxygen Demand (COD), Total Phosphorus (TP), Total Nitrogen (TN), and Ammonia Nitrogen (NH_3-N) was quantified. The integrated modeling approach reveals a distinct spatial purification gradient from the headwaters to the downstream confluence, with the dry season identified as the critical window for pollution management due to reduced dilution capacity. By synthesizing the CPI-based risk ranking with OCM-derived load estimation, this study identifies a synchronous transport-source mechanism: specifically, the strong stoichiometric coupling between organic matter and nutrients (COD-TP and TN-NH_3-N) validates that large-scale pastoral waste and agricultural runoff are not merely parallel but functionally integrated pollution drivers. COD was prioritized as the primary risk indicator within this coupled framework. These findings demonstrate that the synergistic application of concentration-load modeling offers a more robust precision-targeting tool for water quality management in the Third Pole region than traditional single-model assessments, providing a scientific template for ecological preservation in similar alpine basins.

Keywords: high-altitude fragile ecosystem, source apportionment, multi-dimensional diagnostic framework, output coefficient model, nutrient stoichiometric coupling

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Introduction

Water is a unique natural resource, an indispensable component of both nature and human existence [1]. It serves as the core of ecosystems, the source of all life, and a fundamental element for the development of human society and the economy [2-4]. Amid rapid regional economic and climatic shifts, complex interrelated challenges – including regional water scarcity, water pollution, ecological degradation, frequent water-related disasters, and lagging water management – have intensified, escalating the conflict between human activities and sustainable water resource development [5-7]. Pollutants from watershed contamination continuously enter rivers and lakes via surface runoff, exacerbating water pollution in these water bodies [8, 9]. In high-altitude regions, the hydrological cycle is particularly sensitive to climate change, which alters the transport pathways and residence times of pollutants, making traditional water quality management strategies less effective [10]. Comprehensively understanding river water quality and basin pollution loads is crucial for formulating ecological protection measures and water resource management policies to ensure basin ecological stability and sustainable water resource development.

With the socioeconomic development and human activities on the Qinghai-Tibet Plateau (QTP), pollutant emissions have increased significantly, and river water quality indicators frequently exceed standards [11, 12], severely impacting the plateau's riverine environment. The QTP, known as the Third Pole, possesses a fragile self-purification capacity due to its low temperatures and unique microbial communities, which limits the degradation rate of organic matter and nutrients [13]. Recent literature suggests that the expansion of intensive grazing and tourism in the Yarlung Zangbo River tributaries has shifted the pollution profile from natural background weathering to anthropogenic nutrient enrichment [14]. The Niyang River Basin, situated within the ecological security barrier zone of southeastern Tibet, is the second-largest tributary of the Yarlung Zangbo River. Spanning the administrative regions of Nyingchi City's Gongbujiangda County and Bayi District, it serves as a vital water source for both domestic consumption and agricultural production along its banks. Consequently, its water quality directly impacts the drinking water safety of riverside communities.

The development of agriculture, animal husbandry, and tourism within the basin has led to a continuous rise in total water consumption. Simultaneously, non-point source pollutant discharges from both banks have also increased [15, 16], posing threats to the safety of river water quality and exacerbating water environmental issues in the Niyang River. However, existing studies often treat water quality monitoring (concentration) and pollution source estimation (load) as isolated processes, failing to reveal the internal synchronous transport mechanisms of multiple pollutants in alpine terrains [17]. There is an urgent need for a coupled modeling approach that bridges the gap between ambient risk profiling and land-use-driven flux calculation to achieve precision targeting of pollution hotspots [18].

This study develops a multi-dimensional diagnostic framework by coupling the Comprehensive Pollution Index (CPI), a refined Output Coefficient Model (OCM), and stoichiometric correlation analysis, the systematic execution of which is illustrated in the technical roadmap (Fig. 1). By integrating high-resolution water quality monitoring data from nine representative sections across contrasting hydrological seasons with basin-scale land-use and socioeconomic datasets, the framework first performs risk profiling to quantify the spatio-temporal dynamics of COD, TP, TN, and NH_3-N. A critical innovation of this approach lies in bridging the gap between ambient concentration-based assessments and source-driven flux calculations: specifically, the refined OCM is utilized to quantify the pollution contribution from livestock, agriculture, and domestic sectors, while stoichiometric correlation analysis is subsequently employed to validate the synchronous transport-source mechanism. This coupled diagnosis elucidates the functional integration of organic matter and nutrient loads, allowing for the identification of priority control pollutants and their critical management windows. Ultimately, this integrated methodology facilitates a management synthesis for formulating precision-targeted protection measures, such as pastoral waste mitigation and agricultural runoff control, providing a scientific template for the ecological preservation of the Niyang River and similar high-altitude Third Pole aquatic ecosystems.

Materials and Methods

Study Area Description

The Niyang River Basin (NRB), situated within the ecological security barrier zone of southeastern Tibet, is the second-largest tributary of the Yarlung Zangbo River [19]. It drains an area of approximately 17,500 km² and serves as a vital water source for domestic consumption and agricultural production across the administrative regions of Nyingchi City's Gongbujiangda County and Bayi District. Characterized by a high-altitude alpine environment, the basin is a quintessential part of the Third Pole, where the hydrological cycle is highly sensitive to climate change. The region's fragile ecosystem possesses a limited self-purification capacity due to low temperatures and unique microbial structures, making it vulnerable to anthropogenic nutrient enrichment from expanding intensive grazing, agriculture, and tourism (Fig. 2).

To implement the multi-dimensional diagnostic framework, this study delineated the basin based on county-level administrative boundaries and sub-basin topography. Nine representative water quality

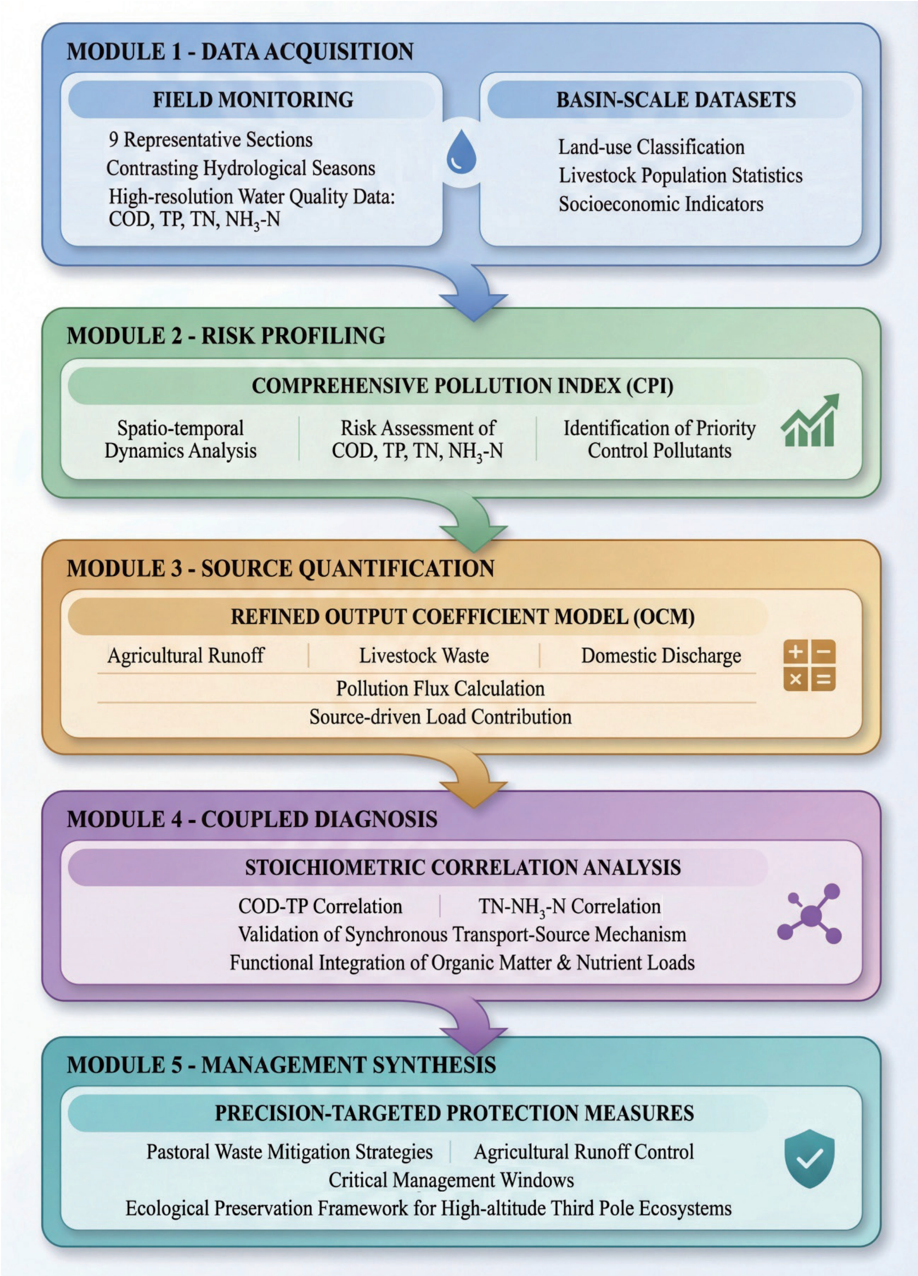

Fig. 1. Technical roadmap of the multi-dimensional diagnostic framework for water quality assessment and pollution load quantification in the Niyang River Basin. This figure depicts an integrated research roadmap that couples water quality risk profiling (CPI) with source-driven load quantification (OCM) and stoichiometric validation to facilitate precision-targeted management for high-altitude aquatic ecosystems.

monitoring stations were selected along the mainstream to capture the spatio-temporal dynamics of pollutants (Fig. 3). These sections cover the transition from natural headwaters to areas impacted by human activities. Field sampling was conducted during the dry season (December 2022) and the wet season (July 2023) to reflect contrasting hydrological conditions. In accordance with the objective of identifying priority control pollutants, four key indicators were analyzed: COD, TP, TN, and NH_3-N. To support the refined OCM, socioeconomic and livestock data were sourced from the Nyingchi City Statistical Yearbook, while land-use datasets were utilized to bridge the gap between ambient risk profiling and land-use-driven flux calculation [20].

Research Methods

Water Quality Risk Profiling: Comprehensive Pollution Index (CPI)

To quantify the spatio-temporal dynamics of river water quality, the CPI was employed to assess the pollution status of the Niyang River mainstream. This method transforms multiple water quality

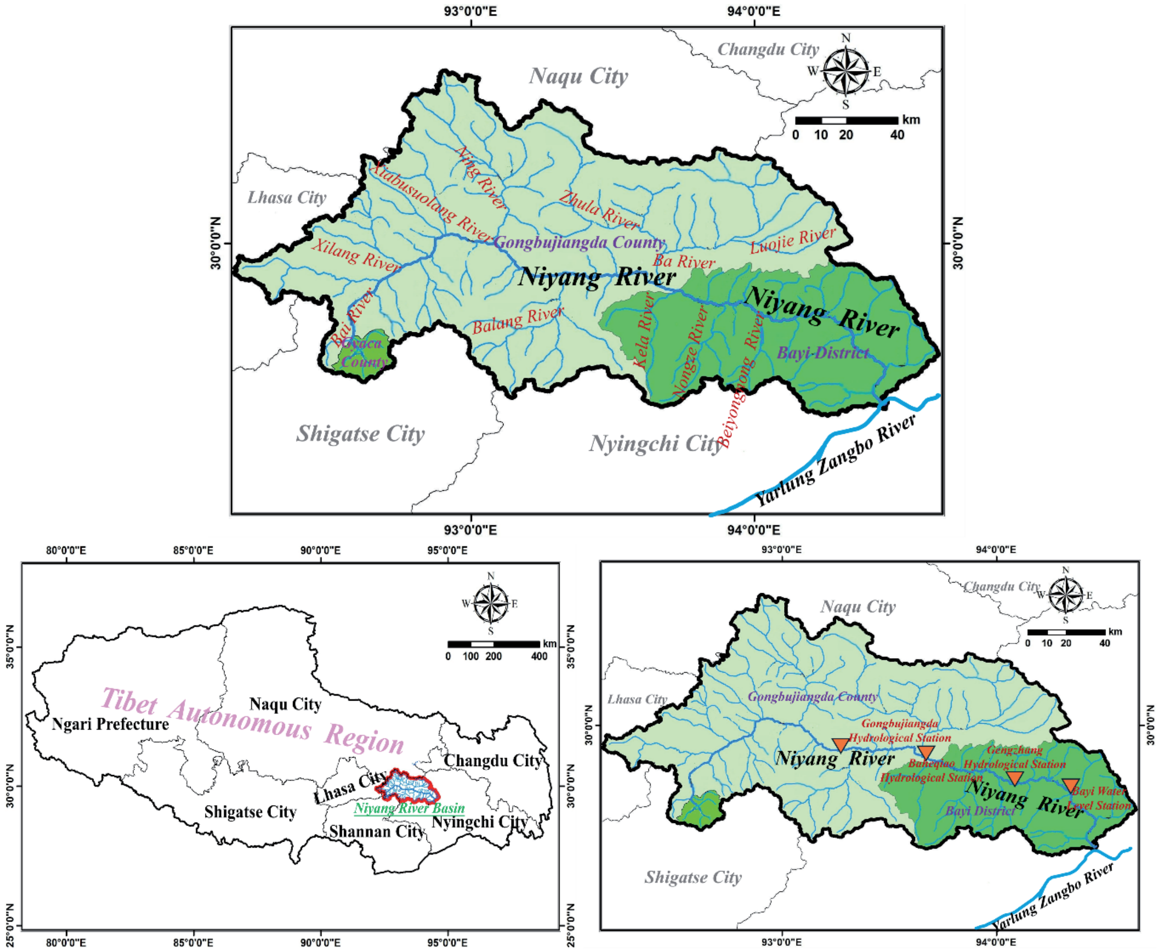

Fig. 2. Layout of the Niyang River water system and hydrological monitoring stations.

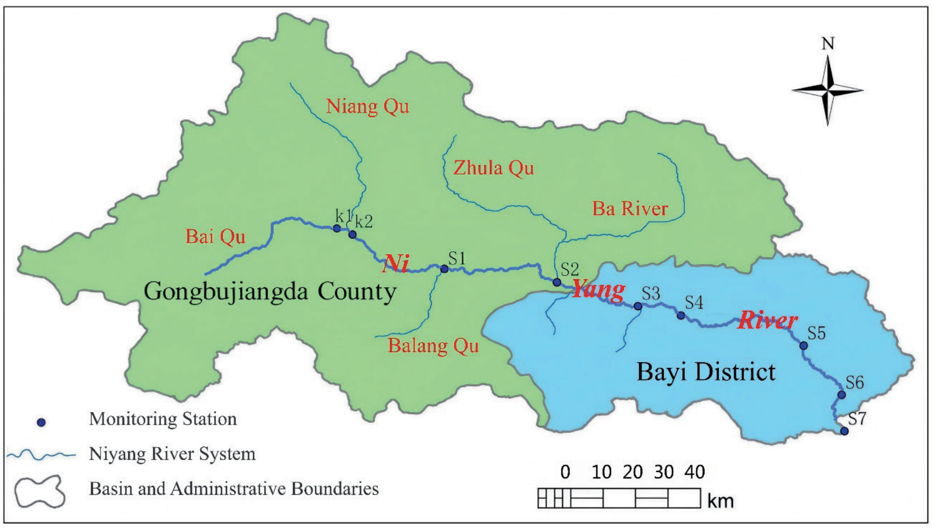

Fig. 3. Location of water quality monitoring stations and spatial distribution of the Niyang River Basin.

parameters into a single comparable value, facilitating the identification of priority control pollutants. The calculation of the single pollution index (P_i), the comprehensive index (P), and the pollution contribution rate (K_i) is as follows:

$$P_i = \frac{C_i}{S_i} \tag{1}$$

$$P = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{2}$$

$$K_i = \frac{P_i}{\sum P_i} \times 100\% \tag{3}$$

Where, C_i is the measured concentration of pollutant i (COD, TP, TN, or NH_3-N); S_i is the background value or threshold from the Environmental Quality Standards for Surface Water (GB 3838-2002) (Class III is used as the baseline for the Niyang River); P represents the overall pollution level, categorized as follows: Excellent ($P \leq 0.15$), Good ($0.15 < P \leq 0.40$), Fair ($0.40 < P \leq 0.50$), Poor ($0.50 < P \leq 0.99$), and Severe ($P \geq 1.0$) [21].

Source-Driven Flux Calculation: Refined Output Coefficient Model (OCM)

To bridge the gap between ambient concentrations and land-use impacts, a refined OCM was utilized to quantify non-point source (NPS) pollution loads. This model specifically accounts for the unique hydrological characteristics of the Third Pole by incorporating a rainfall-runoff influence factor [22]:

$$L_j = \sum_{i=1}^{n} (\alpha \times E_{ij} \times A_i) \tag{4}$$

Where, L_j is the total loss of nutrient j (kg/year); α is the rainfall influence factor, which adjusts the output based on the contrasting hydrological conditions of the wet and dry seasons; E_{ij} is the output coefficient for pollutant j from source i (livestock/poultry, domestic life, or agricultural land-use); A_i represents the activity intensity (e.g., number of livestock, population size, or area of farmland). Data were integrated from high-resolution land-use maps and Nyingchi socioeconomic datasets.

Mechanism Validation: Stoichiometric and Spatial Autocorrelation Analysis

A critical innovation of this study is the application of stoichiometric correlation analysis to validate the synchronous transport-source mechanism. By analyzing the ratios and correlations between C, N, and P, we elucidated the functional integration of organic matter and nutrient loads.

Furthermore, to explore the spatial clustering and hotspots of pollutants, the Global Moran's I index was calculated [23]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{5}$$

Where, I ranges from -1 to 1. $I>0$ indicates spatial clustering; $I<0$ indicates dispersion; $I = 0$ indicates randomness; W_{ij} is the spatial weight matrix; X_i and X_j are water quality values at different monitoring sections.

Statistical processing was performed using Excel 2025 and SPSS 23.0, while spatial mapping and autocorrelation were conducted in ArcGIS 10.8.

The three models are intrinsically linked through a synergistic source-process-response logical chain, where the parameters of one model serve as the validation or contextual baseline for the others. Specifically, the CPI provides the ambient concentration response (C_i), which represents the environmental manifestation of the pollution loads (L_j) quantified by the refined OCM. The rainfall influence factor (α) in the OCM acts as a critical temporal bridge, linking the hydrological seasonality to the spatio-temporal fluctuations observed in the CPI results. Furthermore, stoichiometric correlation analysis functions as a mechanistic validator, bridging the gap between land-use-driven fluxes and in-stream concentrations by ensuring that the elemental ratios (C, N, P) derived from monitoring data align with the specific output coefficients (E_{ij}) of the identified sources. Finally, spatial autocorrelation (Moran's I) provides the geographical alignment, ensuring that the spatial clustering of risk hotspots identified by the CPI corresponds with the high-intensity loading zones predicted by the OCM, thereby creating a cohesive and multi-dimensional diagnostic framework.

Data Sources

The multi-dimensional diagnostic framework developed in this study relies on three primary categories of data: field-monitored water quality data, socioeconomic statistical data, and geospatial environmental datasets.

First, water quality monitoring data were obtained through systematic field sampling and laboratory analysis. Samples were collected from nine representative monitoring sections along the Niyang River mainstream during the dry season (December 2022) and the wet season (July 2023). To ensure high precision in the CPI and stoichiometric analysis, four key parameters – COD, TP, TN, and NH_3-N – were measured following the standard analytical methods prescribed by the Environmental Quality Standards for Surface Water (GB 3838-2002). These data provide the empirical response baseline (C_i) for the risk profiling phase.

Second, socioeconomic and anthropogenic activity data used to drive the refined OCM were primarily sourced from the Nyingchi City Statistical Yearbook (2022-2023). This included detailed statistics for Gongbujiangda County and Bayi District, specifically focusing on population size, livestock and poultry inventory (e.g., Tibetan pigs, cattle, and sheep), and agricultural inputs. These statistical records provided the activity intensity (A_i) required to calculate the non-point source pollution loads across the domestic and pastoral sectors.

Third, geospatial and environmental datasets were integrated to facilitate spatial analysis and model refinement. High-resolution land-use/land-cover data (30 m resolution) were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences. These data were used to delineate the sub-basin boundaries and assign specific output coefficients (E_{ij}) for different land-use types. Additionally, Digital Elevation Model (DEM) data (SRTM 90 m) were utilized for topographical analysis and sub-basin delineation in ArcGIS 10.8. Meteorological data, including seasonal precipitation records used to determine the rainfall influence factor (α), were retrieved from the China Meteorological Data Service Centre for the corresponding sampling periods. In this study, seasonal precipitation was utilized as the primary environmental driver for the refined OCM instead of direct hydrological discharge data. This choice was made because hydrological gauging stations are sparsely distributed in this high-altitude, fragile region (Fig. 2), making it challenging to obtain synchronized flow data for all specific sub-basins. Furthermore, α is a widely accepted proxy in output coefficient modeling to reflect the seasonal transport capacity of non-point source pollutants, which aligns with the data availability and the spatial scale of the Niyang River basin.

Results and Discussion

Spatio-Temporal Dynamics of Water Quality Risk

Based on the CPI model, the water quality risk profiling of the Niyang River mainstream reveals distinct spatio-temporal heterogeneities (Table 1). During the wet season, the overall compliance rate for Class III water quality reached 89%. However, the upstream section K1 (confluence of Niyang and Nyangqu Rivers) exhibited a CPI of 0.52, exceeding the threshold for Class IV water quality, primarily due to the flushing effect of summer rainfall on pastoral and agricultural soils [24]. In contrast, the downstream section S7 maintained excellent quality (P = 0.15, Class I), benefiting from the river's self-purification capacity and increased baseflow dilution.

During the dry season, the compliance rate remained at 89%, but the pollution hotspot shifted to S3 (Baiba Town), where the CPI reached 0.61 (Class IV). This deterioration is attributed to the river's reduced dilution capacity during low-flow periods, coupled with localized domestic discharges from township settlements [25]. Spatially, the water quality showed a deterioration-then-improvement trend along the river course. On an administrative scale, the Gongbujiangda section generally exhibited higher risk levels (P_{avg} = 0.41-0.45) compared to the Bayi District section (P_{avg} = 0.23-0.30), indicating that upstream pastoral activities and natural background weathering contribute significantly to the basin's pollution baseline.

To further identify priority control pollutants, the pollution contribution rate (K_i) was calculated (Fig. 4). The results demonstrate that COD and TN are the dominant pollutants across all sections and seasons, collectively contributing over 60% of the total pollution load. COD contribution rates ranged from 50% to 73% in the wet season and 34% to 70% in the dry season, identifying it as a high-risk indicator for the Niyang River. The high contribution of TN, particularly at section *K*2 (up to 46%), underscores the impact of anthropogenic nutrient enrichment from livestock

Table 1. Spatio-temporal distribution of CPI (P) across monitoring sections.

Season	K1	K2	S1	S2	S3	S4	S5	S6	S7	Gongbujiangda	Bayi District
Wet (P)	0.52	0.48	0.36	0.46	0.33	0.3	0.19	0.16	0.15	0.45	0.23
Dry (P)	0.41	0.4	0.38	0.46	0.61	0.23	0.25	0.23	0.18	0.41	0.3

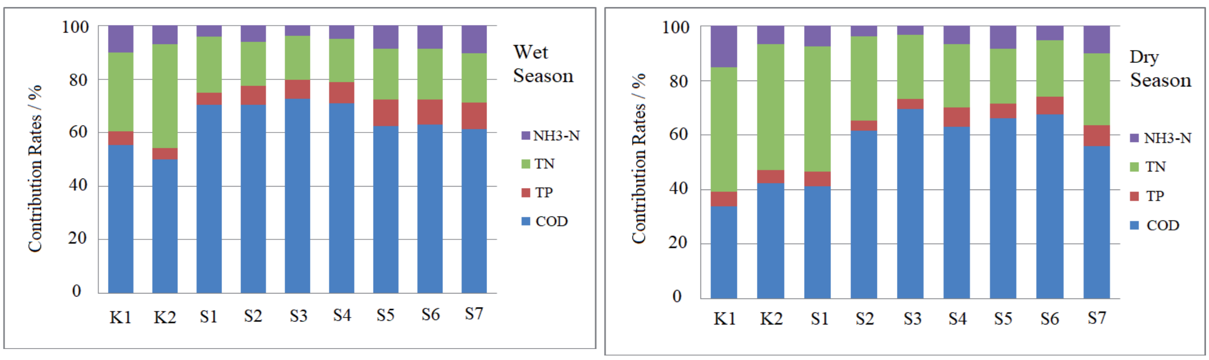

Fig. 4. Percentage of pollutant contribution (%) in sampling sections of the Niyang River.

grazing and agricultural runoff in the upper reaches [26].

Stoichiometric Mechanisms and Source Homogeneity

The stoichiometric correlation analysis was employed to validate the synchronous transport-source mechanism of pollutants (Table 2). During the wet season, a significant positive correlation was observed between COD and TP (r = 0.789, p<0.05), while NH_3-N and TN exhibited a highly significant correlation (r = 0.826, p<0.01). This synchronicity suggests that organic matter and phosphorus are likely co-transported via surface runoff from agricultural lands. In contrast, nitrogenous compounds originate from a shared source, likely pastoral waste and livestock emissions [27].

In the dry season, the correlation pattern shifted, with TP showing strong associations with both TN (r = 0.918, p<0.01) and NH_3-N (r = 0.677, p<0.05). This indicates a transition toward source homogeneity during low-flow periods, where point-source-like discharges (e.g., domestic sewage and concentrated livestock residues) become the primary drivers of nutrient stoichiometry [28]. These variations highlight that the priority management window for runoff-driven pollution (COD-TP) should focus on the wet season, while domestic and livestock waste control (TN-TP) is critical during the dry season.

Quantitative Apportionment of NPS Loads

To trace the anthropogenic drivers behind the water quality patterns, the Improved OCM was utilized to quantify the annual pollutant loads from four primary NPS categories. The total annual discharges of COD, TN, TP, and NH_3-N in the Niyang River basin were

Table 2. Pearson correlation matrix of water quality indicators across hydrological seasons.

Indicators	Season	COD	TP	TN	NH_3-N
COD	Wet / Dry	1/1	0.789*/0.395	0.606/0.289	0.553/-0.183
TP	Wet / Dry		1/1	0.322 / 0.918**	0.499/0.677*
TN	Wet / Dry			1/1	0.826**/0.643
NH_3-N	Wet / Dry				1/1

* Correlation is significant at the 0.05 level; ** Correlation is significant at the 0.01 level.

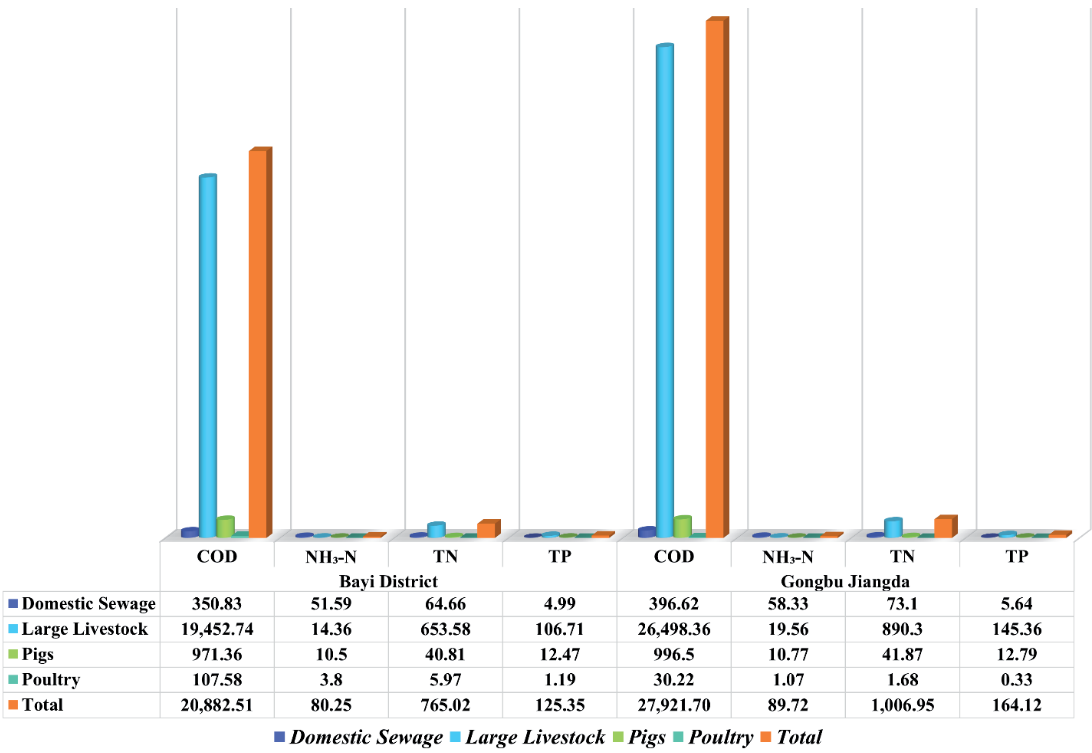

Fig. 5. Estimated annual NPS pollutant loads by source and administrative region (t/a).

estimated at 48,804.21 t, 1,771.97 t, 289.47 t, and 169.97 t, respectively (Fig. 5).

Structural Composition of Pollutant Sources

The structural analysis reveals a high degree of source concentration. As illustrated in Fig. 4, large livestock farming (yaks, cows, etc.) is the absolute dominant contributor to the basin's pollution matrix, accounting for 94.15% of COD, 87.08% of TP, and 87.13% of TN total loads. This reflects the typical pastoral-driven pollution characteristic of the Tibetan Plateau, where livestock manure is often deposited in riparian zones and flushed into the river system during rainfall events.

Conversely, the source profile for NH_3-N exhibits a distinct pattern. Unlike other pollutants, rural domestic sewage is the primary driver for NH_3-N, contributing significantly to the total load – particularly in Gongbujiangda County, where it accounts for 64.29% of the local NH_3-N discharge. This disparity suggests that while organic and nutrient enrichment (COD, TN, TP) is primarily a byproduct of the livestock industry, nitrogenous toxicity (NH_3-N) is more closely linked to the lack of decentralized wastewater treatment infrastructure in rural settlements [29].

Spatial Loading Heterogeneities

Spatially, the upstream Gongbujiangda County exhibits significantly higher pollution loads across all four indicators compared to the downstream Bayi District. Specifically, the COD load in Gongbu Jiangda is 33.7% higher than in Bayi. This spatial gradient aligns with the water quality identification results, where the upstream K1 and K2 sections showed higher risk indices. The higher loading in the upstream is primarily attributed to the larger grazing area and higher density of traditional pastoral activities in the Gongbu Jiangda highlands.

In conclusion, the priority control strategy for the Niyang River must be differentiated: livestock waste management should be the focus for reducing COD and TN/TP basin-wide, while rural sewage treatment upgrading is critical for mitigating NH_3-N pollution, especially in the upstream townships.

Response of River Water Quality to NPS Loading Patterns

The water quality of the Niyang River is intrinsically linked to the basin's socio-economic structure, which is dominated by tourism and alpine agriculture/animal husbandry. With minimal industrial activity, the river's hydro-chemical characteristics are primarily governed by agricultural NPS pollution, particularly during the wet season when high-intensity precipitation facilitates the transport of pollutants from valley-based pastoral and agricultural lands into the mainstream [30].

Spatial Coupling of Loads and Concentrations

To explore the source-sink relationship, a nested analysis was conducted comparing the in-stream pollutant concentrations with the watershed unit area loads (Table 3). The results reveal a strong spatial synchronicity between upland loading and downstream water quality.

COD and Organic Enrichment: The highest COD concentration (26.35 mg/L) was recorded at the administrative boundary between Gongbujiangda and Bayi, followed by a gradual downstream dilution. The average concentration in the Gongbujiangda section (18.48 mg/L) significantly exceeded that of the Bayi section (14.04 mg/L). This trend is highly consistent with the NPS intensity: Gongbujiangda's unit COD load (2166.82 kg/km²) is 127.11 kg/km² higher than Bayi's (2039.71 kg/km²), confirming that higher upstream grazing intensity directly drives organic pollution levels.

Nutrient (TN & TP) Dynamics: TN concentrations peaked at the river source (0.74 mg/L) and showed a clear attenuation trend downstream. The upstream TN concentration (0.59 mg/L) was nearly 2.7 times higher than the downstream (0.22 mg/L), echoing the higher unit area load in Gongbu Jiangda (78.14 kg/km²) compared to Bayi (74.72 kg/km²). Similarly, TP concentrations and loads were both higher in the upstream reaches, although the absolute differences were smaller (Table 3).

The NH_3-N Anomaly: Notably, while NH_3-N concentrations were higher in the Gongbu Jiangda section (0.13 mg/L vs. 0.07 mg/L), the calculated unit area load was slightly lower than in Bayi (6.96 vs. 7.84 kg/km²). This discrepancy suggests that NH_3-N levels in the upper reaches may be influenced by point-source-like discharges from concentrated rural settlements or specific headwater ecological factors rather than purely area-based runoff.

Mechanism of Responsive Relationship

The synergy between the pollution (contribution rates) validates a responsive relationship. The dominance of large livestock as the primary source of COD, TN, and TP (Fig. 6) explains why the Gongbujiangda section – characterized by extensive pastoralism – exhibits poorer water quality. The strong homogeneity between COD-TP and TN-NH_3-N during the wet season further confirms that rainfall-induced runoff is the primary vehicle for transporting these agricultural NPS loads into the Niyang River mainstream [31].

Spatial Autocorrelation and Clustering Patterns of Water Quality

To further elucidate the spatial dependency and aggregation characteristics of pollutants in the Niyang River, the Global Moran's *I* index was calculated using

Table 3. Correlation between NPS unit area loads and average in-stream concentrations.

Pollutant	Region	Unit Area Load (kg/km²)	Avg. Concentration (mg/L)	Correlation Trend
COD	Gongbu Jiangda	2166.82	18.48	Positive Coupling
	Bayi District	2039.71	14.04	
TN	Gongbu Jiangda	78.14	0.59	Positive Coupling
	Bayi District	74.72	0.22	
TP	Gongbu Jiangda	12.74	0.02	Positive Coupling
	Bayi District	12.24	0.01	
NH_3-N	Gongbu Jiangda	6.96	0.13	Spatial Lag/Anomaly
	Bayi District	7.84	0.07	

a GIS-based spatial analysis platform. The Moran's *I* values for COD, TN, TP, and NH_3-N were 0.9486, 0.8592, 0.1406, and -0.3745, respectively (Table 4).

High-Efficiency Clustering of COD and TN

The results indicate that COD (*I* = 0.9486) and TN (*I* = 0.8592) exhibit extremely strong positive spatial autocorrelation. This suggests that the concentrations of these two pollutants are not randomly distributed but show significant spatial dependency.

High-High Clustering: Observed in the upstream Gongbu Jiangda section, where high-intensity pastoral activities create a continuous high-pollution zone.

Low-Low Clustering: Observed in the downstream Bayi section, where the river's self-purification capacity and increased baseflow result in a stable low-concentration zone [32]. This continuity in spatial distribution validates that COD and TN are driven by broad-scale land-use patterns (e.g., extensive grazing) rather than isolated point sources.

Spatial Fragmentation of TP and NH_3-N

In contrast, TP (*I* = 0.1406) showed a weak spatial correlation, indicating that its distribution is more localized and influenced by specific geochemical factors or intermittent agricultural runoff.

Most notably, NH_3-N exhibited a negative Moran's *I* value (-0.3745), suggesting a spatially dispersed or checkerboard pattern. This negative autocorrelation implies that high-concentration segments are often adjacent to low-concentration segments, with no significant clustering. These findings align with

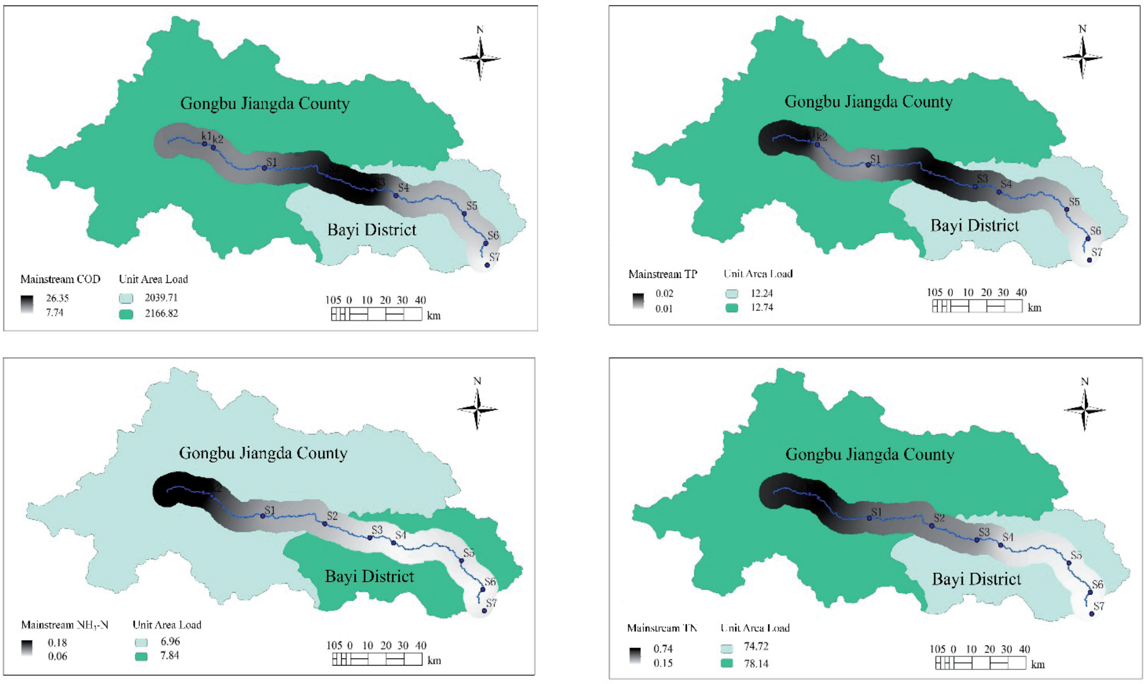

Fig. 6. Spatial distribution of in-stream water quality vs. NPS unit area loads.

Table 4. Global Moran's *I* index and spatial distribution characteristics.

Indicator	Moran's *I* Value	Z-Score	P-Value	Spatial Pattern
COD	0.9486	> 2.58	< 0.01	Strong Positive Correlation (Clustered)
TN	0.8592	> 2.58	< 0.01	Strong Positive Correlation (Clustered)
TP	0.1406	1.65	> 0.10	Weak Correlation (Random)
NH_3-N	-0.3745	< -1.96	< 0.05	Negative Correlation (Dispersed)

the analysis, confirming that NH_3-N is primarily driven by localized rural domestic sewage discharges from scattered settlements, which lack the spatial continuity seen in livestock-driven pollution [33].

Synthesis of Spatial Differentiation

Overall, the Niyang River mainstream demonstrates distinct spatial differentiation. The strong homogeneity and clustering of COD and TN reflect the dominant impact of the upstream livestock industry. The spatial fragmentation of NH_3-N highlights the impact of decentralized anthropogenic activities. These spatial insights suggest that water environment management should transition from uniform basin-wide control to zone-specific targeted intervention, focusing on upstream pastoral clusters for COD/TN and township-level infrastructure for NH_3-N [34].

Integrated Management Strategies and Mitigation Pathways for Watershed Sustainability

The spatial-temporal analysis of the Niyang River basin reveals a complex interplay between traditional pastoralism and aquatic ecosystem sensitivity. The high organic loading (COD) and nutrient enrichment (TN, TP) primarily originate from the upstream grazing clusters, while NH_3-N exhibits a fragmented, settlement-driven pattern. Addressing these challenges requires a shift from conventional end-of-pipe treatment to a holistic Source-Process-Sink management paradigm tailored to the plateau environment.

Riparian Buffer Optimization for Source-Sink Interception

The strong spatial autocorrelation of COD and TN (I>0.85) suggests that the river's water quality is highly sensitive to terrestrial runoff from adjacent pastoral lands. Establishing Ecological Riparian Buffer Zones (ERBZs) serves as a critical Sink to intercept pollutants.

In the high-altitude context of the Niyang River, the efficacy of ERBZs is governed by the Source-Sink theory [35]. For the High-High clustering zones identified in Gongbu Jiangda, a multi-layered buffer strip is essential. This involves:

Mechanical Interception: Utilizing native grasses and shrubs to reduce the kinetic energy of surface runoff, thereby promoting the sedimentation of phosphorus-rich particles [36].

Biogeochemical Transformation: Given the low microbial activity in cold plateau soils, the selection of cold-tolerant rhizospheric species is vital to enhance the denitrification process and organic matter decomposition before nutrients reach the mainstream [37].

Hotspot Targeted Design: In sections with peak concentrations (e.g., K1 and S3), the buffer width should be scientifically extended based on slope and soil permeability to maximize the filtration effect during the intensive wet season.

Circular Nutrient Loops for Livestock-Dominant Pollution Control

The fact that large livestock farming contributes over 87% of the total COD, TN, and TP loads indicates that the basin's carrying capacity is being challenged by traditional extensive grazing. To mitigate this, a circular agricultural system must be implemented to decouple livestock growth from environmental degradation.

As conceptualized in Table 5, this strategy transforms the Linear Waste Model into a Nutrient Recycling Loop.

Manure-to-Fertilizer Conversion: By establishing decentralized manure collection points and centralized organic fertilizer processing plants, the high organic load can be diverted from the river to the agricultural valleys of Bayi District. This effectively reduces the Export Coefficient of the pastoral sector [38].

Land-based Assimilation: Promoting the use of organic fertilizers in crop cultivation not only reduces chemical fertilizer runoff but also improves soil structure and water retention on the plateau. This Synergistic Control addresses the NPS issue at its economic root, ensuring that the nutrient output of the upstream pastoral zone stays within the assimilative capacity of the downstream agricultural zone [39].

Multi-Level Governance and Behavioral Intervention for Decentralized Pollution

The dispersed spatial pattern of NH_3-N (negative Moran's I) and its correlation with rural domestic sewage highlight a governance gap. Unlike the land-use-driven livestock pollution, NH_3-N is a social-ecological

Table 5. Multi-level socio-ecological governance framework.

Level	Governance Focus	Theoretical Basis	Implementation Pathway
Institutional	Regulatory Oversight	Top-down Control	Strict enforcement of Red Lines for grazing; funding for decentralized sewage treatment.
Operational	Technical Support	Process Optimization	Implementing River Chief systems; providing green farming skills training to herders.
Community	Behavioral Norms	Polycentric Governance	Localizing environmental laws into Village Covenants to foster collective action.

problem rooted in decentralized human behavior and inadequate infrastructure.

To ensure long-term sustainability, management must move beyond technical fixes. As NH_3-N pollution is highly localized, the River Chief system should be integrated with community-based monitoring. By transforming abstract legal principles into tangible behavioral guidelines – such as proper waste disposal and restricted grazing zones – the basin can transition toward a co-governance model. This approach empowers local herders and residents as the primary stewards of the Water Tower of Tibet, ensuring the resilience of the Niyang River's water environment [40].

Conclusions

This study systematically investigated the spatio-temporal dynamics and source apportionment of nutrient loading in the Niyang River by developing a multi-dimensional diagnostic framework that couples the CPI, a refined OCM, and stoichiometric correlation analysis. By monitoring nine representative sections across contrasting hydrological seasons, the research successfully bridged the gap between ambient concentration-based risk profiling and land-use-driven pollution flux calculation, identifying a distinct spatial purification gradient and pinpointing the dry season as the critical window for management due to reduced dilution capacity. A key innovation of this work is the validation of a synchronous transport-source mechanism through strong stoichiometric coupling (COD-TP and TN-NH_3-N), which confirms that pastoral waste and agricultural runoff are functionally integrated pollution drivers rather than independent factors, ultimately establishing COD as the primary risk indicator in this high-altitude fragile ecosystem.

The findings demonstrate that the synergistic application of concentration-load modeling provides a robust precision-targeting tool for water quality management in the Third Pole region, offering a scientific template for ecological preservation in similar alpine basins. However, future research must address the evolving challenges posed by climate-driven shifts, such as accelerated glacier melt and permafrost degradation, which significantly alter pollutant transport pathways and residence times. Furthermore, investigating the micro-scale kinetics of nutrient degradation by unique microbial communities under extreme low-temperature conditions and integrating higher-resolution remote sensing data will be essential to refining the Output Coefficient Model, ensuring more dynamic and adaptive water resource management strategies in response to the rapid socioeconomic development of the Qinghai-Tibet Plateau.

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During the preparation of this manuscript, the authors used AI-assisted language tools solely for linguistic refinement, translation assistance, grammar checking, and academic phrasing optimization. These tools were not involved in any aspect of scientific conception, experimental design, data collection, statistical or spatial analysis, model development, or interpretation of results. All intellectual content, methodological frameworks, empirical findings, and conclusions are entirely the work of the human authors. The authors take full responsibility for the accuracy, integrity, and scientific validity of the manuscript.

Conflict of Interest

The authors declare no conflict of interests.

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