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A spatiotemporal analysis of water quality characteristics in the first-level tributaries in Nanchong Section of Jialing River

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ABSTRACT

In this study, the monitoring data of 23 parameters in 25 monitoring sections of the first-level tributaries of Jialing River in Nanchong City during the 13th Five-Year Plan period (2016–2020) were taken as the research object to analyze water environment quality. Results showed that the water quality is gradually improving in this area, and the main pollutant indexes are chemical oxygen demand, total phosphorus, ammonia nitrogen, permanganate index, 5-day biochemical oxygen demand, and dissolved oxygen. Cluster analysis divided the 12 months into two periods and the 25 monitoring sites into three groups based on similarity of water quality characteristics. The water quality of rainy seasons (July–December) was better than that of dry seasons (January–June). Groups 1, 2, and 3 were mainly located in the urban–rural fringe area, mountain area, and urban industrial park, respectively, representing moderate pollution, low pollution, and high pollution areas. Discriminant analysis (DA) presented good results with great discriminatory ability for both temporal and spatial analyses and provided an important data reduction. DA only used nine parameters for temporal analysis, affording approximately 91.7% correct assignations, and 18 parameters for spatial analysis, affording 96% correct assignations. Multivariate statistical analysis showed that the four major pollution sources in the basin are industrial wastewater, agricultural runoff, domestic sewage, and livestock pollution. The research results are relevant to the prevention and control of water pollution in the Jialing River Basin of the Yangtze River Economic Belt. The achievement of Nanchong City and the summary of the experience of winning the battle of pollution prevention and control in China take the lead in implementing the municipal river chief system in Sichuan Province.

Keywords: First-level tributary of Jialing River; Nanchong City; Temporal and spatial variations; Water quality; Sources of water pollutants

1. Introduction

Clean surface water is an essential requirement for human health and economic development. People living near surface water use it for various purposes, such as unrestricted irrigation, fishing, bathing, recreation, and drinking [1–3]. Water quality in an area is considered a function of natural and human factors. Surface water quality depends not only on natural processes, such as precipitation input, erosion and weathering of crustal materials, and biota interrelationships, but also on anthropogenic influences, such as wastewater discharge, fertilizer applications, and livestock breeding [4–6]. Surface water, such as small watersheds, is a dynamic system with high temporal

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and spatial heterogeneity [7,8]. The driving mechanisms for water quality changes are complicated because both natural and anthropogenic factors may be responsible at different temporal and spatial scales [9]. The interacting components of a surface water system determine the variation of physicochemical properties and the growth and change of living organisms over time. Understanding the spatial and temporal patterns of water quality is central to its management as they provide information essential to the restoration and protection of water resources. Therefore, monitoring water quality to study spatiotemporal changes and recognizing the main factors leading to water quality changes and variations provide a reference for effective management of water resources and pollution control.

River water quality analysis and evaluation are essential for water environment planning and management, pollution and prevention, and target assessment [4,10]. In recent years, the application of multivariate statistical techniques, such as cluster analysis (CA), principal component analysis (PCA), factor analysis (FA), multivariate linear regression (MLR), and discriminant analysis (DA), has increased tremendously for analyzing environmental data and drawing meaningful information [10–16]. These multivariate statistical methods have been effectively applied to assess surface water quality [5,11,17], evaluate spatial or temporal variations in groundwater, lake, and coastal water, and identify latent pollution sources [18–21].

The Nanchong Section of Jialing River is an important water source for people's living and industrial and agricultural production in Nanchong City. Some tributaries in the Nanchong Section of Jialing River receive domestic sewage, industrial wastewater, and agricultural water withdrawal, causing the deterioration of river water quality and restricting the economic development of the basin [22,23]. Thus far, few researchers have assessed the water quality of the tributaries of the Jialing River in the Nanchong Section. In 2016, the People's Government of Nanchong City signed the Water Pollution Prevention and Control Goal Responsibility Letter with the people's governments of all districts and counties in Nanchong City. Nanchong Environmental Protection Bureau took the lead in implementing the goal assessment task of the municipal river chief system in Sichuan Province, further strengthening the water quality monitoring and pollution prevention and control of the first-level tributaries of the Nanchong Section of Jialing River [22]. The current water quality and pollution situation can be accurately reflected only by using scientific and reasonable water quality evaluation methods. Water quality can be reasonably evaluated through water quality monitoring. Moreover, targeted water environment management plans and programs can be made, thereby directly affecting the accuracy of water environment management decisions. In this study, the first-class tributaries of the Nanchong Section of Jialing River are selected for water quality evaluation because it reflects a typical case of Nanchong City taking the lead in implementing river chief system assessment in China. This study can provide a reference for other regions. The results obtained from this study will be critical for ecological restoration and protection in the Jialing River Basin and for managing mountainous watershed ecosystems under the River Chief's Project.

Based on 5-year (2016–2020) datasets, different multivariate methods (CA and DA), Spearman's rank correlation coefficient (r_s), single-factor evaluation method, and Geographic Information System (GIS) [23] were used in the present study to explore the spatiotemporal distribution characteristics of water quality in the first-level tributaries of the Jialing River, identify potential pollution sources, determine the change rules of water quality, and propose relevant prevention and control countermeasures. The present study provides a decision basis and technical support for winning the battle of water pollution prevention and control in the Jialing River of Yangtze River Economic Belt.

2. Materials and methods

2.1. Study area

Nanchong City (30°35′–31°51′ N, 105°27′–106°58′ E, 256–899 m above sea level) is located in the northeast of Sichuan Basin and the midstream of Jialing River. The topography is high in the north and low in the south, with low mountains in the north and hills in the south (Fig. 1). With a total population of 7.6 million, it is the second-largest city in Sichuan Province. With an area of 12,479.96 km^2, it is a central city in the northern part of Chengyu Economic Zone, a regional central city in northeast Sichuan, and an important national transportation hub. The climate of Nanchong is a subtropical humid monsoon climate zone with four distinct seasons [22]. The air humidity is high, the wind speed is low, the annual average raining days is as high as 183 d, and the average annual total precipitation is approximately 1,100 mm. Considerable seasonal variability in precipitation exists. The maximum rainfall appears in summer, followed by autumn and spring, and the least occurs in winter.

As the second-largest tributary of the Yangtze River, the Jialing River is an important river system in Nanchong City. Nanchong is rich in water resources with 3,166 km of rivers, most of which belong to the Jialing River system in the Yangtze River Basin. The Jialing River has 25 first-level tributaries. The most important tributaries are Xi River, Dong River, Gouxi River, Baixi River, Luoxi River, and Xichong River. These rivers meet to form a dendritic drainage system.

2.2. Monitoring parameters

Water samples were collected from January 2016 to December 2020 every month. Twenty-five sampling sites (shown in Fig. 2) were selected in the first-level tributary of the Jialing River in Nanchong City, including (1) Dong River, (2) Baixi River, (3) Gouxi River, (4) Majia River, (5) Zhuzhen River, (6) Changtan River, (7) Chaijing River, (8) Xiaohe River, (9) Nicao River, (10) Xi River, (11) Jinxi River, (12) Da'ni River, (13) Qingxi River, (14) Xinjia River, (15) Heshu River, (16) Luxi River, (17) Yuxi River, (18) Luojia River, (19) Ying River, (20) Shengli Bridge, (21) Xichong River, (22) Wanyan River, (23) Qushui River, (24) Quejia River, and (25) Ji'an River. Twenty-three parameters were measured to analyze the main factors influencing water quality. Monitoring parameters included water temperature (TEMP), pH, dissolved oxygen (DO), permanganate index (COD_{Mn}), chemical oxygen demand (COD_{Cr}), ammonia nitrogen (NH_3–N),

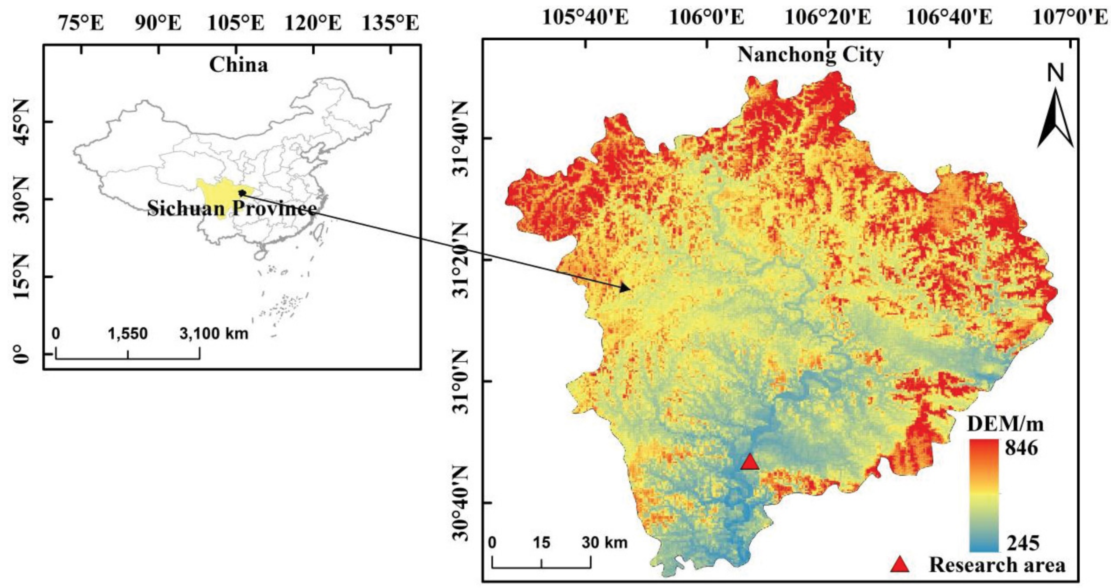

Fig. 1. Location map of the research area. *Note*: The different colors of this figure legend designate the altitude.

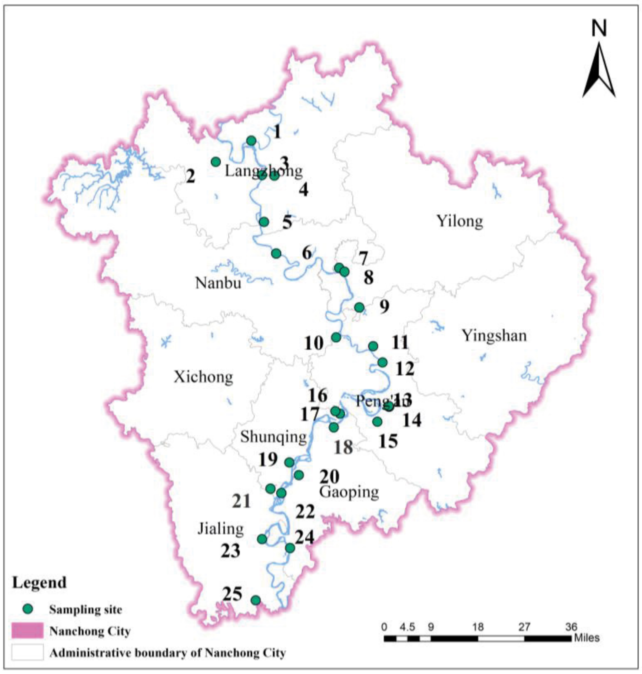

Fig. 2. Monitoring point map of the first-level tributaries in Nanchong Section of Jialing River.

total phosphorus (TP), 5-day biochemical oxygen demand (BOD_5), copper (Cu), lead (Pb), cadmium (Cd), zinc (Zn), fluoride (F^-), arsenic (As), mercury (Hg), selenium (Se), cyanide (CN^-), volatile phenol (VP), hexavalent chromium (Cr^{6+}), oils, sulfides (S^{2-}), anionic surfactants (LAS), and fecal coliform (F. coli). All of these parameters are expressed in mg/L, except for pH, TEMP (°C), and F. coli (CFU/L). The collection, preservation, and analysis of water samples were performed following the instructions in the Technical Specifications Requirements for Monitoring of Surface Water and Waste Water (HJ/T 91-2002) [24]. According to the Environmental Quality Standard for Surface Water (GB3838-2002), the water quality target assessment category is III [25,26]. The phenomenon in which the total nitrogen exceeds the standard in rivers in China is common. The Ministry of Ecology and Environment of the People's Republic of China formulated the Measures for Surface Water Environmental Quality Assessment (Trial) in March 2011 to reflect the state and trend of surface water environmental quality objectively and standardize the national surface water environmental quality assessment [27,28]. The evaluation indexes stipulated in this law are 21 indexes in Table 1 of Environmental Quality Standard for Surface Water (GB3838-2002), except TEMP, total nitrogen, and F. coli. Total nitrogen is not used as daily water quality evaluation indexes [25]. Therefore, the indicator total nitrogen was not included in this study.

2.3. Statistical analysis

This study conducted the investigations through single-factor evaluation method, Spearman's rank correlation coefficient, and multivariate statistical analysis. All data in this study meet normal distribution, and the monitoring parameters have no correlation. All mathematical and statistical calculations were performed using IBM SPSS Statistics 23.0 and Origin 2018 software.

2.3.1. Single-factor evaluation method

According to document No. 22 [2011] of the General Office of the Ministry of Environmental Protection, the Assessment Method for Surface Water Environmental Quality (Trial) issued by the General Office of the Ministry of Environmental Protection stipulates that the single-factor assessment method is adopted for section and river water quality assessment [28]. Therefore, the single-factor

Table 1
Summary of water quality statistics of the first-level tributaries in Nanchong Section of Jialing River during the 13th Five-Year Plan period

	Percentage of water quality categories (%)					
	I	II	III	IV	V	Worse V
2016	/	4.0	20.0	24.0	28.0	24.0
2017	/	12.0	52.0	20.0	/	16.0
2018	/	20.0	48.0	20.0	/	12.0
2019	/	16.0	72.0	4.0	4.0	4.0
2020	/	20.0	64.0	12.0	/	4.0
Changes in 2020 compared to 2016	/	16.0	44.0	–12.0	–28.0	–20.0

evaluation method was adopted in this study to evaluate and analyze 25 monitoring sections on the first-grade tributaries of Jialing River. This method is the most common evaluation method used by environmental monitoring departments in China, which is determined according to the highest index of the section in the evaluation period [22]. Section water quality category is I–II, and the water quality condition is excellent. The water quality category is III, and the water quality condition is good. The water quality is IV, and the water quality is slightly polluted. The water quality is V, and the water quality is moderately polluted. The water quality is classified as inferior V, and the water quality is severely polluted [25–28].

The calculation formula of single-factor evaluation is as follows:

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

where P_i is the single-factor evaluation index, C_i is the measured value of a water quality indicator, and S_i is the standard value of a certain water quality index [12,22,25].

2.3.2. Spearman's rank correlation coefficient (r_s)

Rank correlation coefficient method (r_s) is commonly used to measure whether the change trend of time series is statistically significant or not. Its principle is to rank the sample values of two factors from small to large and calculate by order of each factor sample value instead of the actual data [27,28]. r_s was calculated according to Appendix I, "Quantitative Analysis Method of Pollution Change Trend – Rank Correlation Coefficient Method" in Surface Water Environmental Quality Assessment Method (Trial) (No. 22 [2011] of the Environmental Office) [28]. A significance level of 0.05 and a rank correlation coefficient critical value W_p of 0.9 were selected in this study. The absolute value of r_s was compared with the critical value W_p in Spearman's rank correlation coefficient statistical table. W_p indicates that the change trend is significant. If r_s is positive, then the data series has an upward trend. If r_s is negative, then the data series has a downward trend [27].

Spearman's rank correlation coefficient mathematical model is as follows:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{N^3 - N} \tag{2}$$

$$d_i = X_i - Y_i \tag{3}$$

where r_s is the Spearman's rank correlation coefficient, d_i is the difference between X_i and Y_i, X_i represents the sequence from period i to period n in ascending order of concentration value, Y_i stands for chronological number, and N is the sample number [12,27].

2.3.3. Cluster analysis

CA is a data classification method, which groups the cases into classes based on similarities and dissimilarities and the samples belonging to the same category with the same source [16]. Hierarchical agglomerative technique, which is the most common approach and typically illustrated by a dendrogram, was adopted in this study. Euclidean square distance and Ward's minimum variance methods were used to analyze the temporal and spatial similarity of the first-level tributaries in the Nanchong Section of Jialing River from 12 months and 25 sampling sites [29]. Ward's method was used to generate clusters with minimum intracluster variance, whereas the squared Euclidean distances served as indicators of similarity. CA tends to maximize the similarity of samples within the same cluster and the diversity of different clusters in the overall classification system [3,8,30].

2.3.4. Discriminant analysis

DA is used to classify cases into categorical-dependent values, usually a dichotomy. DA determines the variables that discriminate between two or more naturally occurring groups. DA builds a predictive model to identify the group membership of unknown samples effectively using training samples with prior knowledge of their group membership [31,32]. The identified predictor variables are expected to provide the best discriminations among groups and may be considered the most representative of each group's characteristics [29,33]. The accuracy of the predictive model is determined by the percentage of training samples that are correctly classified. In this study, DA was performed for both of the temporal and spatial groups identified by CA to evaluate the spatial and temporal variations of water quality in first-level tributaries in the Nanchong Section of Jialing River.

3. Results and discussion

3.1. Overall condition of environmental quality in the first-level tributaries

3.1.1. Single-factor evaluation results

The single-factor evaluation results indicated that among the 25 sections of the first-level tributaries of Jialing River in Nanchong City during the 13th Five-Year Plan period, the average annual concentration of all monitoring parameters of 6 sections (Luojia River, Baixi River, Dong River, Xi River, Chaijing River, and Xiaohe River) was within the third national standard limit [25], whereas some parameters of the other 19 sections failed to meet the standards. The parameters with the highest exceeding frequency were COD_{Cr}, TP, BOD_5, NH_3–N, COD_{Mn}, and DO. The average annual concentration of pH, VP, CN^-, As, Hg, Cr^{6+}, Pb, Cd, Cu, Zn, F^-, Se, and S^{2-} in the 25 sections of the first tributaries of Jialing River reached Class I or Class II water quality standards [25]. According to the requirements of the Ministry of Environmental Protection of China, F. coli is used as a reference parameter and does not participate in the single-factor evaluation method. The water quality of Majia River and Wanyan River sections was moderately to severely polluted in the 5-year mean value, whereas the water quality of Qingxi River, Heshu River, and Xichong River were moderately polluted. Dong River had excellent water quality. The spatial GIS distribution map of single-factor evaluation results is shown in Fig. 3. Relevant departments should take the two nonstandard rivers (Majia River and Wanyan River) as key prevention and control objects and Qingxi River, Heshu River, and Xichong River as alert objects.

3.1.2. Trend of water quality in the first-level tributaries

During the 13th Five-Year Plan period, the proportion of qualified sections (water quality Classes I–III) in the first-level tributaries of Jialing River in Nanchong showed an overall upward trend, whereas the proportion of unqualified sections (water quality Classes IV to Worse V) showed a downward trend. Compared with the water quality classes in 2016, Class II increased by 16%, Class III increased by 44%, Class IV decreased by 12%, Class V decreased by 28%, and inferior V decreased by 20% in 2020. Water quality has improved remarkably. Table 1 shows the summary of water quality category statistics. The interannual variation trend of water quality category proportion during the 13th Five-Year Plan period is shown in Fig. 4. According to the annual variation of the comprehensive rate of meeting the standard, the water quality of the first-level tributaries of the Jialing River has been gradually improved in the past 5 y. This finding indicates that the People's Government of Nanchong City took the lead in implementing the municipal river chief system of river target assessment system in the whole province and has achieved results in the key regulation of the first-level branch water environment of Jialing River.

3.1.3. Trend of concentration of major pollution indicators

As is shown in Table 2, the main pollution indexes are COD_{Cr}, TP, NH_3–N, COD_{Mn}, BOD_5, and DO, and the

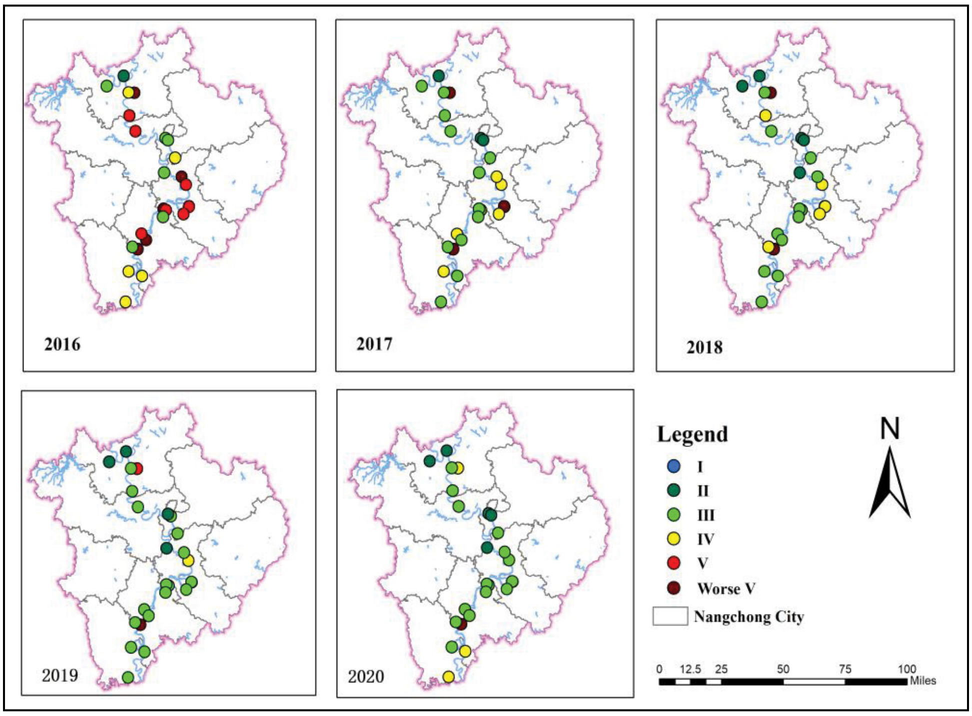

Fig. 3. Spatial GIS distribution of single-factor evaluation results of the first-level tributaries in Nanchong Section of Jialing River.

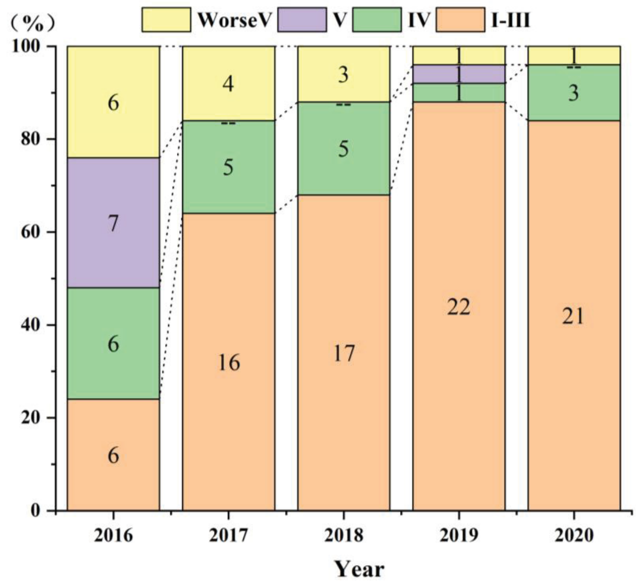

Fig. 4. Interannual variation trend of the proportion of water quality in the first-level tributaries in Nanchong Section of Jialing River during the 13th Five-Year Plan period.

Table 2
Exceeding rate of main pollution indexes in the first-level tributaries in Nanchong Section of Jialing River

Pollution parameter	Exceeding rate of main pollution indexes (%)				
	2016	2017	2018	2019	2020
COD_{Cr}	72.0	28.0	32.0	8.0	16.0
TP	32.0	24.0	12.0	4.0	8.0
NH_3–N	24.0	8.0	12.0	8.0	4.0
COD_{Mn}	32.0	4.0	8.0	0.0	0.0
BOD_5	28.0	12.0	16.0	4.0	4.0
DO	16.0	8.0	4.0	4.0	0.0

over-standard rate of six pollution indicators showed a decreasing trend. BOD_5, COD_{Cr}, and COD_{Mn} mainly characterize organic matter, and NH_3–N and TP mainly represent nitrogen pollutants and phosphate pollutants, which reflect water eutrophication. Moreover, DO is often used to characterize the self-purification ability of the water environment. Therefore, the first-level tributaries in the Nanchong Section of Jialing River showed obvious characteristics of organic pollution and eutrophication during the 13th Five-Year Plan period.

The rank correlation coefficient (r_s) was used to test the annual variation trend of the six main pollution indexes with the highest over-standard frequency. The variation trend of the concentration of major pollution indicators is shown in Table 3. Among them, the concentration of six main pollution indicators showed a decreasing trend. The specific conditions of each indicator are as follows: the COD_{Cr} concentration of 92% of the sections showed a decreasing trend, and the COD_{Cr} concentration of 40% of the sections decreased significantly (r_s < −0.9). The concentration of NH_3–N decreased in 88% of sections, and the concentration of NH_3–N decreased significantly in 24% of sections (r_s < −0.9). Moreover, 88% of the sections showed a decreasing trend of DO, and 16% of the sections showed a significant decrease (r_s < −0.9). COD_{Mn} concentration decreased in 84% of sections and decreased significantly in 16% of sections (r_s < −0.9). BOD_5 concentration decreased in 68% of sections and decreased significantly in 12% of sections (r_s < −0.9).

In conclusion, single-factor evaluation method showed that the water quality of the first-level tributaries of Jialing River in Nanchong City during the 13th Five-Year Plan period (2016–2020) has been improving yearly. The main pollutant indexes in this area are COD_{Cr}, TP, NH_3–N, COD_{Mn}, BOD_5, and DO. The Jialing River Basin in Nanchong City is mainly affected by organic pollution and eutrophication. Majia River and Wanyan River had the worst water quality, followed by Qingxi River, Heshu River, and Xichong River, which were moderately polluted. Dong River had the best water quality.

3.2. Temporal similarity and period grouping

Temporal CA was used to generate a dendrogram (Fig. 5) that grouped the months into two clusters (Period 1, Period 2) with similar physiochemical water quality characteristics. Period 1 covered July–December, which included the high-flow period (June–October) and the mean-flow period (November–December) of Jialing River. Period 2 covered January–June, which included the low-flow period (January–May) of the river. Given the influence of meteorological conditions and hydrological conditions, the duration of the annual water period had a slight deviation. The results of CA were consistent with the trends of water period and seasonal variation. These trends were consistent with the actual situation. The results showed that the water quality of the Jialing River Basin was affected by hydrological conditions (i.e., dry and wet seasons) and seasonal changes. This finding is similar to the results of Shrestha and Kazama [5], Duan et al. [10], Han et al. [15] and Zhang et al. [31], which divided the 12 months into two water periods (dry and wet). Zhang et al. [8] and Xiao et al. [33] divided the 12 months into three periods through spatiotemporal CA, which was completely consistent with the dry season, wet season, and flat season. However, the main pollution parameters to distinguish these water periods were different in different study areas.

As shown in Table 4, the value of Wilks' lambda for the discriminant function was small (0.001), the chi-square value was high (36.559), and the p level (0.000) was less than 0.05. These figures suggested that the temporal DA in this study was significant [17]. The discriminant functions (DFs) and classification matrices (CMs) obtained from DA are shown in Tables 5 and 6, respectively. DA produced a CM with nearly 91% correct assignments, a percentage higher than most of the correct assignments produced by backward stepwise DA [5,17,32,33]. The temporal DA results suggested that TEMP, pH, DO, COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, VP, and As were the most relevant parameters for discriminating between Periods 1 and 2, and they accounted for most of the expected temporal variation in water quality.

Table 3
Change trend of main pollution index concentration in the first tributaries in Nanchong Section of Jialing River during the 13th Five-Year Plan period

Districts and counties	Name of river	DO		COD_{Mn}		BOD_5		NH_3–N		COD_{Cr}		TP	
		r_s	Trend	r_s	Trend	r_s	Trend	r_s	Trend	r_s	Trend	r_s	Trend
	Yuxi River	–0.7	downward	**–1.0**	**downward**	–0.1	downward	–0.6	downward	–0.1	downward	–0.8	downward
Shunqing	Luxi River	–0.6	downward	**–1.0**	**downward**	0.6	upward	**–1.0**	**downward**	–0.87	downward	**–0.9**	**downward**
	Ying River	–0.8	downward	–0.87	downward	–0.4	downward	–0.1	downward	**–0.9**	**downward**	–0.6	downward
	Xichong River	–0.7	downward	–0.5	downward	–0.3	downward	–0.6	downward	–0.7	downward	–0.8	downward
	Shengli Bridge	–0.6	downward	**–0.9**	**downward**	–0.2	downward	–0.7	downward	–0.2	downward	–0.1	downward
Gaoping	Quejia River	0.4	upward	–0.4	downward	0.3	upward	–0.7	downward	0.4	upward	–0.1	downward
	Luojia River	–0.4	downward	–0.4	downward	0.6	upward	0.0	stable	–0.7	downward	0.5	upward
	Wanyan River	**–0.9**	**downward**	**–0.1**	**downward**	**–0.9**	**downward**	**–0.9**	**downward**	**–1.0**	**downward**	**–0.3**	**downward**
Jialing	Qushui River	0.2	upward	–0.7	downward	–0.3	downward	**–1.0**	**downward**	–0.3	downward	–0.6	downward
	Ji'an River	–0.4	downward	–0.7	downward	0.87	upward	–0.7	downward	–0.1	downward	–0.3	downward
	Baixi River	–0.7	downward	0.2	upward	0.1	upward	0.1	upward	–0.7	downward	0.1	upward
	Gouxi River	–0.6	downward	–0.8	downward	0.0	stable	–0.6	downward	**–0.9**	**downward**	–0.6	downward
Langzhong	Majia River	**–1.0**	**downward**	**–1.0**	**downward**	**–0.9**	**downward**	**–1.0**	**downward**	**–0.9**	**downward**	**–1.0**	**downward**
	Zhuzhen River	0.5	upward	–0.4	downward	0.6	upward	–0.3	downward	**–0.9**	**downward**	0.0	stable
	Dong River	**–0.9**	**downward**	0.2	upward	**0.9**	**upward**	0.0	stable	0.2	upward	0.6	upward
Nanbu	Xi River	–0.7	downward	0.0	stable	0.2	upward	–0.3	downward	–0.7	downward	0.5	upward
	Changtan River	–0.7	downward	**–1.0**	**downward**	0.4	upward	–0.6	downward	–0.2	downward	**0.9**	**upward**
	Heshu River	–0.7	downward	–0.7	downward	–0.7	downward	–0.7	downward	**–0.9**	**downward**	**–0.9**	**downward**
	Qingxi River	**–0.9**	**downward**	**–0.9**	**downward**	**–0.9**	**downward**	–0.7	downward	**–0.9**	**downward**	**–1.0**	**downward**
Peng'an	Xinjia River	–0.8	downward	–0.87	downward	–0.5	downward	–0.2	downward	**–0.9**	**downward**	–0.8	downward
	Da'ni River	–0.2	downward	–0.7	downward	–0.3	downward	–0.6	downward	**–0.9**	**downward**	–0.3	downward
	Jinxi River	–0.7	downward	**–1.0**	**downward**	–0.6	downward	–1.0	**downward**	**–0.9**	**downward**	**–1.0**	**downward**
	Chaijing River	–0.6	downward	0.1	upward	–0.1	downward	–0.2	downward	–0.5	downward	0.0	stable
Yilong	Xi River	–0.2	downward	0.6	upward	–0.1	downward	–0.6	downward	–0.7	downward	–0.4	downward
	Nicao River	–0.7	downward	–0.5	downward	–0.7	downward	**–0.9**	**downward**	–0.8	downward	**–0.9**	**downward**

Notes: 1. Bold part in black means significant, and the non-bold part means not significant.
2. When calculating DO by r_s, the inverse of DO concentration is used to participate in the calculation according to the properties of DO.

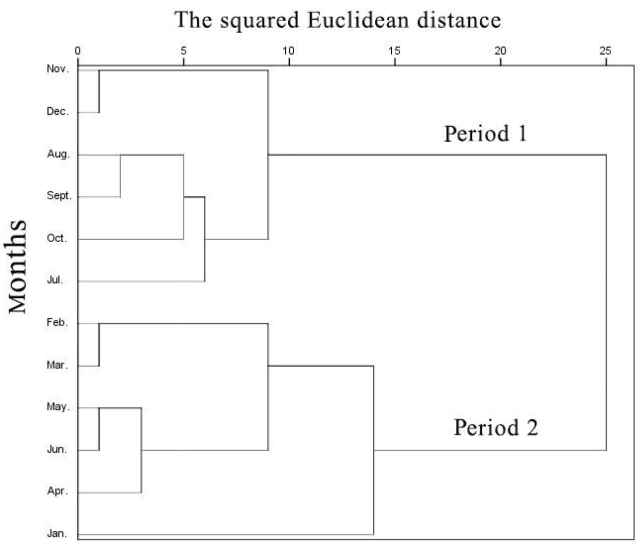

Fig. 5. Dendrogram showing the clustering of monitoring periods in the first-level tributaries in Nanchong Section of Jialing River.

Table 4
Wilks' lambda values

Fun. (s)	1
Wilks' lambda	0.001
Chi-square	36.559
Degree of freedom	9
Significance	0.000

Table 5
Classification function coefficients of temporal DA

Parameter	Period	
	Period 1	Period 2
TEMP	–5,243.391	–5,136.731
pH	1,097,385.939	1,074,730.922
DO	–17,613.505	–17,265.893
COD_{Mn}	–34,834.953	–34,115.829
BOD_5	41,748.791	40,895.842
NH_3–N	–322,513.250	–315,853.125
COD_{Cr}	–12,616.613	–12,352.036
VP	–8,576,271,044.320	–8,395,251,676.931
As	63,111,613.628	61,743,907.543
Constant	–2,978,471.335	–2,857,792.307

The results showed that TEMP in Period 1 (20.50°C) was significantly higher (p = 0.000) than that in Period 2 (17.35°C) and revealed a clear-cut temporal effect (Fig. 6a). The reason was that Period 1 included all the warm months (July–September). Rainfall in Period 1 was also higher than that in Period 2 because Period 1 covered the rainy months. The average concentration of DO in Period 1 (7.52 mg/L) was significantly lower (p = 0.000) than that in Period 2 (8.58 mg/L) (Fig. 6c). A clear inverse relationship was observed between TEMP and DO. This relationship is natural because warm water saturates easily with oxygen and contains minimal DO [5,17]. The DO concentration during most of the period was higher than the second national standard limit (6 mg/L) [24] required for the protection of aquatic life. This finding is consistent with the research results of Zhang et al. [31] on water quality evaluation of the Jialing River Basin in Guangyuan. The average concentrations of COD_{Mn}, BOD_5, NH_3–N, and COD_{Cr} in Period 2 (4.33, 3.7, 0.585, and 20.9 mg/L) were higher than those in Period 1 (3.84, 2.0, 0.399, and 16.7 mg/L) (Fig. 6d–g). These parameters were mainly affected by organic pollution and eutrophication pollution, and the water quality in Period 1 was better than that in Period 2 (dry seasons). This finding is consistent with the conclusion obtained by the previous single-factor evaluation method, that is, the first tributary of the Nanchong Section of Jialing River shows obvious organic pollution and eutrophication pollution characteristics. The main sources of the water pollutant As were surface runoff and industrial wastewater, and the high average concentration of As may be related to wastewater discharges, construction, and agricultural activities [34]. The low As concentration in Period 2 (0.0013 mg/L) may be due to high evaporation rates and low flow rates of water during the dry season (Fig. 6h) [35,36]. Related government departments should pay attention to water quality monitoring in dry seasons.

Table 6
Temporal-varying DA[a]

Group	Proper composition	Period	
		Period 1	Period 2
Period 1	100%	6	0
Period 2	83.3%	1	5
Total	91.7%	7	5

[a]Checked by cross-validation method.

3.3. Spatial similarity and site grouping

The dendrogram showed that the monitoring locations may be grouped into three main clusters to analyze spatial variation (Fig. 7). Ji'an River, Qushui River, Quejia River, Luxi River, Yuxi River, Xinjia River, Qingxi River, Ying River, Xichong River, Luojia River, Shengli Bridge, Jinxi River, Da'ni River, Nicao River, and Heshu River formed Group 1. Chaijing River, Xiaohe River, Xi River, Changtan River, Baixi River, Gouxi River, Dong River, and Zhuzhen River formed Group 2, and the remaining two sites (Majia River and Wanyan River) formed Group 3. The classification of these groups changed with the significance level, and Group 2, Group 1, Group 3 represented low pollution, moderate pollution, and high pollution levels, respectively. The CA results indicated sampling sites with similar natural background values affected by similar pollution sources. In a similar spatial analysis, Zhang et al. [31] divided seven

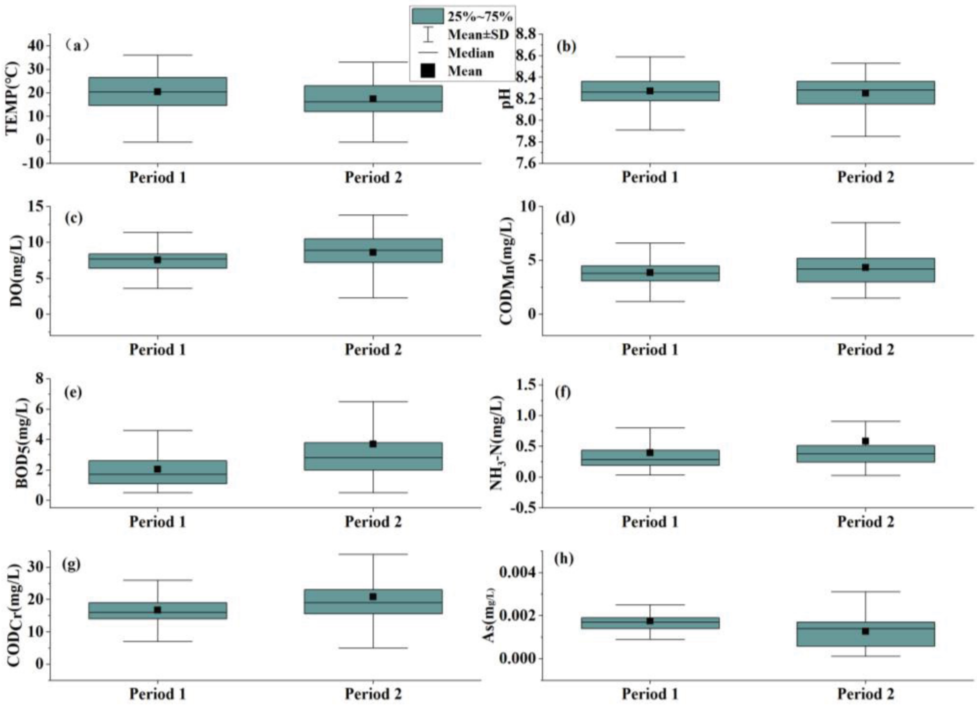

Fig. 6. Temporal variations: (a) temperature, (b) pH, (c) DO, (d) COD_{Mn}, (e) BOD_5, (f) NH_3–N, (g) COD_{Cr}, and (h) As.

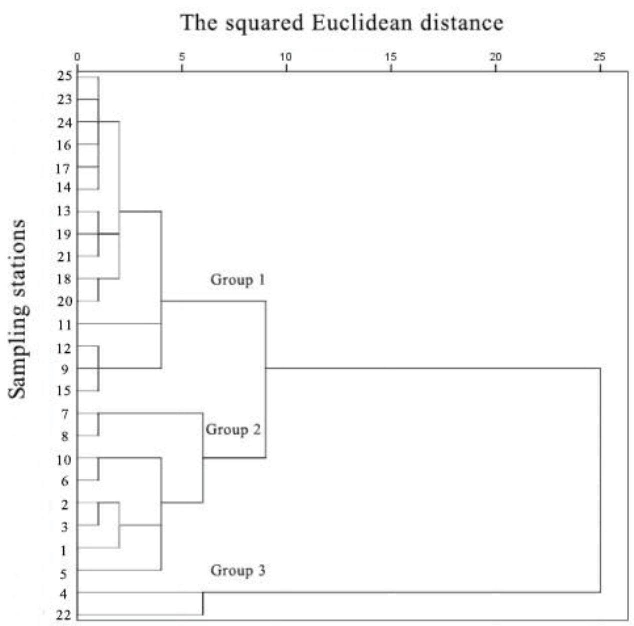

Fig. 7. Dendrogram showing the clustering of monitoring sites in the first-level tributaries in Nanchong Section of Jialing River.

sampling sites into two regions, the low-pollution area and the high-pollution area, the main sources of water pollutants were surface runoff and industrial wastewater. Zhang et al. [8] divided eight monitoring sites into two areas of light pollution and heavy pollution according to different levels of physical and chemical properties and pollution caused by human activities. The main pollution sources in the two regions included agricultural activities, domestic sewage, and industrial wastewater discharge. Duan et al. [10] divided the 28 monitoring sites into two regions (low pollution and high pollution). In addition, some scholars divided the sampling points into three pollution level groups through CA. For example, Varol [3] divided 11 sampling sites into three groups based on similar features.

Table 7
Wilks' lambda values

Fun. (s)	1–2	2
Wilks' lambda	0.000	0.025
Chi-square	127.542	49.558
Degree of freedom	36	17
Significance	0.000	0.000

As shown in Table 7, the Wilks' lambda value and chi-square value of the first discriminant function are 0.000 and 127.542, respectively, and those of the second discriminant function are 0.000 and 49.558, respectively, with p level (0.000) all less than 0.05, this observation indicates that the spatial DA function in this study has strong discriminant ability and good reliability and validity [17,31]. Tables 8 and 9 show the DFs and CMs, respectively, obtained from DA. Spatial DA produced a CM with 96% correct assignments, which is slightly higher than the CM in other reports [5,10,15,17,32,37,38]. DA showed that TEMP, pH, DO, COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, VP, As, oils, TP, Cu, Zn, F^-, Se, LAS, S^{2-}, and F. coli were the discriminating parameters

Table 8
Classification function coefficients of spatial DA

Parameter	Group		
	Group 1	Group 2	Group 3
TEMP	1,831.639	2,064.927	1,495.301
pH	39,899.768	40,139.363	39,081.151
DO	–210.137	–114.434	–350.735
COD_{Mn}	2,119.489	2,063.693	2,095.150
BOD_5	–2,789.268	–2,923.323	–2,453.233
NH_3–N	736.184	807.585	550.922
COD	–473.527	–487.925	–442.793
VP	6,463,457.807	6,439,366.846	5,869,950.656
As	366,036.444	384,912.460	262,190.469
Oils	313,433.073	326,819.104	298,712.984
TP	2,308.515	2,770.229	1,440.633
Cu	431,482.669	442,442.301	394,395.970
Zn	135,324.593	153,019.271	102,204.455
F^-	–70,674.938	–72,757.393	–65,716.488
Se	1,642,074.511	1,721,450.109	1,505,093.717
LAS	4,195.532	3,587.738	–546.646
S^{2-}	405,002.150	428,092.239	373,466.049
F. coli	0.040	0.044	0.032
Constant	–173,890.959	–180,639.209	–161,727.218

Table 9
Spatial-varying DA[a]

Group	Proper composition	Group		
		Group 1	Group 2	Group 3
Group 1	100%	15	0	0
Group 2	100%	0	8	0
Group 3	50%	1	0	1
Total	96.0%	16	8	1

[a]Checked by cross-validation method.

in space. Combined with the previous single-factor evaluation results, the seven parameters of TEMP, VP, As, Cu, Zn, Se, and LAS did not exceed the first national standard limit in this study, and these parameters in the comprehensive evaluation of water quality had little impact on the change of water quality. Moreover, these seven parameters had no significant correlation with other variables. Therefore, 11 of the 18 variables, including pH, DO, COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, oils, TP, F^-, S^{2-}, and F. coli, were selected for follow-up analysis.

Considerable differences between the three groups could be easily seen from the boxplot (Fig. 8). The trends for COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, oils, TP, F^-, S^{2-}, and F. coli (Fig. 8c–k) indicated that the average concentration in Group 3 was the highest, whereas that in Group 2 was the lowest (ANOVA, $p(COD_{Mn}) = 0.000$, $p(BOD_5) = 0.000$, $p(NH_3\text{–N}) = 0.000$, $p(COD_{Cr}) = 0.000$, $p(\text{oils}) = 0.000$, $p(\text{TP}) = 0.000$, $p(F^-) = 0.000$, $p(S^{2-}) = 0.019$, $p(\text{F. coli}) = 0.000$). The average DO (ANOVA, $p = 0.000$, Fig. 8b) in Group 2 was higher than that in Groups 1 and 3. The concentration range of all parameters in Group 3 was also larger than that in Groups 1 and 2, indicating that the concentration of each parameter in Group 3 was at a relatively high level and had large monthly variations. Moreover, the water quality was unstable. The average concentration of pH (ANOVA, $p = 0.007$, Fig. 8a) ranged from 8.23 to 9.30, and all the concentrations were within the limits of national surface water environmental quality standards (6–9) [25]. In the three groups, the average concentration of F. coli was 41,880; 10,500 and 158,558 CFU/L. The average concentration of F. coli in the three groups was higher than the limits of the third national surface water standards (10,000 CFU/L) [25]. F. coli mainly represents the degree of water pollution by fecal contamination. The Jialing River tributaries were seriously polluted by fecal contamination. In Group 1, the average concentrations of COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, oils, TP, F^-, S^{2-}, DO, and pH were 8.06, 2.65, 0.442, 18.9, 0.011, 0.132, 0.284, 0.0085, 8.07, and 8.25 mg/L, respectively, and all were within the limits of the third national surface water standards (6, 4, 1, 20, 0.05, 0.2, 1.0, 0.2, 5, and 6–9 mg/L, respectively) [25]. In Group 2, the mean concentrations of COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, oils, TP, F^-, S^{2-}, DO, and pH were 3.15, 1.87, 0.265, 14.1, 0.010, 0.053, 0.219, 0.0072, 8.96, and 8.29 mg/L, respectively, and all were within the limits of the third national surface water standards [25]. In Group 3, the mean concentrations of COD_{Mn}, BOD_5, NH_3–N, COD_{Cr}, oils, TP, F^-, S^{2-}, DO, and pH were 5.82, 7.80, 2.22, 31.3, 0.030, 0.406, 0.332, 0.0094, 5.17, and 8.23 mg/L, respectively. The average concentration of BOD_5, NH_3–N, COD_{Cr}, and TP was relatively high, exceeding the third national surface water standard (4, 1.0, 20, and 0.2 mg/L, respectively) [25] by 0.95, 1.22, 0.56, and 1.03 times, respectively. The four parameters mainly characterize organic pollution and eutrophication.

From the grouping results, the water quality of Group 3 (Majia River and Wanyan River) was the worst, and the water quality was classified as V to worse V, and the water quality was at a high pollution level (severely polluted). In combination with the terrain, both rivers are located in urban areas (Langzhong and Gaoping). Industrial parks are nearby, which are mainly polluted by point sources, such as chemical raw materials and chemical products. The discharged wastewater contains a large amount of oxygen-consuming organic matter, and the high density of population and high discharge of domestic sewage leads to a large water treatment load.

The water quality of Group 1 was worse than that of Group 2, and some parameters exceeded the standard according to the single-factor evaluation results. The water quality of Group 1 was in Class III to Class IV, and the water quality was moderately polluted. The rivers in Group 1 are mainly located in the urban–rural fringe area. The main pollution sources are domestic sewage, farmland fertilization, and livestock pollutants. The pollution causes are as follows: first, the population is relatively dense, the discharge of domestic sewage is large, and a large amount of domestic sewage is directly discharged into rivers without treatment. Second, the level of village sewage management is low, most of the township sewage treatment plants are not in operation, and small livestock and poultry farming around the

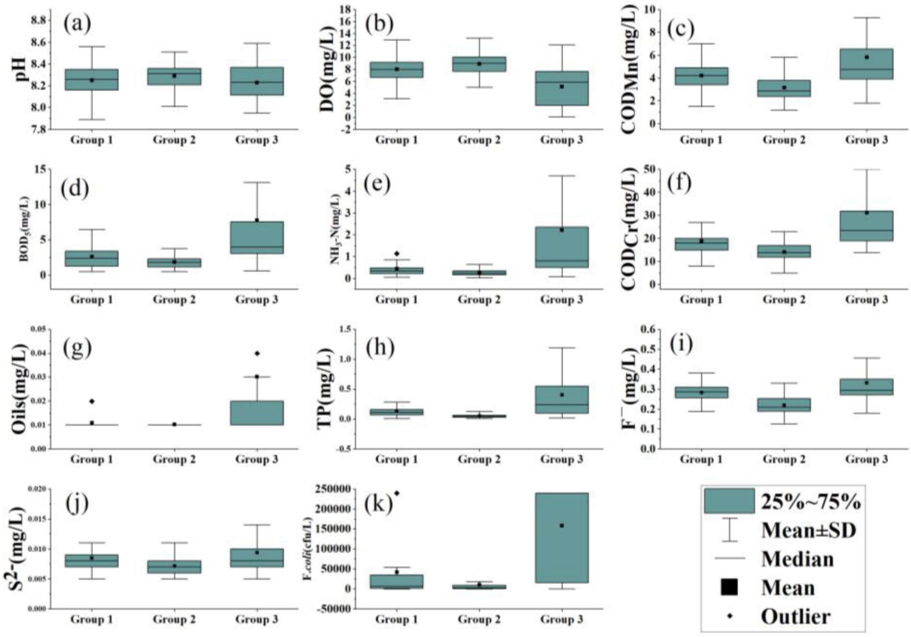

Fig. 8. Spatial variations: (a) pH, (b) DO, (c) COD_{Mn}, (d) BOD_5, (e) NH_3–N, (f) COD_{Cr}, (g) oils, (h) TP, (i) F^-, (j) S^{2-}, and (k) F. coli.

sampling sites account for a large proportion. The major rivers are Da'ni River, Ji'an River, Luxi River, Luojia River, Ying River, Xichong River, Shengli Bridge, and Nicao River. Third, rural areas are dominated by farmland, and some of the pollutants come from the excessive use of fertilizers and pesticides in nearby farming processes, which produce nitrogen and phosphorus nutrients that flow into rivers through rainfall and runoff. The major rivers are Heshu River, Jinxi River, Luojia River, Qingxi River, Qushui River, Yuxi River, and Xinjia River. Fourth, the river flow is small, the flow rate is slow, and pollutants are easy to gather. The major rivers are Quejia River, Ying River, and Yuxi River.

The overall water quality was good in Group 2, and the water quality grade was mainly concentrated in Class II to Class III according to the single-factor evaluation results. The main reasons are as follows: First, many rivers in Group 2 are located in mountainous areas far away from urban areas, with a high proportion of forest area and extensive forest coverage. The rivers located in mountainous areas are Baixi River, Chaijing River, Xiaohe River, Changtan River, and Zhuzhen River. Second, many rivers are mainly polluted by agricultural practices and have a relatively small population with limited human activity and no industrial activity. Third, the river flow is large, the velocity is fast, and the water self-purification ability is relatively strong. For example, Xi River, Dong River, Gouxi River, and Baixi River in Group 2 are the largest and the most important tributaries of the Jialing River in Nanchong with wide river surface and fast flow rate.

In conclusion, multivariate statistical analysis showed that the water quality of the first-level tributaries of the Jialing River has obvious temporal variation and spatial differentiation characteristics combined with hydrological conditions, seasonal changes, and geographical location. The water quality in Period 1 (wet seasons) is better than that in Period 2 (dry seasons). The pollution degree is closely related to urbanization, and the water environment quality in the basin is greatly affected by human activities. Industrial wastewater, agricultural runoff, domestic sewage, and livestock pollutant discharge are the four main factors contributing to the deterioration of water quality. Group 3 is distributed in urban areas and can be classified as the pollution of oxygen-consuming organic matter and nutrients caused by the discharge of domestic sewage and industrial wastewater into river channels. Group 1 is distributed in the urban–rural fringe area, which could be classified as organic pollution and fecal pollution caused by livestock pollutants, agricultural nonpoint sources, and domestic sewage. Group 2 is located in mountainous areas and has relatively good water quality. The departments concerned may take remedial measures according to hydrological conditions and the classifications of rivers.

4. Conclusions

- Single-factor index evaluation showed that the water quality of the first tributaries of Jialing River in Nanchong City has been improving yearly, and the main pollutant indexes in this area are COD_{Cr}, TP, NH_3–N, COD_{Mn}, BOD_5, and DO. The Jialing River Basin in Nanchong is mainly affected by organic pollution and eutrophication.
- According to multivariate statistical analysis, all studied variables showed considerable temporal differences and partial spatial variability. CA classified 12 months into two periods (Period 1, July–December, Period 2, January–June), exactly consistent with dry and wet seasons, and 25 monitoring sites into three groups (Group 2, lightly polluted regions, Group 1, moderately polluted regions, and Group 3, highly polluted regions) based on different levels of pollution caused by physicochemical properties

and anthropogenic activities. DA provided good results with great discriminatory ability for both temporal and spatial analyses. DA also provided an important data reduction because it only used 9 parameters for temporal analysis, affording approximately 91.7% correct assignations, and 18 parameters for spatial analysis, affording 96% correct assignations. Thus, this study demonstrated that multivariate statistical methods are useful for interpreting complex data sets in the analysis of temporal and spatial variations in water quality and the optimization of regional water quality monitoring networks.

- The four major pollution sources in the basin are industrial wastewater, agricultural runoff, domestic sewage, and livestock pollution. Nanchong City has established a relatively perfect river chief system and city-controlled small watershed target assessment mechanism. The relevant government departments can conduct pollution control according to the temporal and spatial characteristics of the Jialing River Basin, focusing on key areas of the basin and key pollution sources, such as industry, agriculture, urban life, and livestock and poultry breeding, to consolidate the hard-won achievements of water pollution prevention and control in the past 5 y. We will continue to promote the implementation of various local target assessment systems and a series of measures, such as the "One River, One Policy," to strengthen assessment and reward and punishment methods. Responsible units should also strive to obtain financial, material, human, scientific, and technological support through multiple channels to stabilize and improve the prevention and control of water pollution.

Ethics approval and consent to participate

Not applicable.

Consent for publication

With the consent of all authors, hereby assign to Desalination and Water Treatment, the copyright in the above identified article to be transferred, including supplemental tables, illustrations or other information submitted in all forms and media throughout the world, in all languages and format, effective when and if the article is accepted for publication.

Availability of data and materials

The datasets used during the current study are available from the corresponding author on reasonable request. Acknowledgments.

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Author contributions

X.Y. (Postgraduate Student) wrote and revised the manuscript. Z.X.L. (M.D), L.S. (M.D) made significant contributions to data acquisition, analysis, and interpretation. Y.F.Q (M.D), S.L.T (M.D) and Y.Y.Z. (Postgraduate Student) helped organize the manuscript data. Y.X.L. (Professor) and Q.M.Q. (Professor) made key changes to important academic content and were responsible for the final revision.

Conflict of interest

The authors declare that they have no conflict of interest.

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