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Research Article

Evaluation of water quality and water resources carrying capacity using a varying fuzzy pattern recognition model: A case study of small watersheds in Hilly Region

Su-duan Hu[1,2,3], Wen-da Liu[1,3], Jun-jian Liu[1*], Jiang-Yulong Wang[1,3], Jun-jie Yang[1,3], Zhao-yi Li[4], Zhi-yang Tang[5], Guo-qiang Wang[6], Tian-cun Yu[6]

[1] *Langfang Integrated Natural Resources Survey Center*, *China Geological Survey*, *Langfang* 065000, *Hebei*, *China*.
[2] *Key Laboratory of Groundwater Sciences and Engineering*, *Ministry of Natural Resources*, *Shijiazhuang* 050061, *China*.
[3] *Innovation Base for Natural Resources Monitoring Technology in the Lower Reaches of Yongding River*, *Geological Society of China*, *Langfang* 065000, *Hebei*, *China*.
[4] *Chinese Academy of Geological Sciences*, *Beijing* 100037, *China*.
[5] *Chengde Water Authority*, *Chengde* 067000, *Hebei*, *China*.
[6] *Pingquan Water Authority*, *Chengde* 067500, *Hebei*, *China*.

Abstract: Water scarcity and environment deterioration have become main constraints to sustainable economic and social development. Scientifically assessing Water Resources Carrying Capacity (WRCC) is essential for the optimal allocation of regional water resources. The hilly area at the northern foot of Yanshan Mountains is a key water conservation zone and an important water source for Beijing, Tianjin and Hebei. Grasping the current status and temporal trends of water quality and WRCC in representative small watersheds within this region is crucial for supporting rational water resources allocation and environment protection efforts. This study focuses on Pingquan City, a typical watershed in northern Hebei Province. Firstly, evaluation index systems for surface water quality, groundwater quality and WRCC were established based on the Pressure-State-Response (PSR) framework. Then, comprehensive evaluations of water quality and WRCC at the sub-watershed scale were conducted using the Varying Fuzzy Pattern Recognition (VFPR) model. Finally, the rationality of the evaluation results was verified, and future scenarios were projected. Results showed that: (1) The average comprehensive evaluation scores for surface water and groundwater quality in the sub-watersheds were 1.44 and 1.46, respectively, indicating that both met the national Class II water quality standard and reflected a high-quality water environment. (2) From 2010 to 2020, the region's WRCC steadily improved, with scores rising from 2.99 to 2.83 and an average of 2.90, suggesting effective water resources management in Pingquan City. (3) According to scenario-based prediction, WRCC may slightly decline between 2025 and 2030, reaching 2.92 and 2.94, respectively, relative to 2020 levels. Therefore, future efforts should focus on strengthening scientific management and promoting the efficient use of water resources. Proactive measures are necessary to mitigate emerging contradiction and ensure the long-term stability and sustainability of the water resources system in the region. The evaluation system and spatiotemporal evolution patterns proposed in this study can provide a scientific basis for refined water resource management and ecological conservation in similar hilly areas.

Keywords: Varying fuzzy pattern recognition model; Dynamic assessment; Small watershed; Water quality evaluation; Water resources carrying capacity

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*Corresponding author: Jun-jian Liu, *E-mail address*: liujunjian@mail.cgs.gov.cn

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Introduction

In Northern China, where precipitation is generally low and water scarcity is severe, water resources have become a key bottleneck constraining local economic development (Liu et al. 2021; Liu et al. 2022). In hilly areas characterized by shallow water table and well-developed bedrock fissure aquifers, interaction between surface water and groundwater are usually active (Geng et al. 2020). Moreover, these areas are subject to significant hydrometeorological variability and anthropogenic disturbances (Li et al. 2023). Safe drinking water for local residents is particularly vulnerable due to the typically single source of water supply (Wan et al. 2022). Therefore, understanding the quality of surface water and groundwater, as well as the dynamics of Water Resource Carrying Capacity (WRCC) and their influencing factors at the watersheds scale, is of both theoretical and practical significance. These concerns are also central to ongoing research on ecosystem evolution, and the regulation and restoration of small watersheds in hilly terrains (Mo et al. 2024).

Water bodies in such region contain multiple constituents related to water quality, such as total nitrogen, total phosphorus, dissolved oxygen, and etc., which interact dynamically and may constraints one another (Rozental et al. 2024). Due to the inherent fuzziness and uncertainty in evaluating water quality, various mathematical methods have been developed to quantify overall water quality more reliably (Mohammadi et al. 2024; Raheli et al. 2024). such as common approaches include single-factor index method (Ben Abbou et al. 2024), pollution index method (Huynh et al. 2024), and machine learning-based modelling techniques (Eid et al. 2024; Zhai et al. 2024). Each of these methods has distinct advantages and has contributed to resolving the complexities of integrated water quality assessment (Fouad et al. 2024; Herrera-Muñoz et al. 2024). However, due to the large number of uncertain factors in aquatic environments and the the fuzzy nature of sample affiliation when multiple indicators are involved, Professor Chen Shouyu introduced the concepts of relative affiliation degree and relative affiliation function, and subsequently developed the Varying Fuzzy Pattern Recognition (VFPR) model (Sun et al. 2024). This model uses relative affiliation to characterize the association between observed values and reference standards, effectively addressing the issue of fuzzy boundaries between evaluation indicators. Furthermore, by adjusting model parameters, it can simulate both linear and nonlinear relationship among variables, leading to more stable and reliable evaluation results. As a result, the VFPR model has been increasingly used in water quality assessments (Nguyen et al. 2024; Qin et al. 2020).

Water Resources Carrying Capacity (WRCC) evaluation is approach for understanding the relationship between water resources, socio-economic development and ecological and environmental protection (Zhang and Duan, 2024), which involves a number of aspects such as natural resources, human activities and economic development (Qiu et al. 2021; Yang et al. 2024; Zhang et al. 2024). Common methods for WRCC evaluation include the traditional water balance method (Yang et al. 2024), ecological footprint method (Zhang et al. 2024), and the water resources sustainability index (Wang et al. 2024a; Xu et al. 2024). These methods emphasize the concept of sustainable development and provide important value for the formulation of scientific water resources management policies and the promotion of long-term socio-economic development (Wang et al. 2024). Among these, the Pressure-State-Response (PSR) model stands out for its systematic structure, operational simplicity, data accessibility, and cross-regional comparability. It has been widely used in evaluating ecosystem health in wetlands, oceans, rivers, and other natural systems because of its logic, flexibility, and comprehensiveness framework (Peng et al. 2024; Wang et al. 2022). In the PSR model, "Pressure" indicator represents the stress exerted on the ecological environment by human development; "State" indicator reflects the current conditions and dynamic change in the ecological system; and "Response" indicator captures the actions and strategies implemented by society to mitigate or prevent adverse environmental impacts. The model reflects the interaction between human socio-economic activities and the natural environment—humans extract natural resources and discharge waste into the environment, thus affecting their quality and sustainability. In turn, changes in the resource environment affect public awareness and behaviors, prompting regulatory and policy responses aimed at reducing anthropogenic pressures. By integrating the PSR model into the construction of WRCC evaluation index system, it becomes possible to mechanistically explain the evolution of WRCC and uncover its internal driving forces (Gao et al. 2024).

In hilly regions, water resources are often vulnerable to both natural and anthropogenic factors, making the assessment of water quality and WRCC crucial for achieving sustainable water management. This study aims to conduct a refined evaluation of these parameters using the VFPR model, with small watersheds serving as the basic units of analysis.

The northern foothills of the Yanshan Mountain represent a core area for water conservation in the Beijing-Tianjin-Hebei Region and serve as a vital water source for Beijing-Tianjin-Hebei (Feng et al.

2022). The area is characterized by the development of fractured bedrock aquifers, shallow groundwater levels, frequent seasonal interruptions in surface water flow. These hydrogeological features, combined with sensitivity to hydrometeorological changes and human disturbances, make both surface water and groundwater quality particularly vulnerable, and significantly reduce the region's WRCC (Gao et al. 2023; Shan et al. 2024).

Pingquan City, Chengde, Hebei Province, lies within this sensitive mountainous zone. Although the region receives limited annual precipitation, its water quality has generally remained good. However, recent monitoring at Dangba state-controlled cross-section has reported occasional exceedances in nitrogen and phosphorus concentrations, indicating episodic eutrophication (Shan et al. 2022). Of particular concern is Panjiakou Reservoir, located downstream in the Puhe River Basin. As the water source of the Luan River diversion project, safeguarding its water quality is of utmost importance. According to Luan River Diversion Project Management Bureau, the water body of Panjiakou Reservoir has shown moderate eutrophication. Total nitrogen always exceeds the Class V national water quality standard, while total phosphorus concentrations remain within Class Ⅲ year-round, posing a serious risk to water supply security. Against this backdrop, this study takes Pingquan City as a representative case and constructs evaluation index systems for surface water quality, groundwater quality, and WRCC using PSR framework. The VFPR model is then applied for comprehensive assessment. The results provide a scientific foundation for water environment protection and resource management in the region. This work is of great significance for enhancing water resources governance, ensuring water supply and food security, supporting regional economic development, and maintaining ecological stability.

1 Study area

Pingquan City is located in the northeastern part of Chengde City, Hebei Province, China, spanning longitudes 118°21′03″ E to 119°15′34″ E and latitudes 40°24′0" N to 40°40′17″ N. Situated at the eastern end of the Yanshan Mountain Range and the junction of Hebei, Inner Mongolia and Liaoning Province. Influenced by topography, latitude and other factors, the region experiences a continental monsoon climate, with an annual average precipitation of 537.6 mm, approximately 60% of which occurs in July to August. The average annual temperature is 7.3°C, with significant seasonal variation ranging from −20°C in winter to 40°C in summer. The annual cumulative temperature exceeds 3,200°C.

The rivers in Pingquan City belong to two major river systems: the Luan River and Liao River. The Luan River system includes the Laoniuhe River, Puhe River, and Qinglonghe River, while the Liao River system consists of the Dalinghe River and Laohahe River. These rivers are primarily in upper reaches within the territory of Pingquan City, making it an important water source conservation and ecological barrier area with extremely significant ecological status. The watershed areas of the Puhe River and Laohahe River are 1,337.5 km^2 and 909.9 km^2 respectively, and are relatively abundant in water resources, with visible surface runoff in most regular years. In contrast, the Qinglonghe River, Laoniuhe River, and Dalinghe River basins have smaller watershed areas of 339.6 km^2, 279.9 km^2, 427.1 km^2, respectively. These basins contain limited water resources, and their secondary tributaries generally do not converge in the territory., resulting in predominantly seasonal rivers. The total area of Liao River Basin within Pingquan City is approximately 1,337.0 km^2, accounting for 40.6% of the city's total area, while the Luan River Basin spans 1,957.0 km^2, accounting for the remaining 59.4%. The main rivers in Pingquan City and their geographic locations are shown in Fig. 1 and Table 1.

The total water resources in this area is approximately 309 million m^3, while the long-term average availability is only 126 million m^3, resulting in a per capita water availability of just 651 m^3, far below the national average of 2,100 m^3. This severe shortage classifies Pingquan as the most water-scarce county among eight counties and three districts in Chengde City. In addition to the low total volume, the spatial and temporal distribution of water resources is highly uneven, further complicating water development and utilization efforts, and posing a significant constraint on the city's economic and social development.

The land use patterns in Pingquan City are diverse, primarily encompassing cultivated land, forest land, garden plots, grassland, unutilized land, water bodies, and construction land, with significant spatial heterogeneity across regions (Fig. 2). Cultivated land is concentrated in river valleys, intermontane basins, and alluvial fan foothills, serving as the core agricultural production zone. Garden land is distributed in the township areas, including Pingquan Town and

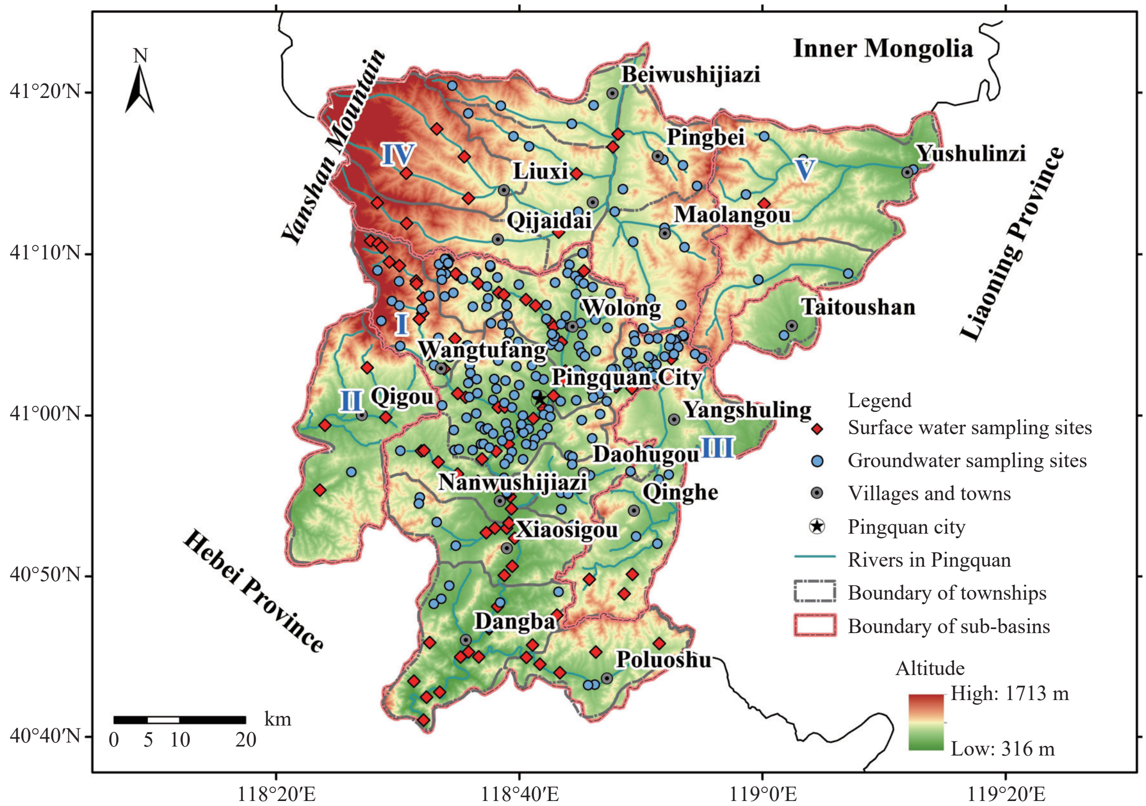

Fig. 1 Location of Pingquan City and the surface water and groundwater sampling sites (Ⅰ: Puhe River Basin; Ⅱ: Laoniuhe River Basin; Ⅲ: Qinglonghe River Basin; Ⅳ: Laohahe River Basin; Ⅴ: Dalinghe River Basin)

Table 1 Statistical summary of major rivers in Pingquan City

River	River class	Watershed area /km^2	Proportion /%	Source location	Receiving body
Laohahe River	Primary tributary of Liao River	909.9	27.6	Dawopu Village, Liuxi Manchu Township	Liao River
Dalinghe River	Primary tributary of Liao River	427.1	13.0	Laowopu Village, Taitoushan Township	Bohai Sea
Qinglonghe River	Primary tributary of Luan River	339.6	10.3	Fengjiadian Village, Songshutai Township	Luan River
Laoniuhe River	Primary tributary of Luan River	279.9	8.5	Fenghuangling Village, Qigou Township	Luan River
Puhe River	Primary tributary of Luan River	1,337.5	40.6	Anzhangzi Village, Wolong Township	Luan River
Total		3,294	100		

Yushulinzi Town, the specialized economic crop belts. Forest land spans nine townships, such as Pingquan Town and Liuxi Town, functioning primarily for ecological and water conservation. Grasslands are mainly distributed in four townships, while unused land is widely scattered across eleven townships represented by Pingquan Town. Water bodies—including rivers, reservoirs, and wetlands—are aligned along five major rivers like the Puhe and Laohahe, forming a regional aquatic ecological network. Construction land, comprising urban and rural settlements, industrial-mining areas, and transportation facilities, is predominantly located in densely populated areas and along key transportation corridors.

2 Materials and methods

2.1 Sample collection and data sources

2.1.1 Surface water and groundwater sampling

Based on the principles of representativeness, scientific rigor, and practical feasibility, sampling sites for surface water and groundwater were established in small watershed units across Pingquan City (Fig. 1). The sampling layout considered key factors such as land use types, pollution source distribution, and regional hydrogeological conditions, while also accounting for the seasonal flow interruptions commonly

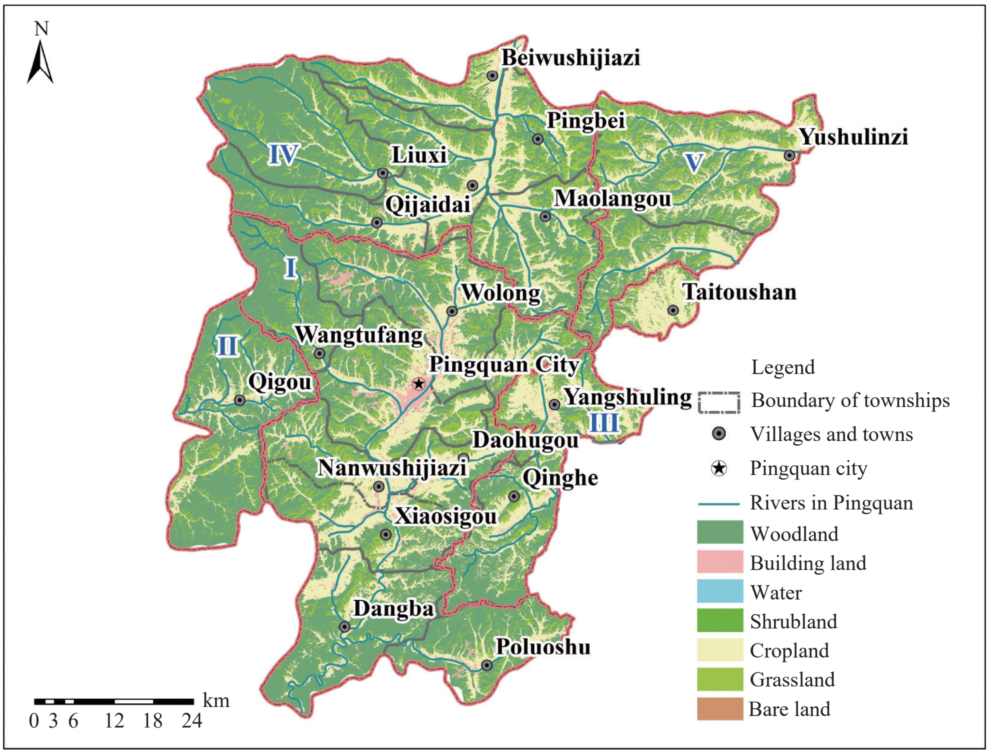

Fig. 2 Land use patterns of Pingquan City (Ⅰ: Puhe River Basin; Ⅱ: Laoniuhe River Basin; Ⅲ: Qinglonghe River Basin; Ⅳ: Laohahe River Basin; Ⅴ: Dalinghe River Basin)

observed in the area. Sampling sites covered a range of hydrogeological environments, including rivers, shallow unconfined and deep confined aquifers, and diverse land use zones. In July 2022 and July 2023, surface water and groundwater samples were systematically collected from five sub-watersheds to capture water quality characteristics during flood season.

Surface water samples were obtained from major rivers, lakes, and reservoirs in the study area. A total of 100 sampling sites were selected to represent different hydrological units and areas affected by human activities. The spatial arrangement ensured comprehensive coverage by factoring in flow dynamics, proximity to pollution sources, and land use. Water samples were collected approximately 0.5 meters below the surface using a plexiglass water sampler, transferred into pre-cleaned polyethylene bottles, stored at 4°C and promptly transported to the laboratory for analysis. In-situ measurements of parameters such as water temperature, pH, Dissolved Oxygen (DO), and Electrical Conductivity (EC) were conducted using a portable multi-parameter water quality meter. Meanwhile, sampling time, weather conditions, and surrounding environmental characteristics, were also recorded.

Groundwater samples were collected from 236 sites, including different types of domestic and irrigation wells, representing both shallow and deep groundwater systems. Prior to sampling, the static water level was measured using a water level meter. Water was then extracted using a bailer or sampling pump to ensure the acquisition of representative samples. At the same time, relevant well information was documented, including water level depth, total well depth pumping rate, screen location, and well usage status. Field parameters such as pH, EC, DO, and water temperature were also measured on-site. Groundwater samples were similarly stored in coolers at 4°C and delivered to the laboratory without delay.

All laboratory analyses were conducted following standardized protocols, including Environmental Quality Standards for Surface Water (GB 3838—2002), Technical Specifications for Environmental Monitoring, Water and Wastewater Monitoring Methods (4_{th} Edition), and Analytical Methods for Groundwater Quality. Tested indicators included: chloride, nitrate, pH, Chemical Oxygen Demand (COD), ammonia nitrogen, fluoride, iron, total phosphorus, zinc, Total Dissolved Solids (TDS), and nitrite. Detailed information regarding analytical methods and detection limits is summarized in Table 2.

2.1.2 Data sources for Water Resources Carrying Capacity (WRCC)

The total amount of water resources in Pingquan

Table 2 Analytical methods and detection limits for water quality indicators

Indicator	Analytical methods		Detection limit/mg/L
Chloride	Silver Nitrate Titration Method	DZ/T0064.50-2021	\
Nitrate	Ultraviolet Spectrophotometry	DZ/T0064.59-2021	0.08
pH	Electrode Method	HJ1147-2020	\
COD	Acidic Potassium Permanganate Titration Method	DZ/T0064.68-2021	\
Ammonia Nitrogen	Nessler Reagent Photometric Method	DZ/T0064.57-2021	\
Fluoride	Ion Chromatography	DZ/T 0064.54-2021	0.1
Iron	Flame Atomic Absorption Spectrophotometry	DZ/T 0064.25-2021	0.016
Total Phosphorus	Ammonium Molybdate Spectrophotometric Method	GB/T 11893-1989	0.01
Zinc	Flame Atomic Absorption Spectrophotometry	DZ/T 0064.83-2021	0.05
TDS	Gravimetric Method	DZ/T0064.9-2021	0.1
Nitrite	Spectrophotometry	DZ/T 0064.60-2021	0.0002

City is limited and exhibit significant spatial and temporal variability. In recent years, accelerated industrialization and urbanization have intensified the imbalance between water supply and demand, making water scarcity a critical constraint on the city's economic and social development.

WRCC assessment requires three main categories of data: Natural water resources, socio-economic indicators and spatial data. Natural water resources data encompass variables including precipitation, evaporation, surface water availability, groundwater resources, total annual water volume, and water quality compliance rate. Among them, annual precipitation is a key determinant of interannual water availability. The water resources development and utilization rate reflects the degree of exploitation and the potential for sustainable use. The water production modulus indicates natural variability in water availability across regions, while per capita water resources provide a direct measure of water abundance in the study area. Additionally, non-conventional water resources such as rainwater harvesting and recycled water play a vital role in supplement traditional surface water and groundwater supplies, especially under conditions of scarcity.

From the demand side, the major water-consuming sectors include domestic, industrial, agriculture, and ecological uses. The increases in population, industrial, and agricultural activity exacerbate water demand, while rapid economic development can intensify environmental degradation and pressure on WRCC. Therefore, socio-economic data, such as population size and distribution, industrial output, agricultural and domestic water consumption, sewage treatment capacity, and water resources development and utilization rate, are used to analyze the balance between supply and demand. Additionally, indicators such as water use intensity per unit of agricultural and industrial output, and the proportion of ecological water use, are used to reflect both pressure on resources and policy responses for mitigation and sustainability.

Spatial data include Digital Elevation Model (DEM), land-use types, and vector map of water system of the study area were used to assist spatial analysis of WRCC.

All data related to WRCC in Pingquan City were sourced from authoritative sources, including the Pingquan Water Resources Bulletin, Pingquan Statistical Yearbook, Pingquan Environmental Bulletin, and the Statistical Bulletin on National Economic and Social Development of Pingquan City.

2.2 Construction of evaluation index system

The construction of the index system is a fundamental step in evaluating water quality and WRCC. Based on the principles of scientific rigor, comprehensiveness, systematicity and feasibility, and drawing upon existing evaluation systems, national standards, and data availability, separate index systems were developed for surface water quality, groundwater quality, and WRCC in Pingquan City.

2.2.1 Water quality evaluation index system

Considering that current water pollution in the region is primarily attributed to eutrophication, heavy metals, and persistent organic pollutants, this study selected nine representative parameters for the surface water quality assessment: Chloride, nitrate, pH, Chemical Oxygen Demand (COD), ammonia nitrogen, fluoride, iron, total phosphorus and zinc. Similarly, nine parameters were chosen for evaluating groundwater quality: Total Dissolved Solids (TDS), chloride, iron, zinc, COD, ammonia nitrogen, nitrite, nitrate, fluoride. These indicators comprehensively reflect sensory characteristics, eutrophic status, heavy metal contamination, and overall water quality conditions. The "Surface water quality standards (GB 3838—2002)" and "Groundwater quality standards (GB/T 14848—2024)" were used as the evaluation standards (Table 3 and Table 4).

2.2.2 WRCC evaluation index system based on the PSR model

Based on the concept of WRCC and the Pressure-State-Response (PSR) framework, the WRCC was evaluated through 17 indicators categorized into three subsystems: The pressure (WRPCC), the state (WRSCC), and the response (WRRCC). The indicators were selected from five aspects: Socio-economic development, water resources endowment, resources utilization, resources management capacity, environmental condition.

At the same time, based on the literature and the national water resource development and utilization, the indicators were divided into five evaluation grades. As shown in Table 5, grades 1-2 represent a high or favourable carrying capacity, grades 2-3 indicate an acceptable level, and grades 3-5 reflect a poor or strained WRCC.

2.3 Evaluation using the Varying Fuzzy Pattern Recognition (VFPR) model

A reasonable evaluation model is crucial for comprehensively assessing water quality and WRCC. The chosen model must account for complex practical conditions and inherent uncertainty in the water environment. Traditional assessment methods, which rely on rigid classification criteria, fail to address key challenges, such as fuzzy boundaries between water quality classes, continuous transitions in carrying capacity levels, nonlinear relationships between indicators, and hierarchical interactions. These limitations hinder their applicability in capturing the dynamic nature of water systems. In contrast, the VFPR model, developed by Professor Chen Shouyu, provides an effective solution. By introducing the concepts of relative affiliation functions and fuzzy boundaries, the VFPR model transforms discrete classification processes into continuous affiliation relationships. It allows for dynamic simulation of both linear and nonlinear relationships among indicators by adjusting model parameters. This feature is particularly beneficial in evaluating complex water systems, where indicator interactions and thresholds are not

Table 3 Index system and water quality standard for surface water /mg/L

Class		Ⅰ	Ⅱ	Ⅲ	Ⅳ	Ⅴ
Indicator	Chloride	250	250	250	300	500
	Nitrate	10	10	10	15	20
	pH (Dimensionless)	6–9			<6 or >9	
	COD	15	15	20	30	40
	Ammonia Nitrogen	0.15	0.5	1	1.5	2
	Fluoride	1	1	1	1.5	1.5
	Iron	≤0.3				
	Total Phosphorus	0.02	0.1	0.2	0.3	0.4
	Zinc	0.05	1	1	2	2

Table 4 Index system and water quality standard for groundwater /mg/L

Class		Ⅰ	Ⅱ	Ⅲ	Ⅳ	Ⅴ
Indicator	TDS	300	500	1,000	2,000	2,000
	Chloride	50	150	250	350	350
	Iron	≤0.3				
	Zinc	0.05	0.5	1	5	5
	COD	1	2	3	10	10
	Ammonia Nitrogen	0.02	0.1	0.5	1.5	1.5
	Nitrite	0.01	0.1	1	4.8	4.8
	Nitrate	2	5	20	30	30
	Fluoride	1	1	1	2	2

Table 5 WRCC index system and grading criteria

Indicator system			Grade				
Subsystems	**Indicators**	**Unit**	**1**	**2**	**3**	**4**	**5**
Pressure (WRPCC)	Water consumption per capita	m^3/person	200	300	400	600	900
	Per capita ecosystem water use	m^3/person	50	20	10	5	3
	Water consumption intensity per GDP unit	$m^3/10^4$ Yuan	80	110	250	600	700
	Wastewater discharge per GDP unit	$m^3/10^4$ Yuan	7	10	15	20	30
	Population density	person/km^2	10	100	300	600	1,000
	Per capita GDP	Yuan/person	50,000	35,000	21,000	7,000	4,000
	Share of tertiary industry in GDP	%	55	50	45	40	35
State (WRSCC)	Modulus of water production	10^4 m^3/km^2	120	90	50	10	5
	Water resources per capita	m^3/person	3,000	2,200	1,700	1,000	500
	Annual precipitation	mm	1,600	800	600	400	200
	Exploitation rate of water resources	%	10	20	40	60	100
	Share of groundwater on total water supply	%	5	20	30	40	50
	Share of alternative water resources	%	5	2.5	1	0.5	0.1
	Urbanization rate	%	30	40	60	80	90
Response (WRRCC)	Agricultural water use intensity	$m^3/10^4$ Yuan	600	800	1,200	1,500	2,000
	Industrial water use intensity	$m^3/10^4$ Yuan	25	45	70	110	150
	Ecological water use proportion	%	5	3	2	1	0.5

always clear-cut. The VFPR model determines the relative membership degree between observed sample indicators and corresponding standard intervals. It thereby reduces classification errors and misjudgement caused by boundary ambiguities common in traditional methods. As a result, the VFPR model significantly improves the robustness, objectivity, and accuracy of water quality and WRCC assessments. Therefore, the VFPR model was adopted in this study for comprehensive assessment.

2.3.1 Normalization of samples

Given n water quality samples to be evaluated, each of which is described by m evaluation indicators. These samples can be represented in matrix form as an indicator eigenvalue matrix X.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} = (x_{ij}) \tag{1}$$

Where: x_{ij} is the value of indicator i for sample j, i=1, 2, ⋯, m, j=1, 2, ⋯, n.

Let c represent the number of evaluation grades. The corresponding standardized indicators matrix Y, comprising the standard values of the m indicators at each of the c grades, is:

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1c} \\ y_{21} & y_{22} & \cdots & y_{2c} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mc} \end{bmatrix}_{m\times c} = (y_{ih}) \tag{2}$$

Where: y_{ih} is the standardized value of indicator i at grade h, i=1, 2, ⋯, m, h=1, 2, ⋯, c.

To eliminate the influence of differing measurement scales and ensure consistency in indicator directionality (e.g. inverse indicators such as total nitrogen and total phosphorus, and positive indicators such as dissolved oxygen or transparency), the original data are normalized using specification Equations (3) and (4):

$$r_{ij} = \begin{cases} 0, \quad x_{ij} \geqslant y_{ic} \text{ (inverse index) or} \\ \quad x_{ij} \leqslant y_{ic} \text{ (positive index)} \\ \dfrac{x_{ij} - y_{ic}}{y_{i1} - y_{ic}}, \quad y_{i1} < x_{ij} < y_{ic} \text{ (inverse index) or} \\ \quad y_{i1} > x_{ij} > y_{ic} \text{ (positive index)} \\ 1, \quad x_{ij} \leqslant y_{i1} \text{ (inverse index) or} \\ \quad x_{ij} \geqslant y_{i1} \text{ (positive index)} \end{cases} \tag{3}$$

$$s_{ih} = \begin{cases} 0, \quad y_{ih} = y_{ic} \text{ (positive index or} \\ \quad \text{inverse index)} \\ \dfrac{y_{ih} - y_{ic}}{y_{i1} - y_{ic}}, \quad y_{i1} < y_{ih} < y_{ic} \text{ (positive index) or} \\ \quad y_{i1} > y_{ih} > y_{ic} \text{ (inverse index)} \\ 1, \quad y_{ih} = y_{i1} \text{ (positive index or} \\ \quad \text{inverse index)} \end{cases} \tag{4}$$

Where: r_{ij} is the relative affiliation degree of indicator i in sample j to a specific grade; s_{ih} is the normalized value of the standard threshold for indicator i at grade h.

After applying specification, the sample matrix $X_{m\times n}$ and the standard matrix $Y_{m\times c}$ are both transformed into values ranging between 0 and 1, representing their respective relative affiliation degrees and grade clustering centers. This transformation facilitates pattern recognition and classification through subsequent comparison.

2.3.2 Assignment of indicator weights

Water quality indicators reflect different aspects of the water body's status, its impact, and the degree of difference in water quality. Since water quality assessment involves multiple interrelated indicators, it is necessary to determine appropriate weights to reflect each indicator's contribution to the overall evaluation.

Commonly used methods for determining indicator weights include Principal Component Analysis (PCA), Analytical Hierarchical Process (AHP) (Sun et al. 2024), entropy weighting, among others (Song et al. 2024). PCA reduces the dimensionality of multiple indicators into a few comprehensive principal components, maximizing the retention of the original data variance. This method provides an objective means to determine the indicator weights based on their statistical contribution.

In this study, PCA was conducted on surface water, groundwater, and WRCC datasets using SPSS software. The absolute values of the loadings of each indicator on the extracted principal components were weighted by contribution rates and averaged. These values were then normalized to produce the final weight vectors for the indicators related to surface water and groundwater quality, and WRCC.

$$w_{si}=\{0.101 \quad 0.135 \quad 0.119 \quad 0.100 \quad 0.110 \quad 0.146 \quad 0.078 \quad 0.102 \quad 0.109\}$$

$$w_{gi}=\{0.128 \quad 0.116 \quad 0.127 \quad 0.109 \quad 0.119 \quad 0.090 \quad 0.108 \quad 0.099 \quad 0.105\}$$

$$w_{ci}=\left\{\begin{matrix} 0.064 & 0.063 & 0.063 & 0.063 & 0.056 \\ 0.050 & 0.055 & 0.062 & 0.058 & 0.065 \\ 0.053 & 0.050 & 0.039 & 0.065 & 0.068 \\ 0.063 & 0.062 & & & \end{matrix}\right\}$$

2.3.3 Integrated evaluation grade determination

To quantify the difference between each water quality sample and the evaluation standards across grades, the generalized weight indicator distance d_{hj} is calculated as:

$$d_{hj}=\left\{\sum_{i=1}^{m}\left[w_i\left|r_{ij}-s_{ih}\right|\right]^p\right\}^{\frac{1}{p}} \tag{5}$$

Where: w_i is the weight of indicator i; p is a model parameter taking values 1 or 2, corresponding to Hemming distance and Euclidean distance, respectively; and the other symbols retain their previous meanings.

After computing the generalized weight distance, the combined relative affiliation degree u_{hj} of sample j to grade h is given by:

$$u_{hj}=\begin{cases} 0 & h<a_j \text{ or } h>b_j \\ \dfrac{1}{\sum\limits_{k=a_j}^{b_j}\left\{\dfrac{\sum\limits_{i=1}^{m}\left[w_{ij}\left(r_{ij}-s_{ih}\right)\right]^p}{\sum\limits_{i=1}^{m}\left[w_{ij}\left(r_{ij}-s_{ik}\right)\right]^p}\right\}^{\frac{a}{p}}} & a_j\leqslant h\leqslant b_j \\ 1 & h=a_j=b_j \end{cases} \tag{6}$$

Where: a is the optimization parameter, typically set to 1 or 2, representing the least square criterion or the least squares criterion, respectively. The other symbols retain their previous meanings. By adjusting parameters a and p, the model can simulate different linear and nonlinear relationships between indicators and evaluation grades, usually four combinations of (a, p) are considered to enhance robustness.

$$\begin{cases} a=1 \\ p=1 \end{cases}, \begin{cases} a=1 \\ p=2 \end{cases}, \begin{cases} a=2 \\ p=1 \end{cases}, \begin{cases} a=2 \\ p=2 \end{cases}$$

After calculating the combined relative affiliation u_{hj} to all grades, the integrated evaluation grade value for sample j can be derived as:

$$H=\sum_{h=1}^{c}u_{hj}h \tag{7}$$

Where: H is the comprehensive grade level of the water quality or WRCC sample.

By substituting the normalized samples, standards grades, and indicator weights into Eqs. (6) and (7), the integrated evaluation grade values are obtained. The final evaluation result is computed as the average over the four parameter combinations (a, p), providing a stable and reliable comprehensive assessment.

According to the "Surface water quality standards (GB 3838—2002)" and "Groundwater quality standards (GB/T 14848—2024)", water quality evaluation results are divided into five classes:

Class I to III: Good water quality, suitable for centralized drinking water sources.

(1) Class I: Best quality;

(2) Class II: Good quality;

(3) Class III: Moderate quality;

(4) Class IV: Poor quality, only suitable for agricultural and some industrial uses;

(5) Class V: Worst quality, unsuitable for drinking purposes.

Similarly, referring to regional water resources conditions, utilization status, and ecological demands, WRCC is divided into five grades (Table 6). In this case, lower values represent better carrying, with Grade I being the best and Grade V the worst.

3 Results and discussion

3.1 Evaluation results of surface water and groundwater quality

The evaluation results obtained from the VFPR model were integrated into a platform and visualizes using geostatistical analysis, producing spatial distribution maps of surface water and groundwater quality across Pingquan City. The results indicated that the overall water quality in Pingquan City was highly satisfactory. Both surface water and groundwater fell within the range of Class I to Class III standards, fully complying with the Class III centralized drinking water source requirements as specified in the "Surface water quality standards (GB 3838—2002)" and "Groundwater quality standards (GB/T 14848—2024)". This confirms the high quality of regional water resources. Further analysis revealed that the average values of the water quality evaluation for surface water and groundwater were 1.44 and 1.46, respectively. These values fell between Class I (best quality) and Class II (good quality), essentially meeting the requirements of Class II water quality for national control sections. This clearly indicates that the water resources in Pingquan City maintain a high level of water quality, providing a strong guarantee for domestic water use and the sustainable development of the local ecological environment.

Spatial distribution characteristics showed that the surface water quality across the sub-basins ranged from 1.19 to 2.47 (Fig. 3). Among them, the Laohahe River and Dalinghe River basins exhibited the best water quality, with average comprehensive class values of 1.26 and 1.30, respectively. These two sub-watersheds are the source of their respective rivers, and exhibit better background water quality because of less anthropogenic pollution. The average comprehensive classes of the Laoniuhe River Basin and the Qinglonghe River Basin were 1.77 and 1.79, respectively, indicating generally good water quality. However, the water quality in some areas of the two sub-basins was slightly poorer than Class II standard. The average water quality class of the Puhe River Basin was 1.43. While the water quality in the upper reaches of the Puhe River was good exceeding Class II standards, but the quality in the middle reaches where the city center of Pingquan is located was declined, with some sections falling below Class II. The water quality was improved downstream of the urban area due to natural self-purification processes such as degradation and sedimentation.

In terms of land use types, the Laohahe River and Dalinghe River basins are predominantly covered by orchards and forests, with minimal human interference. The dominant functions are ecological and water source conservation, resulting in many water quality parameters meeting Class I baseline standards and excellent water quality. In contrast, the urban area of Pingquan City is dominated by construction land with high population density and intensive domestic and

Table 6 Evaluation grades of Water Resources Carrying Capacity (WRCC)

Grade	State	Characterization of the grade
I	Extra High	Human activities have minimal impact on water resources and the water environment. Water resources are abundant with high development potential and a good water ecosystem that can support rapid economic and social development.
II	High	Human activities have relatively limited impact on water resources and the environment. Water supply and demand are basically balanced, but it is necessary to optimize the structure of water use and vigilance against localized pressure.
III	Moderate	Human activities exert a moderate impact on water resources and the environment. The use is generally reasonable, but supply-demand tension is emerging. It is necessary to strengthen water conservation management and controlled development scale. The water ecosystem shows some degradation, though basic functionality maintains.
IV	Slight Low	Human activities significantly affect water resources and the environment. Water shortage is evident, with reliance on external water transfers. The water ecosystem is severely damaged, system functionality is greatly affected, and ecological degradation risks are high.
V	Low	Human activities severely threaten water resources and the environment. Water resources are seriously scarce, ecological crises are prominent, requiring strict water use restrictions and implementation of inter-basin water transfers.

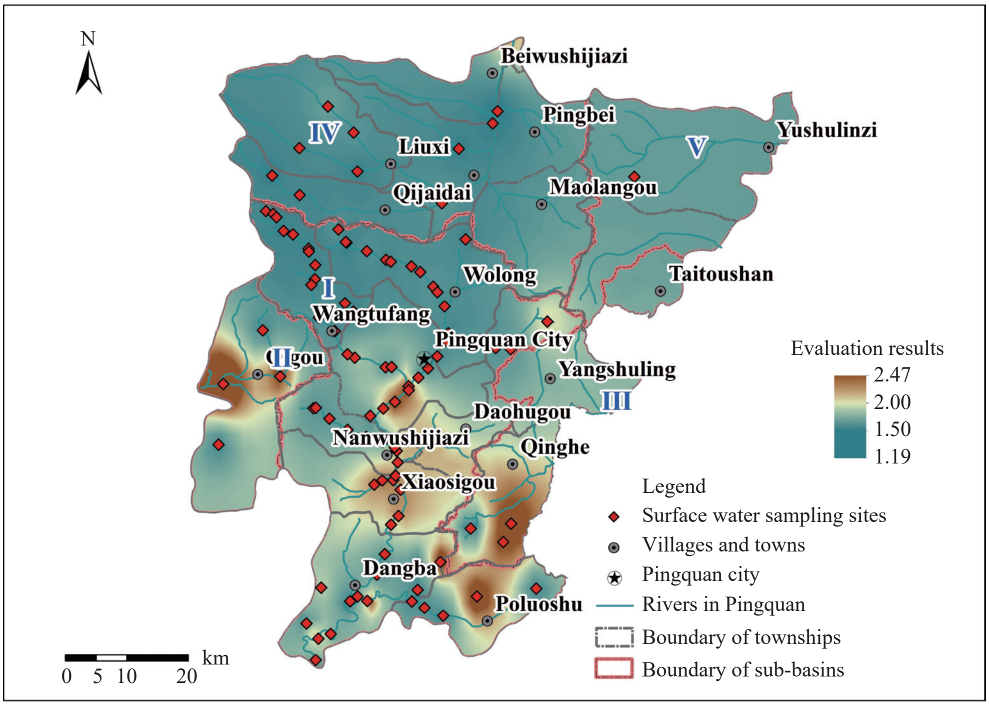

Fig. 3 Evaluation results of surface water quality in Pingquan (Ⅰ: Puhe River Basin; Ⅱ: Laoniuhe River Basin; Ⅲ: Qinglonghe River Basin; Ⅳ: Laohahe River Basin; Ⅴ: Dalinghe River Basin)

industrial water use. Studies indicated that nitrates in urban water bodies mainly derive from the discharge of nitrogenous waste (Sun et al. 2024). Untreated or insufficiently treated industrial and domestic sewage significantly elevates nitrate concentrations. Water quality data analysis confirms elevated nitrate levels in urban waters, ranging from 0.22 mg/L to 126.58 mg/L with an average of 27.2 mg/L. Similar findings by Wang et al. (2024) attribute nitrate pollution primarily to domestic sewage and organic matter inputs. Therefore, the surface water quality in the urban area of Pingquan City was declined. However, downstream sections of the Puhe River showed water quality improvement again attributed to the river's natural self-purification capacity.

Overall analysis revealed that the surface water quality in Pingquan City was generally good. However, certain river sections decline in water quality due to pollution from residential wastewater discharge. As shown in Fig. 4, approximately 18% of surface water quality samples exceeded the Class II water quality standard for nitrate content. This highlights the need to strengthen the operation and management of the sewage treatment plant, and to implement effective water treatment measures, ensuring that domestic sewage is treated promptly and discharged in compliance with environmental standards.

The comprehensive groundwater quality evaluation in the small watersheds of Pingquan City showed that groundwater quality across sub-basins ranged between 1.03 and 2.32 (Fig. 5). Among them, the groundwater quality in Laohahe River Basin was the best, surpassing the Class II water quality standard with an average score of 1.34. This basin benefits from a relatively low population density and limited groundwater extraction, contributing to better water quality. The groundwater quality in the Laoniuhe River and Qinglonghe River basins was also relatively good, with an average value of 1.49. Nonetheless, water quality slightly decreased in more densely populated township area. The average value of the comprehensive groundwater quality class in the Dalinghe River Basin was 1.53, with some sampling points nearing the threshold of Class II water quality standard. For the Puhe River Basin, the average value for groundwater quality was 1.47. Groundwater quality in the upper reaches of the basin was better,

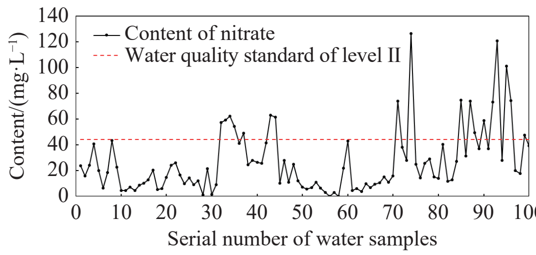

Fig. 4 Statistical map of nitrate content in surface water samples

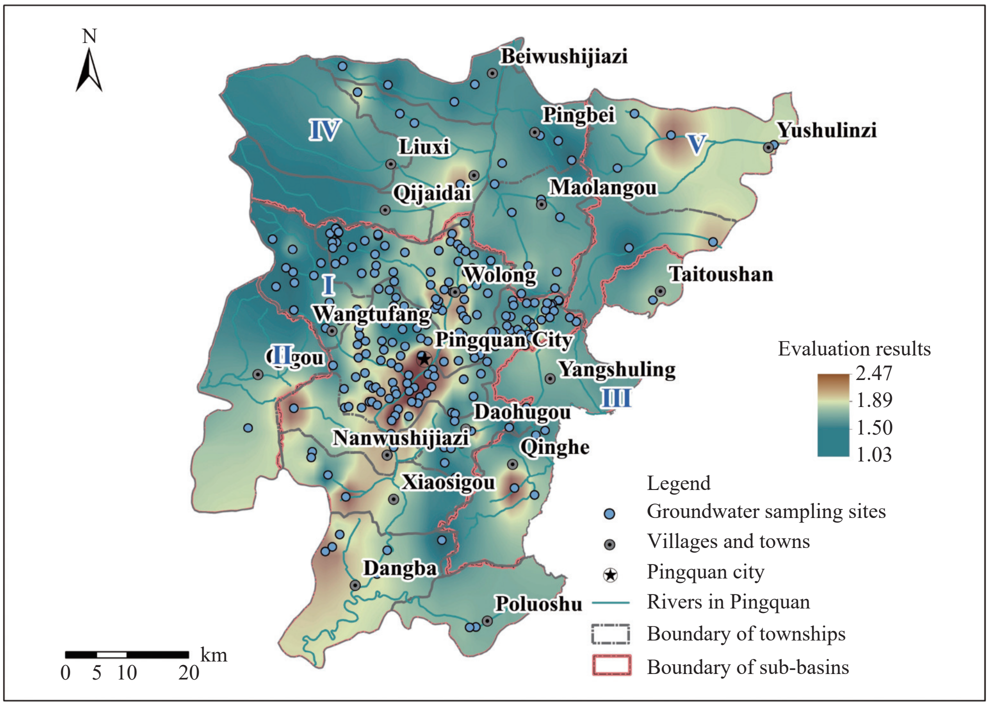

Fig. 5 Evaluation results of groundwater quality in Pingquan (Ⅰ: Puhe River Basin; Ⅱ: Laoniuhe River Basin; Ⅲ: Qinglonghe River Basin; Ⅳ: Laohahe River Basin; Ⅴ: Dalinghe River Basin)

while water quality near the city center of Pingquan was slightly poorer, falling below Class Ⅱ standard.

Analysis indicated that the overall groundwater quality in Pingquan City is relatively good; however, approximately 13% of the groundwater samples exceeded Class II water quality standard, primarily concentrated in the middle section of the Puhe River Basin. Further analysis of the original water quality data revealed that elevated nitrate levels are the primary reason of these exceedances. As shown in Fig. 6, the nitrate content at most sampling points was between Class II and Class III of the standards. Notably, about 58% of the groundwater samples surpassed Class II standard and roughly 20% even exceeded Class III. Given that groundwater is the main water source for domestic and agricultural use in Pingquan City, the observed nitrate pollution raises concerns. The decline in groundwater quality and increase in nitrate content are closely related to human activities, including excessive use of agricultural fertilizers, improper disposal of domestic sewage and waste, discharge of livestock and poultry manure, irrigation with contaminated water, and industrial emissions. For example, in the Dalinghe River Basin, where some pastoral lands are distributed, the discharge of untreated livestock and poultry manure significantly leads to nitrate pollution in groundwater and a decline in water quality. Further accelerated urbanization, population growth, and industrial activities in the urban areas have intensified groundwater extraction and sewage discharge, further affecting groundwater quality.

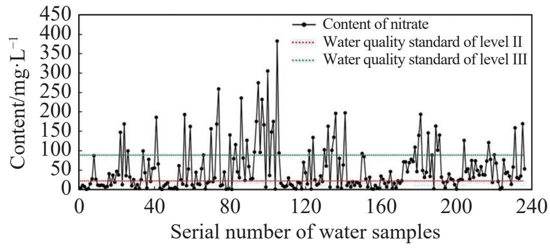

Fig. 6 Statistical map of nitrate content in groundwater samples

Although groundwater quality in Pingquan City was generally good, it is necessary to pay attention to areas with prominent nitrate pollution. Future water resource development and utilization should emphasize strengthened groundwater protection and management. Measures such as zoning for pollution prevention and control, strict regulation of groundwater abstraction permits, and enhanced groundwater monitoring and assessment are essential to ensuring the sustainable use of water resources.

3.2 Evaluation results of WRCC in Pingquan City

The WRCC in Pingquan City from 2010 to 2020 ranged between 2.83 and 2.99, with an average value of 2.90, which was close to Grade III. This indicates a moderate WRCC level, meaning that human activities have certain impacts on water resources and the water environment. While the utilization of water resources is basically reasonable, the balance between supply and demand is tightening. Consequently, it is necessary to strengthen water conservation management and control the scale of development. The regional water ecosystem has suffered some damage, and its functioning has been affected to a certain extent, though basic system operation remains intact.

The WRCC in Pingquan City has remained relatively stable in the past 11 years, showing only a slight upward trend, and the WRCC value in 2020 increased by about 3%, compared to 2010. Evaluations of the three WRCC subsystems—pressure (WRPCC), state (WRSCC), and response (WRRCC)—revealed average values of 2.60, 3.69 and 2.22 respectively over the same period (Fig. 7). These results indicate that while the WRPCC and WRSCC showed little change, the WRRCC improved markedly, rising from 2.67 in 2010 to 1.96 in 2020. This improvement reflects effective reduction of pressure on WRCC through enhanced response measures such as increased water consumption intensity in agricultural and industrial outputs, and higher ratios of ecological water use, contributing to the overall slight improvement in Pingquan City's WRCC.

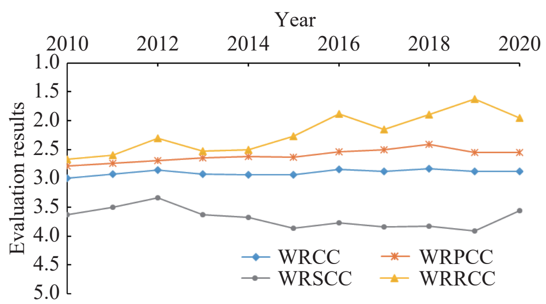

Fig. 7 Evaluation results of WRCC in Pingquan City

A separate analysis was conducted on the WRCC of the Luan River Basin and Liao River Basin (including Laohahe River Basin and Dalinghe River Basin) in Pingquan City (Fig. 8). The WRCC of the Luan River Basin was the highest among the basins and showed continual improvement over the years. In contrast, the WRCC of the Liao River Basin remained slightly lower and relatively stable during the past 11 years. The Luan River Basin benefits from relatively abundant water resources, a higher level of the economic development, adequate water utilization, and the presence of a sewage treatment plant that supports ecological water supply. Conversely, the Liao River Basin has relatively fewer water resources and slightly lower economic development, which have made its water resource utilization rate and degree of protection and restoration are lower, resulting in a somewhat reduced WRCC compared to the Luan River Basin. Looking forward, it is recommended to strengthen water resources management by intensifying the implementation of the "water conservation priority" policy, promoting green development concepts, encouraging water-saving practices across society, and further improving water use efficiency. These efforts will contribute to reducing water consumption, water use intensity, and wastewater discharge, thereby enhancing the carrying capacity of water resources to support sustainable social and economic development.

3.3 Reasonableness analysis of the results

3.3.1 Uncertainty analysis

The evaluation of WRCC involves multiple indicators, inevitably introducing some random errors in the quantification processes. Monte Carlo method (Wang et al. 2022) was used to simulate such random errors to verify the accuracy of VFPR model. Sixteen parameters, including resident population, ecological water use, total water resources, and water supply from other sources within the watershed, were selected as random variables. This study assumes that these random variables follow a Gaussian (normal) distribution, a common and suitable choice for representing the distribution of unknown real values, as supported by prior literature. Model parameters for the simulation were set as follows: The mean μ equals X_{ij}; standard deviation σ is $0.1 \times X_{ij}$, reflecting a 10% variability to analyze the influences of random errors; the number of simulation runs (N) was set to 1,000.

The simulation results showed that the average values obtained through Monte Carlo closely matched the original VFPR model calculations and fell within the 95% confidence intervals (Fig. 9). This confirms that the results derived from the VFPR model in this study possess high accuracy and reliability.

3.3.2 Comparison Analysis of the Results

To further verify the scientific validity and rationality of the evaluation results, this study also constructed a WRCC evaluation index system for Chengde City and applied the VFPR model for

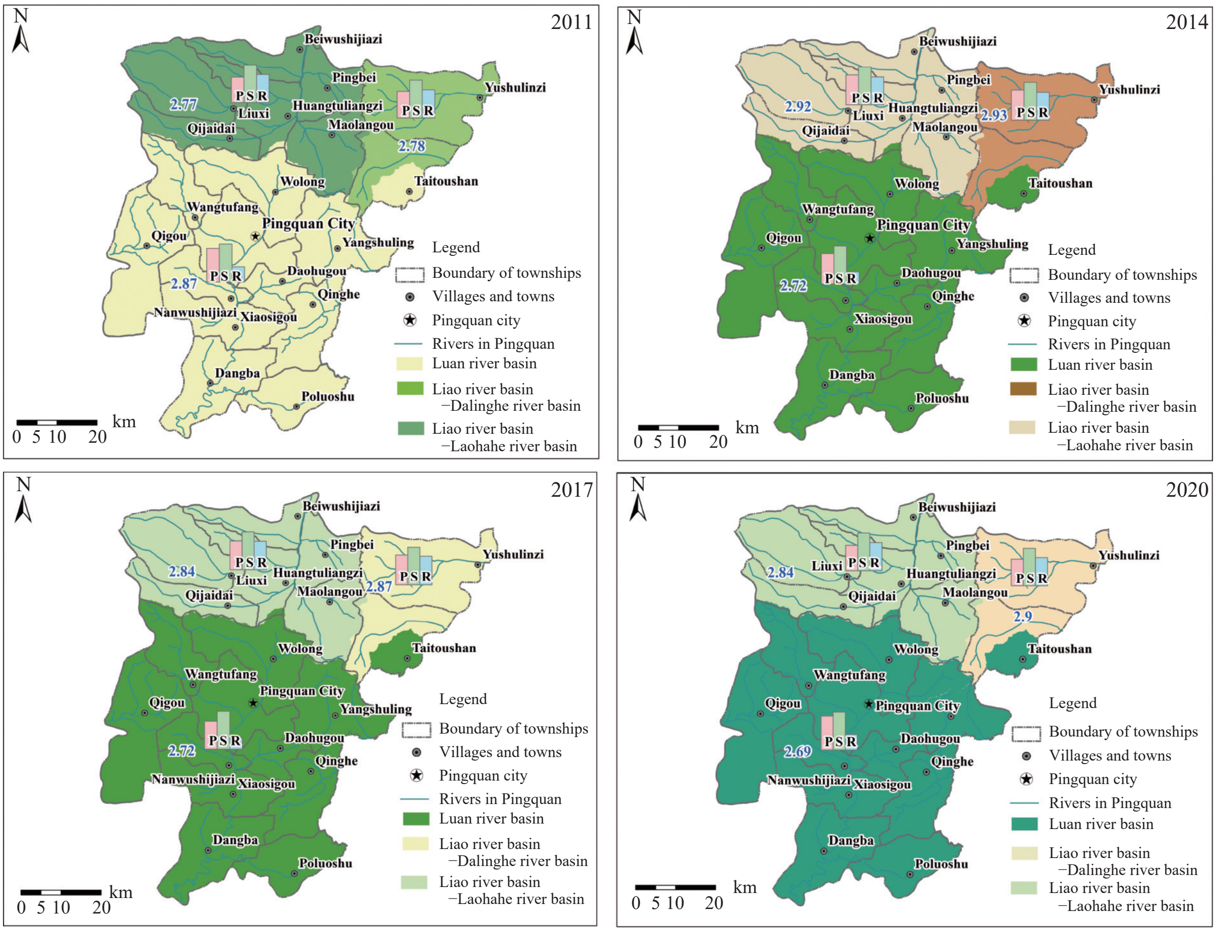

Fig. 8 Spatial and temporal variation statistics of WRCC in Pingquan City

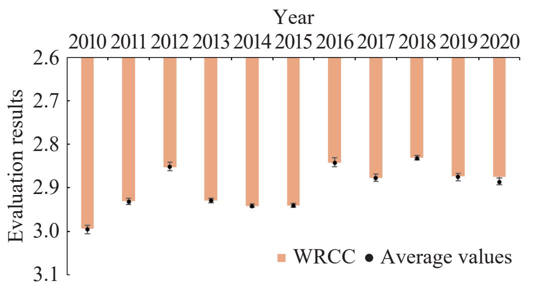

Fig. 9 Uncertainty analysis of VFPR model (colored bars are original average values of VFPR, solid black dots indicate Monte Carlo simulation means, error bars are 95% confidence intervals)

assessment. The results are shown in Fig. 10. The findings indicate that the WRCC patterns of Pingquan City and Chengde City are similar. From 2010 to 2020, both regions exhibited a slight improvement trend in WRCC, consistent with the overall gradual trend of WRCC across Hebei Province.

The WRCC of both Pingquan and Chengde fluctuated around Grade III, underscoring the severe water scarcity issues faced by both cities. In terms of water resources endowment, both areas possess relatively limited local water resources. From 2010 to 2020, the average water production modulus was 45,500 m^3/km^2 for Pingquan and 50,600 m^3/km^2 for Chengde, only one-sixth of the national average level of 281,000 m^3/km^2. The per capita water resources were 330.34 m^3 and 567.84 m^3, respectively, significantly lower than the national benchmark value of 2,014 m^3 per capita, with Pingquan even falling below the internationally recognized threshold for extreme water scarcity level of 500 m^3.

For a more detailed analysis, this study also evaluated the WRCC subsystems for Chengde City. The average WRPCC values for Pingquan and Chengde were 2.60 and 2.76, respectively, both situated between Grade II and Grade III, showing a slow downward trend. This suggests that strict water resources management policies have partially alleviated the pressure on WRCC.

Regarding the state subsystem, the average WRSCC for both cities was 3.69, positioned between Grade III and Grade IV, reaffirming the current state of water scarcity. In response to this challenge, both Pingquan and Chengde City have

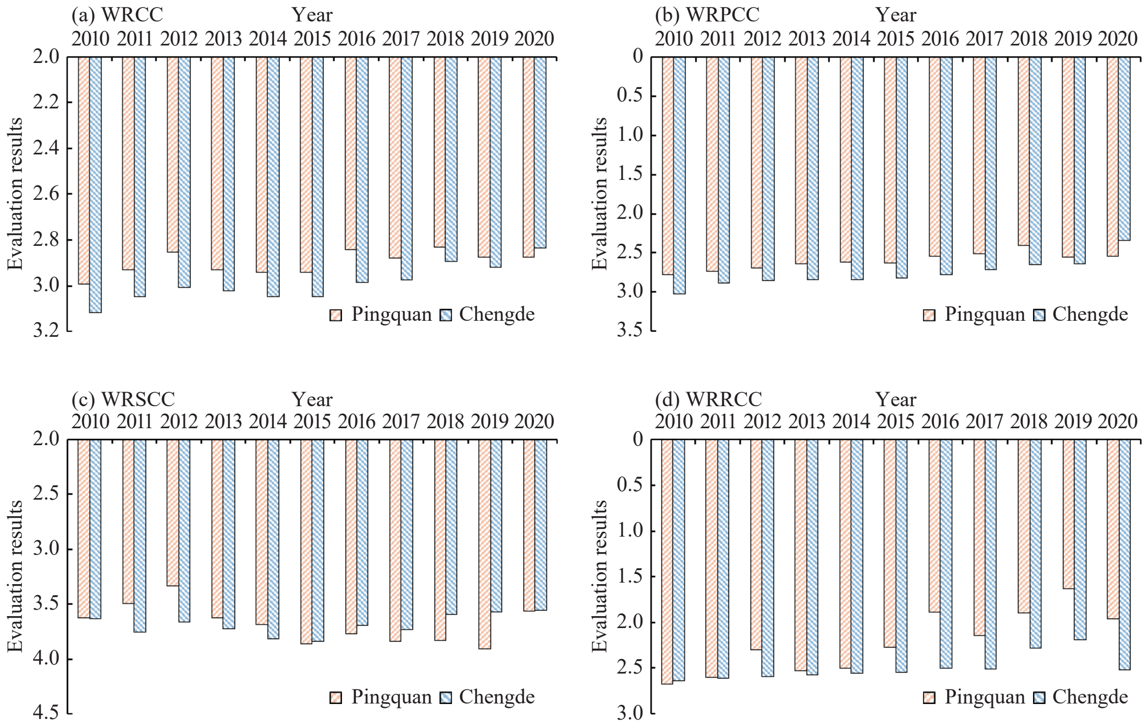

Fig. 10 Comparison of WRCC evaluation results between Pingquan City and Chengde City

been actively implementing major projects, including inter-basin water transfers, water conservancy infrastructure, and sewage treatment plant construction. These initiatives aim to increase external and unconventional water supply, these projects are expected to significantly enhance the effective supply of water resources in the future, improve water supply structures, and effectively alleviate water scarcity, thereby ensuring a reliable water resources foundation for sustainable regional development.

In the response subsystem, the average WRRCC values for Pingquan and Chengde cities were 2.22 and 2.50, respectively, both between Grade II and Grade III, showing a slow upward trend. This indicates progressive improvements in water use efficiency in both cities. The original data also showed that through widespread application of water-saving technologies and continuous optimization of industrial structure, the water consumption intensity for agricultural output and industrial outputs has significantly decreased. Meanwhile, the proportion of ecological water use has increased, reflecting growing attention to ecological water needs during water resources development and utilization. In addition, efforts to enhance reclaimed water reuse, rainwater harvesting, and other diversified water reuse strategies have significantly boosted water recycling rates, laying a solid foundation for sustainable water resource management.

3.4 Predictions of future scenarios

Based on the 14th Five-Year Plan of Pingquan City and considering the fundamental drivers of WRCC, this study employed a nonlinear time-series analysis method to predict the future scenarios of WRCC. A combination of population growth model, economic structure analysis model, and water resources supply-demand balance model was used to analyze historical data and predict trends in key variables such as total water resources, per capita water availability, and water consumption per GDP unit in Pingquan City.

Drawing from the urbanization and population growth trends reported in the "Pingquan City Statistical Yearbook 2020", and referencing projections from the "14th Five-Year Plan of Pingquan City" and the "Hebei Province 14th Five-Year Population Development Plan", the total permanent resident population of Pingquan City for 2025 and 2030 was reasonably projected. Using trend analysis, it is estimated that by 2025, the total permanent resident population of Pingquan City will exceed 520,000, including an urban population of 327,600 and an urbanization rate of around 61%. Based on a linear extrapolation model, by 2030 the permanent resident population is expected to reach 560,000, with an urbanization rate of around 71%.

Referring to the city's GDP growth target (approximately 6% per year) and projected industrial added value targets outlined in the "14th Five-Year Plan of Pingquan City", and combining this with historical data from local and provincial economic bulletins, predictions for water consumption per GDP unit were made. The results suggest that by 2025, the regional GDP of Pingquan City will reach around 23.2 billion yuan, and by 2030, approximately 30.1 billion yuan. Correspondingly, water consumption per GDP unit is projected to be around 45.3 m^3 in 2025 and 38 m^3 in 2030. Meanwhile, the added value of the service sector is projected to exceed 9 billion yuan in 2025 and reach 12 billion yuan by 2023, further enhancing its role in supporting economic and social development. Assuming stable agricultural output, Pingquan's industrial output value is expected to reach 10.6 billion yuan in 2025 and 14.6 billion yuan in 2030.

In addition, according to the "Decomposition Program of Red Line Control Targets for Total Water Consumption in Hebei Province under the Strictest Water Resource Management System (2021–2025)", groundwater consumption in Pingquan City will be controlled at 0.7617 billion m^3 in 2025, while the surface water and alternative water sources are expected to be increased concurrently to meet rising demand.

In summary, the WRCC for Pingquan City in 2025 and 2030 are projected to be 2.92 and 2.94, respectively, both falling between Grade II and Grade III and close to Grade III, indicating a moderate level of water resources carrying capacity (Fig. 11). Literature also predicted that by 2030, the WRCC of Hebei Province will be around Grade III, which is consistent with the evaluation results in this study and reinforce their validity. Compared with 2020, Pingquan's WRCC is projected to decline by 1.7% in 2025 and 2.2% in 2030. This downward trend was mainly due to population growth and industrial expansion, which together decrease per capita water resources.

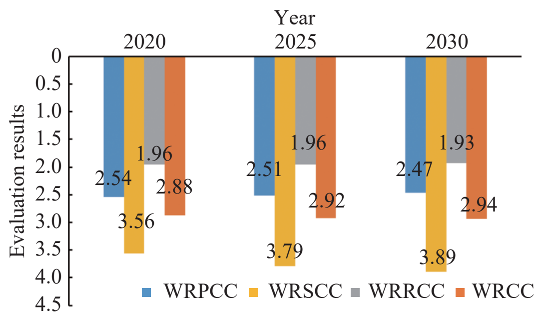

Fig. 11 Predictions of the future WRCC in Pingquan City

Disaggregated evaluation of the WRPCC, WRSCC, and WRRCC subsystems showed that WRPCC is expected to show improvement, WRSCC will increase slightly due to worsening supply-demand balance, and WRRCC will decline. This is largely because the projections assume a constant total amount of water resources. As the population grows and industry accelerates, per capita water availability declines, thereby intensifying water scarcity and leading to a projected decline in future WRCC.

In light of the predicted decline in WRCC, it is suggested that Pingquan City take proactive measures to enhance water conservation and management across all sectors:

(1) Industrial water conservation: The city should encourage enterprises to adopt advanced water-saving technologies and equipment, thereby improving the reuse rate of industrial water and reducing overall water consumption.

(2) Urban water-saving measures: Strictly implementation of urban water conservation policies is essential. This includes expanding public awareness campaigns on water conservation, promoting the use of water-saving devices, and fostering a culture of responsible water use among residents.

(3) Agricultural and rural water management: Efforts should focus on optimizing agricultural planting structures, promoting water-saving irrigation technologies, and improving the efficiency of water use in rural areas to reduce agricultural water demand.

(4) Ecological water use: Water conservation in ecological and urban landscapes should be enhanced through rational planning, design, and use. Improving water-use efficiency in parks, green spaces, and public landscapes will contribute to reduced non-essential water consumption.

(5) Development of alternative water sources: The city should accelerate the development and utilization of alternative water sources, such as rainwater harvesting, reclaimed water reuse, and treated greywater to supplement conventional water supplies.

(6) Integrated basin water resources management: It is essential to strengthen unified planning and management of water resources across the entire. Efforts should be directed toward promoting intensive, efficient, and circular use of water resources, ensuring a coordinated balance between supply and demand.

By implementing these measures, Pingquan City can effectively mitigate the pressures contributing to the decline in WRCC and lay a solid foundation for the sustainable development of its water resources, thereby supporting long-term socio-economic growth and ecological stability.

4 Conclusion

Focusing on the hilly areas, this study evaluated the surface water, groundwater quality and water resources carrying capacity of small watersheds in Pingquan City by using the PSR (Pressure-State-Response) model and the Variable Fuzzy Pattern Recognition (VFPR) model, with sub-watershed serving as evaluation units. The main conclusions are as follows.

The overall water quality of surface water and groundwater in Pingquan City was relatively good. The average comprehensive evaluation values were 1.44 and 1.46, respectively. Surface water quality across the sub-watersheds ranged from 1.19 to 2.47, meeting the the national Class II water quality standard for state-controlled sections. Although the overall surface water quality was satisfactory, certain river sections experienced quality decline due to domestic sewage discharges. The groundwater quality ranged from 1.03 to 2.32, with some areas in the urban core slightly exceeding the Class II standard due to the extensive exploitation of groundwater for domestic and industrial use, as well as improper discharge of wastewater. Approximately 20% of the groundwater samples exceeded the Class III standard in terms of nitrate content.

From 2010 to 2020, the WRCC in Pingquan City fluctuated between 2.83 and 2.99, with an average value of 2.90, indicating a moderate level of carrying capacity. Human activities have exerted a certain impact on water resources and water environment. Although the utilization of water resources in the region was relatively reasonable, the water ecosystem experienced slight disturbance, which affected system functioning to some degree but still allowed basic operation to continue. In recent years, through the implementation of various response measures—such as reducing agricultural and industrial water intensity and increasing ecological water use—the pressure on WRCC has been effectively alleviated, contributing to a gradual improvement in WRCC.

The reliability of the evaluation results was confirmed through Monte Carlo uncertainty analysis and comparative analysis with WRCC assessment results of Chengde City. Future scenario projections for 2025 and 2030, based on local development plans and socio-economic trends, suggested a slight decline in WRCC to 2.92 and 2.94, respectively, compared to 2020. These results indicate that Pingquan City will face increasing challenges in balancing water supply and ecological demand. The persistent contradiction between regional water scarcity and the cumulative ecological impact of human activities highlights the urgency of proactive planning and management. Therefore, to address these emerging challenges, it is recommended that Pingquan City continue optimizing the structure and spatial pattern of water resources utilization. Measures such as increasing the amount of water diversion and transfer through the construction of water conservancy projects, promoting the use of water-saving technologies and products, and enhancing water use efficiency should be prioritized. These efforts will support improved planning, management and decision-making in the development and utilization of water resources, thereby gradually improving WRCC and providing a strong foundation for sustainable economic and social development.

Acknowledgements

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