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Network Topology and Digital-Intelligent Empowerment for Three Water Integration in the Upper Yellow River

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Abstract

The integrated governance reform of water resources, water environment, and water ecology (Three Water Integration, TWI) is essential for addressing complex ecological risks in river basins. However, existing studies lack an integrated digital-intelligent platform to support basin-wide assessment. This study develops a framework that integrates a digital-intelligent platform with network analysis to quantify governance evolution and propose county-level strategies. We apply the framework to the Upper Yellow River Basin (2000–2024) using multi-source data. We construct a “Sustainable Water Cube Space” network, identifying four stable indicator clusters: socio-economy, water resources, water environment, and water ecology. We also identify 18 key “bridge” indicators based on network centrality. Network stability tests (Jaccard similarity = 0.76) and multi-temporal topological evolution analysis reveal a governance paradigm shift: the focus transitioned from economy-driven to ecology-economy-coordinated development from 2000 to 2022. We also observe that economic growth has decoupled from environmental degradation, with the correlation between these indices dropping from 0.72 to 0.34. Attribution analysis identifies pollution control (42%) and ecological restoration (35%) as the primary drivers of improvement. Finally, we propose differentiated governance strategies for eight counties based on their local characteristics. This study provides a replicable, data-driven framework for quantifying TWI governance evolution and informing county-differentiated strategies at the watershed scale.

Keywords: three water integration; coupled network analysis; digital intelligence platform; Upper Yellow River; SDG indicators

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1. Introduction

Sustainable watershed governance faces complex coordination challenges that span multiple dimensions. In the context of ecological civilization development, governance paradigms are shifting from single-element management toward the integrated reform of water resources, water environment, and water ecology—known as “Three Water Integration” (TWI). This framework has become a core strategy for China’s water governance and has been consistently reinforced in national water pollution control policies [1–3]. However, translating this paradigm into practical, quantifiable governance tools remains a critical challenge that requires urgent attention.

Contemporary research on coordinated water governance has evolved into four interconnected thematic strands, yet each reveals critical limitations in addressing the complexity of “Three Water Integration” (TWI). First, regarding assessment frameworks, while recent scholarship has moved from single-dimensional indicators to integrated paradigms [3–5], these frameworks largely treat water environment, resources, and ecology as parallel systems. This failure to account for structural interdependencies limits the analytical depth of existing TWI models [3]. Second, although network analysis and complexity theory are well-established for studying social-ecological resilience [1,6] and identifying development pathways via indicator proximity [7,8], their systematic integration to characterize the coupled dynamics of TWI at the watershed scale remains absent [6,9]. Third, while digital-intelligent platforms have demonstrated success in multi-sectoral data integration and coupled system modeling [10–12], the simultaneous coupling of such platforms with network-based indicator analysis for county-differentiated governance is not yet fully operationalized. Finally, despite the proven value of SDG-aligned network approaches in identifying systemic tensions among water, food, energy, and economic development [2,9,13–18], these frameworks have not been extended to produce spatially differentiated, county-scale governance strategies in regions like the Yellow River Basin. A summary of representative studies across these four thematic streams is provided in Table A1 (see Appendix A).

These gaps are compounded by methodological and application-level barriers. At the methodological level, studies remain confined to specific disciplinary pathways—such as hydrology, ecology, or economics—which prevents the simultaneous capture of cross-element feedback and multidimensional transmission [4,5,19]. Furthermore, the structural instability inherent in traditional network analysis often limits its applicability for long-term, reliable policy monitoring [15]. At the application level, the lack of a unified digital management platform results in data silos and decision-support delays across administrative sectors, which hinders the implementation of evidence-based, county-differentiated governance strategies [12].

Recent methodological advances have opened viable pathways to fill these gaps. Complex network analysis has proven effective in identifying cascading effects in human-nature coupled systems [6,9]. For example, Chen et al. (2025) employed network analysis to reveal complex interactions among ecosystem services in the Yangtze River Economic Belt [20]; Zhou et al. (2025) used complex networks to examine the impacts of demographic changes on agricultural production under urban–rural transition scenarios [21]. In the domain of SDG assessment, Ma et al. (2025) proposed an “SDG space” to quantify priorities and spillover effects across different country groups [16]; Gong et al. (2024, 2025) further analyzed complementarities in sustainable development pathways and demonstrated that the governance paradigm in the lower Yellow River basin (Shandong Province) is shifting from an economy-driven to an ecology–economy-coordinated structural evolution [17,18]. Meanwhile, rapid advances in digital intelligence technologies have made real-time collection and decision-oriented analysis of multi-source heterogeneous data feasible, providing robust technical support for constructing a watershed-scale coupled network with both structural stability and temporal interpretability.

The Upper Yellow River basin (from Guinan to Minhe in Qinghai Province) provides a typical empirical context for addressing these challenges. As a key water source conservation area for the Yellow River headwaters, this region experiences per capita water resources of less than 500 m³ and faces multiple pressures, including water scarcity, combined point and non-point source pollution, and aquatic ecological degradation. The effectiveness of watershed governance here is critical not only for local ecological security but also for downstream areas, which receive approximately 7×10^9 m³ of water annually while possessing per capita water resources of only 344 m³. Any systemic degradation in

the upper reaches can propagate downstream, affecting water resource availability and socioeconomic stability through weakened ecosystem services and exacerbated water security risks.

To address these gaps, this study takes the Upper Yellow River basin (2000–2024) as the research area. By integrating a TWI database with a digital-intelligent management platform, we construct a “Sustainable Water Cube Space” coupled network incorporating 53 SDG-aligned indicators. This framework moves beyond existing isolated assessments by reinterpreting “product proximity” as indicator co-improvement probability—a conceptual extension that transforms economic complexity theory into a tool for environmental governance. Methodologically, we achieve a systematic integration of proximity networks, betweenness centrality, and complexity indicators to resolve the challenge of producing temporally stable, county-differentiated governance strategies. Our innovation lies not in the individual components, but in the coupling of a cross-sectoral digital platform with network analysis, providing a replicable paradigm for data-driven, evidence-based basin management. Guided by these objectives, this study addresses three fundamental scientific questions: Q1: How do the 53 SDG-aligned TWI indicators in the Upper Yellow River basin form stable coupling clusters across spatial and temporal dimensions, and what structural mechanisms underlie these patterns? (H1: TWI indicators exhibit persistent modular clustering that reflects systematic interdependencies rather than random co-variation.) Q2: Can the temporal evolution of network topology (2000–2022) reveal a quantifiable governance paradigm shift from economy-driven to ecology–economy-coordinated development? (H2: Changes in bridging indicator composition and inter-cluster correlation strength will reflect a measurable decoupling of economic growth from pollution pressure.) Q3: How can bridge indicators identified through network analysis be translated into differentiated, evidence-based governance strategies at the county scale? (H3: Counties with distinct network positions and indicator profiles require structurally different intervention priorities, derivable from betweenness centrality and complexity metrics.) These questions directly correspond to the three literature gaps identified above and provide a structured framework for the methodological design and result interpretation that follows.

2. Materials and Methods

2.1. The Study Site

The study area is located in the southeastern part of Qinghai Province, encompassing the upper reaches of the Yellow River from Guinan to Minhe (99° E–103° E, 34° N–37° N). This region spans approximately 39,022 km² and includes eight county-level administrative units: Guinan, Gonghe, Guide, Tongren, Jianzha, Xunhua, Hualong, and Minhe (Figure 1). The topography is characterized by significant vertical differentiation, with elevations ranging from 2000 to 4500 m. The ecosystem comprises alpine meadows (42%), forests (15–18%), wetlands (3–5%), and various agricultural lands. The river system includes the main stem of the Yellow River, 14 tributaries, eight large reservoirs, and two major wetlands. As a key water conservation area, this region plays a vital role in sustaining downstream water quality and ecological security [2].

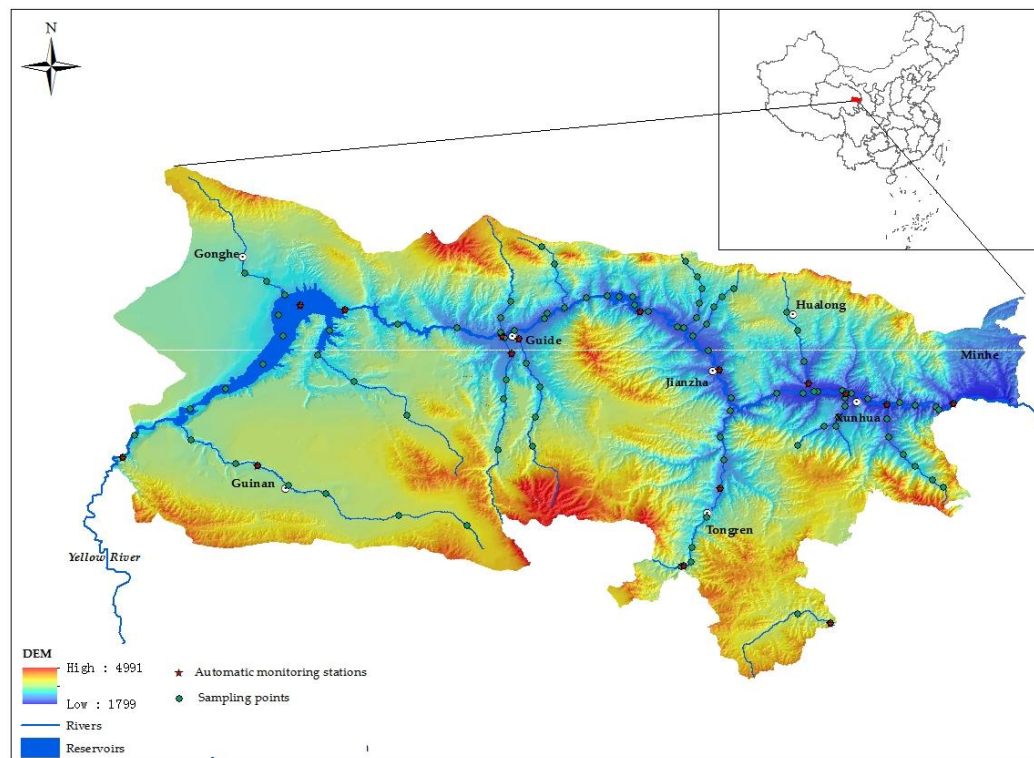


Figure 1. Study area map of the Upper Yellow River Basin (Guinan-Minhe segment), Qinghai Province, China.

2.2. Evaluation Indicator System and Analysis Methods

2.2.1. Digital Intelligent Platform Construction

To support the integrated monitoring, assessment, and supervision of TWI, this study adopted a top-level design combining microservices and modularization. By integrating a data lakehouse architecture and stream-batch processing, we established a foundational TWI database and a comprehensive management platform. This platform enables the centralized management of multimodal, multi-source, heterogeneous data, providing unified data support for subsequent calculations and spatiotemporal analysis.

The platform adopts a “5 + 2” digital intelligent comprehensive management overall architecture, which is, from bottom to top, the infrastructure layer, lakehouse integration layer, intelligent middleware layer, service support layer, and interaction application layer. Two guarantee systems, namely the standard specification system and the operation and maintenance security system, run through all levels of the architecture. From the aspects of technical standards, management specifications, and safety protection, they provide comprehensive support for the long-term stable, efficient, and safe operation of the platform, ensuring the reliability and security of data and business applications.

2.2.2. TWI Evaluation Indicator System

Based on the integrated database, we developed a multi-dimensional evaluation system comprising 53 indicators aligned with the Sustainable Development Goals (SDGs). The 53 SDG-aligned indicators were selected through a structured three-step process: (1) a systematic literature review of TWI-relevant indicators applied in Chinese watershed governance studies; (2) expert consultation with regional water authority practitioners to assess local applicability; and (3) data availability screening to ensure complete time-series coverage across all eight counties for the period 2000–2024. Equal weighting was applied

across indicators within each cluster, reflecting the absence of an established domain-specific weighting scheme for integrated TWI assessment. We acknowledge this as a methodological limitation and note that future work incorporating stakeholder-derived or entropy-based weighting may refine the results.

To accommodate the absence of an established domain-specific weighting scheme, equal weighting was applied across indicators within each cluster. The evaluation framework is divided into five core operational dimensions.

(1) Water environment quality assessment: We follows the Environmental Quality Standards for Surface Water (GB 3838-2002)[22]. We used the single-factor method to categorize standard chemical parameters (pH, dissolved oxygen, permanganate index, ammonia nitrogen, and total phosphorus). For heavy metals in sediments (Hg, Pb, Cd⁶⁺), a comprehensive index method was applied using regional background values to identify pollution hotspots. Non-point source loads were attributed through hydrological segmentation and source apportionment across wet and dry seasons [23].

(2) Water resources assessment: We employed the Tennant method to determine ecological flow thresholds [24], mapping monthly runoff as a percentage of average flow to ecological classes. Human disturbance intensity was quantitatively characterized by calculating the reclaimed water reuse rate and the water resources utilization rate.

(3) Comprehensive water ecological assessment: We integrated the Shannon-Wiener, BMWP, and Simpson diversity indices to characterize plankton and benthos communities. A comprehensive Ecological Quality Index (EQI) integrated three core parameters—vegetation coverage, biodiversity, and habitat connectivity—to evaluate ecological health.

(4) Water conservation function: Water conservation capacity was estimated via a water balance model calculating the difference between precipitation, evapotranspiration (MODIS ET) [25], and runoff. Soil and water conservation functions were estimated using a locally calibrated Revised Universal Soil Loss Equation (RUSLE) model to compute the annual erosion modulus [26].

(5) Wetland area: Remote sensing inversion methods were used to monitor wetland areas. We applied the Normalized Difference Water Index (NDWI) to extract boundaries from multi-temporal Landsat images to evaluate spatial trends [27].

2.2.3. Assessment Time Framework

The assessment period spans from 2000 to 2024. We selected 2000, 2005, 2010, 2015, and 2020 as baseline nodes to construct long-term evolution sequences across five distinct time slices, supplemented by continuous annual data to fill intervals. This temporal setup directly aligns with three major national policy milestones to evaluate governance effectiveness: the Action Plan for Prevention and Control of Water Pollution (abbreviated as the “Ten Measures for Water”, 2015), the period of intensified ecological civilisation construction (2019–2021), and the period of high-quality development strategy promotion (2022–present) [3]. By matching indicator evolution trends with the timing of these policy nodes, the actual effectiveness of governance interventions at each stage can be systematically evaluated.

2.2.4. Spatiotemporal Pattern Analysis Methods

The analytical framework used to process the integrated data and evaluate basin dynamics comprises three core methods.

(1) Trend analysis: Linear regression was used to extract long term slopes of each indicator to identify overall development trends. For indicators exhibiting abrupt change points, segmented regression models were applied to identify breakpoint years [28], which was then compared with policy nodes (e.g., the “Ten Measures for Water” in 2015,

the ecological civilisation strengthening period 2019–2021) to discern the actual response effects of policy implementation.

(2) Policy effect evaluation: The synthetic control method and propensity score matching (PSM) were employed to construct counterfactual scenarios [29], separating the net effect of policy interventions from the contribution of natural changes. Counties that received formally designated watershed governance interventions—specifically those included in the national “Three Waters” co-governance pilot programme launched in 2015—were assigned to the treatment group, while counties sharing comparable biophysical and socioeconomic characteristics but not yet subject to the intervention during the study window were assigned to the control group. For PSM, matching was performed on a set of pre-intervention covariates including per capita GDP, population density, and the proportional composition of land-use types (cultivated land, forest, and built-up area), as well as their linear trends over the five years preceding the intervention, to ensure baseline comparability between treated and control units. The outcome variables were defined as the annual TWI composite score and its three sub-index scores (water environment, water resources, and water ecology), measured at the county level. The synthetic control method complemented PSM by constructing a weighted combination of control counties that best reproduced each treated county’s pre-intervention outcome trajectory, thereby providing a county-specific counterfactual against which post-intervention TWI trajectories were compared. The difference between observed and counterfactual trajectories was taken as the estimated net policy effect.

(3) Spatial hotspot analysis: The Getis-Ord statistic was used to identify high-value and low-value clusters of indicators [30]. Combined with kernel density estimation, hotspot distribution maps were generated to provide spatial guidance for differentiated management.

The above analyses were implemented using the Python scientific computing ecosystem, with specific tools including networkx (network analysis), scikit-learn (data preprocessing), pandas (data management), and GDAL/rasterio (remote sensing image processing).

2.3. Construction of the Coupling Network for the “Sustainable Water Cube Space”

2.3.1. Framework Translation Logic

We translated the economic “product space” framework from national comparative advantage analysis to watershed TWI-coordinated governance. Instead of characterizing export co-occurrence, indicator proximity (ϕ) is redefined as the conditional probability that two TWI indicators synergistically improve or degrade within the same county and year [7,8,17,18]. Formally, the proximity between any two indicators i and j is defined as the smaller of their two directional conditional probabilities:

$$\phi_{ij} = \min(P(\Delta I_i > 0 \mid \Delta I_j > 0), P(\Delta I_j > 0 \mid \Delta I_i > 0))$$

This symmetric and conservative approach ensures that co-improvement must be mutually reinforcing rather than unidirectional. Proximity values range from 0 to 1, and only indicator pairs with $\phi > 0.55$ were retained as significant edges.

2.3.2. Proximity Network Construction and Community Detection

Using the standardized time-series database across eight counties (2000–2024), we calculated the synergistic relationships for all indicator pairs, yielding a 53×53 symmetric proximity matrix. Filtering with the threshold ($\phi > 0.55$) ensured that the network’s modularity (Q) consistently exceeded the random-network benchmark of 0.3 [8]. A weighted undirected network was then constructed, and the Louvain algorithm was applied to

maximize modularity Q and identify stable indicator communities [31]. These communities represent functional, synergistic units across the TWI and socioeconomic subsystems.

2.3.3. Bridge Indicator Identification

Three centrality indices were calculated and combined to systematically characterise intervention nodes. Betweenness centrality (BC) measures the frequency with which an indicator acts as a “bridge” on the shortest paths between other nodes, and a high BC value indicates cross-subsystem coupling hub [32]. Eigenvector centrality (EC) accounts for neighbour weights, capturing high-order cascade effects and being sensitive to systemic risk propagation [33]. The Complexity Indicator (IC_j) adapts the Method of Reflections from economic complexity theory to quantify the structural sophistication of each TWI indicator [7,8]. A binary county–indicator matrix was first constructed for each year, in which a county–indicator cell was assigned a value of one if the county achieved above-median performance on that indicator and zero otherwise. Two summary measures were then derived from this matrix: diversity, defined as the number of indicators on which a given county performs above the median, and ubiquity, defined as the number of counties that perform above the median on a given indicator. These two measures were iteratively updated in alternating steps—each county’s score being re-expressed as the average ubiquity of the indicators it achieves, and each indicator’s score being re-expressed as the average diversity of the counties that achieve it—until the values converged, typically within 18 to 20 iterations. IC_j was finally extracted from the eigenvector associated with the second-largest eigenvalue of the normalised county–indicator matrix and rescaled so that higher values correspond to indicators that require broader and rarer governance capabilities simultaneously. This procedure reveals “hidden transformations” in TWI governance—structural recombinations that remain invisible to aggregate scoring yet become detectable through the co-achievement topology of the proximity network.

2.3.4. Network Stability Tests

To ensure the scientific validity of the network, the Jaccard coefficient was used to measure the overlap degree of sets in adjacent years, and a high value indicates topological robustness [15]; community robustness was measured by the modularity Q value ($0-1$), and $Q > 0.3$ is statistically significant; indicator significance was tested by two-tailed permutation test ($\alpha = 0.05$), compared with the random network benchmark [6].

3. Results

3.1. Construction of the Integrated TWI Database and Integration of the Digital Intelligence Platform

3.1.1. Multi-Source Heterogeneous Data Submission

We constructed a comprehensive TWI database containing 2.5 million records, integrating water environment surveys, water resources monitoring, ecological investigations, basic geography, and remote sensing imagery for the Upper Yellow River Basin. The compiled database consists of 65% structured, 15% semi-structured, and 20% unstructured data. To ensure long-term data reliability, all data types were centralized within a relational database and object storage framework under strict quality control protocols, achieving an overall data efficiency rate of 98.2%.

3.1.2. Digital and Intelligent Platform Construction

Functional modules such as TWI situation monitoring and evaluation, comprehensive display of water ecological environment situation, and water ecological environment

supervision application in the Yellow River Basin (Guinan to Minhe section) were developed. Based on the standardized API interfaces and interactive dashboards of the “5 + 2” platform, the closed-loop management of the whole process from source data access to evaluation and analysis was realized. This enables management departments to obtain key indicators, conduct situation research and judgment, and initiate emergency responses within hours, promoting the transformation of decision-making mode from experience-driven to data-driven, and providing comprehensive support for ecological protection and supervision. The functional of Digital Intelligent Platform is shown in Figure 2.

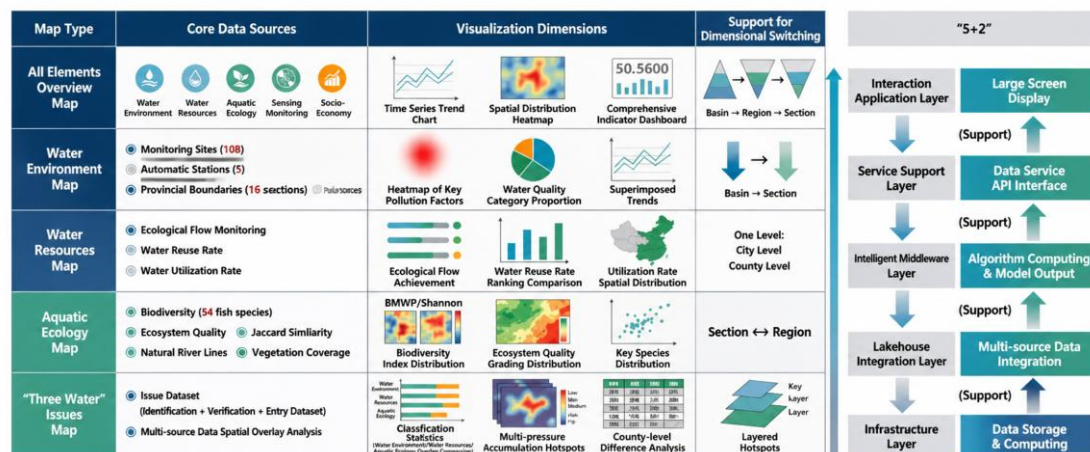


Figure 2. Functional design and application of the digital intelligent platform for TWI Management.

3.2. Comprehensive Evaluation of the TWI System

3.2.1. Evaluation Framework

A multi-dimensional evaluation system benchmarking 53 SDG indicators was constructed, covering four dimensions: water environment, water resources, water ecology, and ecosystem functions. It integrates 9 core evaluation modules (Table 1), realizing a full-chain closed loop from source data collection, data processing, scientific evaluation and analysis to decision support output.

Table 1. Core assessment modules and their data sources.

Evaluation Module	Data Source	Monitoring Frequency	Spatial Coverage	Quality Indicator
Water Environment Quality	108 collection points, 16 national/provincial control points, 5 automatic stations	Monthly/Daily	Main stream, Tributaries	Compliance rate 99.3%
Sediment Pollution	145 sampling points	Annual	Key river sections	Validity rate 98.2%
Ecological Flow	Daily flow from 5 control stations	Daily	5 main sections	Continuous monitoring
Water Resources Utilization	Water use statistics, Remote sensing evapotranspiration	Monthly	Full coverage of 8 counties	Data completeness rate 98%
Aquatic Organisms	600 on-site collected samples	Flood season sampling	54 fish species, Zooplankton	Species identification rate 99%
Ecological Quality Index (EQI)	Remote sensing, On-site investigation	Multi-period	Whole basin coverage	Accuracy 85%
Water Conservation	MODIS ET, Precipitation, Runoff	Monthly	Whole basin	Model verification $R^2 = 0.85$
Soil and Water Conservation	Remote sensing interpretation, DEM, Precipitation	Annual	Whole basin	RUSLE local calibration

Wetland Monitoring	Landsat images	5-year interval, Annual	15 rivers, 8 lakes and reservoirs	NDWI accuracy 90%
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3.2.2. Water Environment Evaluation

Empirical assessments demonstrate that the overall water quality in the study area remained stable and satisfactory from 2021 to 2024. The proportion of monitoring sections achieving excellent or good water quality (Class I–III) across 15 major rivers consistently fluctuated between 98.3% and 100%.

3.2.3. Water Resources Evaluation

Hydrological monitoring indicates that ecological flow requirements were generally met, with the average water development and utilization rate remaining below the critical warning line across the basin. However, significant spatial disparities exist at the county scale: the water resource development and utilization rate in Minhe County reached a high level of 38.74%, whereas in Tongren City, it remained at a low level of only 4.29%. Furthermore, a gap remains between the current reclaimed water reuse rate and national sustainability targets.

3.2.4. Water Ecological Monitoring and Functional Evaluation

Biological surveys capturing 600 comprehensive records identified a healthy aquatic community structure, comprising 54 fish species and over 120 zooplankton species. The EQI exhibited a significant upward trend compared to the 2000 baseline. From 2000 to 2023, the average annual water conservation volume reached $4.21 \times 10^8 \text{ m}^3$, accompanied by a steady increase in soil and water conservation functions, as evidenced by a gradual reduction in the annual soil erosion modulus. Concurrently, wetland areas expanded across most administrative units, with the most pronounced growth rates observed in Guinan, Jianzha, and Tongren.

The platform’s analytical integration reduced emergency response times for flood-season non-point source pollution by 75%, compressing the operational window from 24 h to 6 h. This shift was validated during the 2023–2024 flood season, where the platform automatically captured and closed pollution incidents via a digital workflow tracking discovery, automated classification, task assignment, and final remediation.

3.3. Construction and Analysis of the “Sustainable Water Cube Space” Coupling Network

3.3.1. Identification of Stable Indicator Clusters and Synergistic Structures

By applying Louvain community detection to the symmetric proximity matrix, we identified four cross-temporally stable indicator clusters that define the multidimensional structure of the watershed system.

Cluster 1 (socio-economic development) includes 8 indicators such as GDP, per capita income, industrial structure, employment rate, population density, proportion of the tertiary industry, industrial output value, and urbanization rate, reflecting the development pressure dimension. Cluster 2 (water resources sustainability) includes 6 indicators such as surface water quality category, drinking water quality, per capita available water volume, water use efficiency, reclaimed water reuse rate, and ecological flow satisfaction, forming the water supply security dimension. Cluster 3 (water environment quality) includes 15 indicators such as total pollutant discharge, COD/ammonia nitrogen/total phosphorus concentration, pesticide use intensity, industrial wastewater compliance rate, urban sewage treatment rate, and point and non-point source pollution load, depicting the pollution pressure dimension. Cluster 4 (aquatic ecology and ecosystem functions) includes 6 indicators such as the proportion of ecological red line area, vegetation coverage,

biodiversity index (Shannon-Wiener, BMWP), water conservation capacity, soil and water conservation function, and wetland protection rate, representing the ecological protection dimension.

Network analysis revealed the synergistic structure between cross-cluster indicators. For example, water environment pollution is negatively correlated with water resources utilization (inhibitory relationship), and economic development is weakly correlated with ecological functions (trade-off relationship). These relationships are quantitatively expressed in the network topology with different weights and connection modes. A total of 18 key “bridge” indicators were identified, with Betweenness Centrality (BC) > 0.55 and Eigenvector Centrality (EC) > 0.60. These indicators carry cross-cluster cascading effects and play a key controlling role in the resilience and evolution of the system structure.

3.3.2. Key “Bridge” Indicators and Cascading Effects

Topological analysis identified 18 critical bridge indicators acting as cross-cluster hubs based on centrality thresholds (Betweenness Centrality $BC > 0.55$; Eigenvector Centrality $EC > 0.60$). The structural role of these indicators underwent major historical transitions.

From 2000 to 2015, the core “bridge” indicators of the network were concentrated in the economic dimension, with the Betweenness Centrality (BC value) of indicators such as consumption expenditure, disposable income, and industrial output growth rate all exceeding 0.65. Economic indicators showed a strong positive correlation with environmental pollution indicators (correlation coefficient exceeding 0.72), and the connection between clusters showed a one-way strong flow characteristic, manifested as the economic indicator cluster (Cluster 1) unidirectionally linked to the pollution indicator cluster (Cluster 3).

Around 2015, the network indicator system underwent significant changes, with approximately six emerging ecological–economic coupling indicators entering the “bridge” role, including water consumption per 10,000 yuan of GDP, surface water quality target achievement rate, sewage treatment rate, and ecological red line area protection rate.

From 2019 to 2022, the network structure exhibited further changes. The distribution of BC values shifted from concentrated (dominated by a few economic indicators) to decentralised (jointly influenced by multiple ecological–economic coupling indicators), with the average BC value decreasing from 0.68 to 0.51. A two-way feedback pattern was observed between the water resources cluster (Cluster 2) and the ecological cluster (Cluster 4). The correlation coefficient between economic and pollution indices decreased from 0.72 in 2000 to 0.34 in 2022.

3.3.3. Network Quantification of Governance Paradigm Evolution

Across the seven sequential time nodes evaluated (2000, 2005, 2010, 2015, 2019, 2021, and 2022), the network exhibited high structural robustness, maintaining an average adjacent Jaccard similarity coefficient of 0.76. Although the modularity Q value slightly decreased from 0.42 (2000) to 0.38 (2022), it remained well above the random benchmark, confirming stable community organization.

The calculation results of the complexity index (IC_j) showed that in 2000, the pollution cluster (IC₃ = 1.45) was significantly higher than the ecological cluster (IC₄ = 0.62), indicating that economic development was mainly driven by pollution; by 2022, the water resources cluster (IC₂ = 1.12) and the ecological cluster (IC₄ = 1.09) tended to be equal, and both were higher than the economic cluster (IC₁ = 0.89), indicating that ecological–economic coordination had become dominant.

Topological changes driven by key policy events. After the 2015 Central Ecological Civilization Construction Conference, a new strong relationship emerged between Cluster 2 and Cluster 4, and the Betweenness Centrality (BC) of relevant bridge indicators increased from 0.35 to 0.52. From 2019 to 2021, the in-depth implementation of the Yellow River Basin Ecological Protection and High-Quality Development Strategy led to resource efficiency indicators represented by “water consumption per 10,000 yuan of GDP” with BC values exceeding 0.65, becoming a new generation of bridge indicators.

From 2000 to 2024, the coupled network exhibited a structural evolution characterised by systematic shifts in topology parameters. The modularity Q value, betweenness centrality (BC), and complexity indicator (IC) followed distinct quantitative trajectories across the study period, with the network transitioning through single-centre, multi-centre competitive, and multi-centre balanced configurations at four critical time points, as shown in Figure 3.

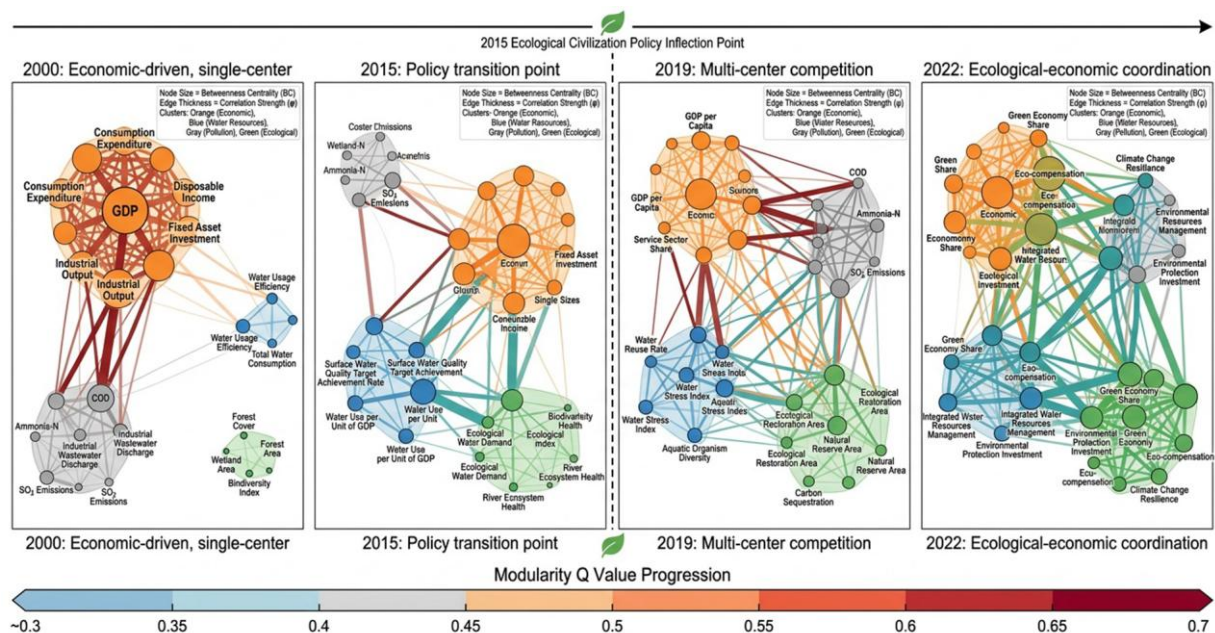


Figure 3. Network topology evolution trajectory of governance paradigm evolution (2000–2024). Among them, the four indicator clusters represent socio-economic development (red), water resources sustainability (blue), water environment quality (orange), and aquatic ecology (green). The node size indicates Betweenness Centrality (BC value), and the edge thickness indicates the correlation strength between clusters.

3.3.4. County-Level Spatial Heterogeneity and Differentiated Governance Directions

Hierarchical network analysis revealed distinct geographical-ecological typologies across the eight county-level administrative regions, leading to targeted governance strategies.

High-Altitude Ecological Priority Type (Guinan, Guide, and Jianzha Counties): Characterized by an ecological cluster $BC > 0.70$ and an economic cluster $BC < 0.35$. Situated at altitudes between 3200 and 3800 m, these counties feature high vegetation coverage (58%–71%) and robust water conservation capacity, yet low per capita GDP (21,000–28,000 yuan). In 2023, the EQI reached good levels in Jianzha (0.58) and Guide (0.55). The proposed strategy centers on ecological compensation coupled with ecotourism, prioritizing wetland restoration and regional eco-compensation to unlock the value of ecological assets.

Low-Altitude Economic–Ecological Balance Type (Minhe, Hualong, and Xunhua Counties): Defined by economic ($BC > 0.52$) and pollution ($BC > 0.60$) dominance. Located at lower altitudes (1600–2200 m), these areas feature dense industrial activity, high water resource utilization rates (38.74% in Minhe; 33.41% in Xunhua), and severe agricultural non-point source pollution. Guide and Tongren recorded the highest COD pollution loads at 100.1 t/a and 62.2 t/a, respectively, with agricultural runoff accounting for 47.4% of total inputs. The recommended strategy prioritizes a graded pollution control system, implementing water–fertilizer integration for agriculture alongside centralized industrial park wastewater treatment.

Balanced Development Type (Tongren City): Displaying balanced water resource ($BC > 0.58$) and ecological ($BC > 0.58$) centralities, with economic and pollution metrics at 0.46 and 0.48, respectively. Located at intermediate altitudes (1900–3100 m), Tongren exhibits optimal eco-economic coordination, featuring a 100% water quality compliance rate, the highest EQI (0.65), and significant gains in water conservation. The strategy focuses on eco-cultural integration, using investment in sustainable tourism infrastructure to position the city as an ecological civilization demonstration area that can drive green growth across neighboring counties.

4. Discussion

4.1. Theoretical Contribution of the “Sustainable Water Cube Space” Framework

This study extends the economic product space framework to the domain of watershed-scale-coordinated governance involving the water environment, water resources, and water ecology. While proximity networks, Louvain clustering, and centrality analyses are well-established individually, their purposeful integration in this study offers three primary theoretical advances: (1) the conceptual reinterpretation of “product proximity” as inter-indicator co-improvement probability—bridging economic complexity theory and environmental governance for the first time at watershed scale; (2) the coupling of a unified digital-intelligent platform that resolves cross-sectoral data fragmentation with network-based indicator analysis, enabling governance outputs that are simultaneously evidence-based, temporally trackable, and spatially differentiated; and (3) the generation of a quantifiable governance paradigm trajectory (rather than qualitative policy narrative), which offers methodological transferability to other data-scarce, multi-sector watershed governance contexts. The original framework characterizes national development pathways through product proximity. In this study, we reinterpret this concept as the probability that two TWI indicators co-improve or co-degrade across multiple counties, thereby quantifying the strength of association between indicators. This translation represents a paradigm upgrade from single-element assessment to multidimensional coupling analysis.

In traditional governance models, water quality, water resources, and ecological management are handled by different administrative sectors, and decision-making lacks insight into cross-dimensional interactions. Through coupled network analysis, this study identifies four temporally stable indicator clusters and 18 critical “bridge” indicators, revealing latent synergies and trade-offs among different dimensions. This framework engages productively with existing social–ecological network research: Bodin et al. (2019), Chen et al. (2025), and Zhou et al. (2025) have fully demonstrated the value of network approaches in coupled human–natural systems [1,20,21]. The contribution of this study lies in extending this methodological toolkit to the multidimensional coupling analysis of Sustainable Development Goal (SDG) indicators, thereby providing a replicable paradigm for sustainability assessment in similar watershed contexts.

4.2. Systematic Improvement in Governance Capacity Driven by the Digital Intelligence Platform

The digital intelligence platform constructed in this study integrates 2.5 million multi-source heterogeneous data records from different administrative sectors, time periods, and formats, thereby breaking the “data silo” pattern that characterizes traditional governance models. The platform enables unified data storage and management, achieving a 500-fold improvement in query efficiency (average number of retrievable records per query expanded from 50 to 25,000).

Nine core assessment modules operate synergistically within the platform, enabling automatic identification of non-point source pollution during flood seasons. Once a pollution indicator exceeds the preset threshold, the system automatically triggers an alarm, compressing the emergency response time from 24 h to 6 h. This rapid response allows most pollution events to be intercepted before they spread. Furthermore, the “One Map for Three-Water Issues” facilitates integrated multi-factor analysis, allowing managers to visually identify areas facing the triple pressures of water quality exceedance, water resource scarcity, and ecological degradation on a single map.

Regarding the regulatory workflow, the traditional model followed a linear sequence: “patrol personnel identify problems—manual recording—reporting—dispatching response.” Under this model, treatment outcomes were often not systematically recorded, creating an information gap between problem identification and feedback. The mobile application developed in this study restructures this workflow. When patrol personnel identify a suspected problem on-site, they create a task directly within the application. The system automatically assigns the task to the responsible unit, and remediation progress is transmitted in real time. This establishes a complete closed-loop process: “anomaly detection—task creation—field verification—remediation tracking—database entry.” As a result, every stage of the regulatory process is documented and traceable, achieving full digitalization of the regulatory workflow.

4.3. Policy Effectiveness Assessment and Driver Mechanism Analysis

It should be noted that while the synthetic control method and PSM are employed to isolate net policy effects from background natural variation, the proximity network analysis underlying the “Sustainable Water Cube Space” framework is inherently associational in nature. Observed co-improvement patterns among indicators reflect structural interdependencies but do not establish direct causal pathways. Residual confounding from climate variability—particularly precipitation fluctuations and temperature trends across the study period—cannot be fully excluded. Accordingly, the governance implications derived from this study should be interpreted as evidence-informed associations rather than confirmed causal mechanisms.

4.3.1. Policy Turning Points and Their Network Responses

The evolution of the network topology reveals three distinct policy-driven inflection points. The 2015 inflection point, driven by the national “Water Ten Measures,” marked the formal integration of water environment parameters into routine administrative tracking, causing eco-economic coupling indicators to emerge as critical bridge nodes for the first time. The 2019–2021 stage, characterized by intensified ecological civilization priorities, witnessed a 15.3% increase in the EQI alongside a structural stabilization of water conservation functions. During this phase, the network transitioned from an economy-dominated center to an eco-centric configuration. The 2022 high-quality development milestone further decentralized the network topology, reducing the average betweenness centrality from 0.68 to 0.51 and solidifying a multi-centered balanced configuration where economic expansion successfully decoupled from environmental degradation.

4.3.2. Multivariate Drivers of Indicator Changes

The decomposition of driving factors reveals that the direct effect of pollution source control is the most significant, contributing 42% of the observed improvement (including measures such as wastewater treatment plant construction, standardized management of industrial parks, and agricultural non-point source pollution control). Ecological restoration contributes 35% (encompassing returning farmland to forest, wetland protection, vegetation restoration, and related measures that not only reduce pollution but also actively enhance ecological carrying capacity). Engineering measures (e.g., ecological embankments, constructed wetlands) contribute 15%, and climate change contributes 8%. These results reveal the true sources of policy effectiveness: the areas in which government investment has been greatest—pollution control and ecological restoration—have indeed produced significant effects.

Another important finding is the quantification of transboundary ecosystem service values. The average annual water conservation volume in the Upper Yellow River region is approximately $4.21 \times 10^8 \text{ m}^3$. This value provides a scientific pricing basis for transboundary water rights allocation and ecological compensation mechanisms, enabling downstream provinces to clearly understand the ecosystem service value contributed by upstream ecological protection.

4.3.3. Attributional Uncertainties

It should be noted that the causal analysis in this study carries certain uncertainties. During 2023–2024, the study region experienced anomalously heavy rainfall (precipitation 23% higher than normal years), resulting in apparent improvements in some water quality and flow indicators. Without proper explanation, such changes could easily be misinterpreted as improvements attributable to governance effectiveness, when in fact they were primarily driven by climatic factors. Regarding the separation of policy effects from climate change contributions, the analysis indicates that the two contributions are broadly comparable, each accounting for approximately 40–60%, and complete separation is difficult to achieve. This means that while policy effects can be confirmed as significant for certain indicators, the role of climatic factors cannot be ignored. Explicit articulation of these uncertainties paradoxically enhances the scientific credibility of the assessment results.

4.3.4. Managerial Implications

The findings of this study carry several direct implications for watershed governance practitioners. First, the identification of four stable indicator clusters provides managers with a structurally grounded basis for prioritizing inter-sector coordination efforts, rather than treating TWI indicators in isolation. Second, the county-level paradigm trajectories offer a spatially differentiated decision tool: counties still in the economic-priority phase should be guided toward eco-economic coupling through targeted ecological compensation policies, while those approaching eco-priority phases require sustained investment in water quality monitoring infrastructure. Third, the digital-intelligent platform demonstrated in this study is not merely an analytical tool but an operational governance infrastructure that can support real-time adaptive management, cross-departmental data sharing, and early-warning responses to ecological threshold breaches. These implications suggest that SDG-aligned, network-informed governance frameworks can move beyond academic analysis to directly inform basin-level administrative planning and resource allocation decisions.

4.4. Limitations and Future Research Directions

While this study advances the integrated assessment of Three Water Integration (TWI) governance through a digital-intelligent platform and a product-space-derived proximity network, several limitations should be acknowledged.

First, the geographic specificity of the Upper Yellow River Basin in Qinghai Province—shaped by its unique plateau hydrology, sparse population distribution, and distinctive socioeconomic structure—may limit the direct transferability of the proposed framework to other watershed contexts. Governance priorities and indicator coupling patterns identified in this region may not fully reflect the dynamics of basins with contrasting climatic, ecological, or institutional conditions. Cross-regional validation studies that apply the Sustainable Water Cube Space framework across diverse settings would therefore be valuable to test its robustness and reveal context-dependent variations in network structure.

Second, as acknowledged in Section 4.1, the proximity network is inherently correlation-based; consequently, the identified indicator associations reflect statistical co-occurrence patterns rather than causal mechanisms. To move beyond correlation toward causal inference, future work should incorporate quasi-experimental designs (e.g., difference-in-differences, propensity score matching) or structural equation modeling. Such approaches would enable more rigorous attribution of governance outcomes to specific policy interventions, thereby strengthening the evidence base for decision-making.

Third, although the current indicator system is comprehensive and aligned with the SDG framework, it relies primarily on county-level aggregated data. This spatial granularity may obscure intra-county heterogeneity in environmental conditions and governance performance, potentially masking localized degradation hotspots or successful interventions. Future iterations of the framework would benefit from incorporating higher-resolution spatial data—such as gridded remote sensing products, township-level statistics, or sub-county administrative units—to improve the precision of county-differentiated governance strategies and better inform place-based policy design.

Collectively, addressing these limitations through cross-regional validation, causal inference methods, and finer spatial resolution will further strengthen the analytical power, policy relevance, and broader applicability of the Sustainable Water Cube Space framework for TWI governance.

5. Conclusions

This study coupled a digital-intelligent platform with network analysis to evaluate Three Water Integration (TWI) governance in the Upper Yellow River Basin, successfully bridging macro-scale policy with localized administrative execution. Empirically, the centralized “5 + 2” platform architecture unified 2.5 million fragmented records from disparate administrative sectors, achieving a 500-fold improvement in data retrieval efficiency. By translating the economic product space framework to environmental governance, we identified four cross-temporally stable indicator clusters and 18 critical bridge indicators based on co-improvement probabilities, effectively uncovering hidden cross-system synergies and trade-offs. Topological evolution analysis indicates a systemic transition from economy-driven to ecology–economy-coordinated development, as the correlation coefficient between economic and pollution indices dropped from 0.72 to 0.34, suggesting a progressive decoupling of economic growth from environmental pressure. Finally, based on localized network positions and spatial heterogeneity, we formulated differentiated, evidence-based county-level strategies: ecological compensation and ecotourism for high-altitude priority zones, graded pollution source control for low-altitude industrial zones, and eco-cultural integration for balanced development zones. Overall, this data-driven framework enhances real-time adaptive management and system monitoring, offering a

replicable paradigm for sustainable watershed governance in analogous regional contexts globally.

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Appendix A

Table A1. Summary of representative literature across four thematic streams.

No.	Reference	Study Context	Core Methodology	Key Indicators/ Concepts	Research Gap Addressed by This Study
1	[4]	Global watershed management	Eco-engineering decision scaling	Flow regimes, climate uncertainty	Lacks multi-indicator network structure
2	[5]	Taihu Basin, China	Ecosystem service integration; multi-scenario analysis	Water quantity, quality, scarcity	No structural coupling of indicator interdependencies
3	[3]	National (China)	Theoretical framework review	Water ecological assessment paradigm	Lacks empirical network operationalization
4	[1,6]	Social-ecological systems (global)	Network analysis; resilience theory	Social-ecological interdependencies	Not applied to TWI indicator systems
5	[20]	Yangtze River Economic Belt	Network analysis of ecosystem services	Land use, ecosystem service interactions	No governance paradigm trajectory quantification
6	[21]	China (agricultural systems)	Complex networks; geographic analysis	Agricultural production efficiency, urban-rural dynamics	No water governance or TWI application
7	[7,8]	National economies (global)	Product space; economic complexity	Product proximity, comparative advantage	Not applied to water governance indicators
8	[15,17,18]	National/global SDG systems	SDG interaction networks; Louvain clustering	SDG interlinkages, complementarities	Not operationalized at watershed/county scale
9	[9]	Global SDG literature	Systematic critical review of network methods	SDG policy planning evidence base	No empirical watershed application with digital platform
10	[12]	Water environment management (China)	Multi-centre cloud platform; cross-sectoral integration	Water quality data, platform architecture	No coupling with network-based indicator analysis
11	[13]	China (national SDG–water nexus)	SDG interaction accounting; scenario modelling	Water pollution, SDG trade-offs	No county-scale differentiated governance output
12	[16]	Global (196 countries)	SDG achievement trajectory analysis	SDG disparities, development pathways	Not applied to sub-national watershed governance

13	[2,14]	Yellow River Basin	System dynamics; resource constraint modelling	Water–food–energy–economy nexus	No TWI coupling network or paradigm shift quantification
14	[10,11,19]	Yellow River Basin/river basins	Coupled human–natural system modelling; socioeconomic–river interaction	Multi-sector basin dynamics	No indicator network structure or digital platform coupling

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