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Temporal and spatial variations in water quality of Changjiang River Basin in Luzhou, China based on multivariate statistical techniques

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ABSTRACT

This study evaluated the spatial and temporal variations of water quality to understand further the water quality in the Changjiang River Basin in Luzhou, China. Data of 16 water quality parameters at nine monitoring stations from 2011 to 2016 were analyzed on the basis of the cluster analysis (CA) and discriminant analysis in multivariate statistical analysis methods, with 612 samples per parameter. Results showed that the CA divided the observation months into three periods according to the similarity of water quality characteristics. Periods 1 (December–May), 2 (July–September), and 3 (June, October, and November) corresponded to the dry, wet, and flat seasons, respectively. The nine sites were divided using space analysis into two groups (A and B),which corresponded to light and moderate pollution, respectively. The important parameters representing temporal and spatial differences were water temperature, flow rate, five-day biochemical oxygen demand, fecal coliform bacteria, electrical conductivity, ammonia nitrogen, oils, fluoride, and arsenic. Optimizing the monitoring frequency or sampling points, strengthening the monitoring of nine important parameters simultaneously, and controlling the pollution of polluted river are suggested on the basis of the results. This study can provide a scientific basis for water quality monitoring and functional zoning of the Luzhou section of the Changjiang River Basin.

Keywords: Changjiang River Basin; Temporal and spatial variation; Water quality parameter; Multivariate statistical technique

1. Introduction

The problem of river pollution has become increasingly serious with the rapid development of the modern economy. River water quality is affected not only by natural factors, such as precipitation and atmospheric deposition, but also by artificial ones,such as industrial wastewater, domestic sewage, and farmland surface runoff [1]. Therefore, long-term monitoring and evaluation of river systems are needed to obtain reliable information to prevent and control river pollution [2]. Fundamentally, rivers are seasonal and regional [3]. Studying the temporal and spatial variation characteristics of river water quality can provide dynamic information for the effective management of water environment. Therefore, effective evaluation of the temporal and spatial changes of river water quality has become an important means of water environmental management decision making [4,5].

Multivariate statistical techniques are effective for analyzing the spatial and temporal variations of water quality and have been used extensively in practical applications [1–2,6,7]. Solidoro et al. [8] studied the nutritional development level of the Venetian Lagoon by using multivariate statistical methods on the basis of the characteristics of spatiotemporal changes of water quality. Caccia et al. [9] used regression analysis and found that the water quality of Biscayne Bay was influenced by land use. Shrestha et al. [10] used cluster analysis (CA) and discriminant analysis

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(DA) to identify important changes in water quality parameters and studied the methods of optimizing the monitoring network. Bu et al. [11] used CA, factor analysis, and grid method to explain the deteriorating process of water quality from upstream to downstream.

The Changjiang River enters the northern part of Luzhou from Yibin and flows from the west to the east through Naxi, Jiangyang, and Longmatan Districts and Hejiang Counties and then into Jiangjin City in Chongqing, wherein water quality will directly affect the Three Gorges Reservoir Area and the middle and lower reaches of Changjiang River [12,13]. The Luzhou section of the Changjiang River Basin is an important water source for the people of Luzhou and for industrial and agricultural production, and its quality considerably influences the water downstream in Chongqing. Some tributaries of the Luzhou section of the Changjiang River Basin accept the perennial discharge of domestic sewage, industrial wastewater, and agricultural water withdrawal along the coast, thereby causing the deterioration of river water quality and restricting the economic development of the basin [14,15]. At present, few researchers have evaluated the water quality of the area. However, the effect of the water quality in Luzhou on those of Chongqing, the Three Gorges Reservoir Area, and the middle and lower reaches of the Changjiang River cannot be ignored. Therefore, the Luzhou section of the Changjiang River was taken as the research object for this study and used the CA and DA in multivariate statistical methods to study the temporal and spatial variations of the water quality in Changjiang River. This study aims to understand the spatial and temporal differentiation characteristics of the water quality in the Luzhou section of the Changjiang River Basin and identify the source of pollution. The results of this study can aid in determining the main causes of water environment pollution in the region to develop suitable water ecological environment management measures. They also provide a scientific basis for ecosystem management, environmental protection, water pollution prevention, and optimization monitoring points in Changjiang River Basin [16]. Furthermore, this study plays a protective and guiding role in the water quality of Chongqing.

2. Experimental site, materials, and methods

2.1. Study site and monitoring parameters

Luzhou (27°39′ N–29° 20′ N, 105° 08′ E–106° 28′ E) is located in the southeast of Sichuan Province (Fig. 1) at the intersection of Changjiang and Tuojiang Rivers [17]. It is an important port in the Hainan Channel and the upper reaches of Changjiang River. The total area of the city's administrative division is 12,236.2 km^2, the cultivated land is 4,110 km^2, and the water area is 376 km^2. In addition, the total topogra-

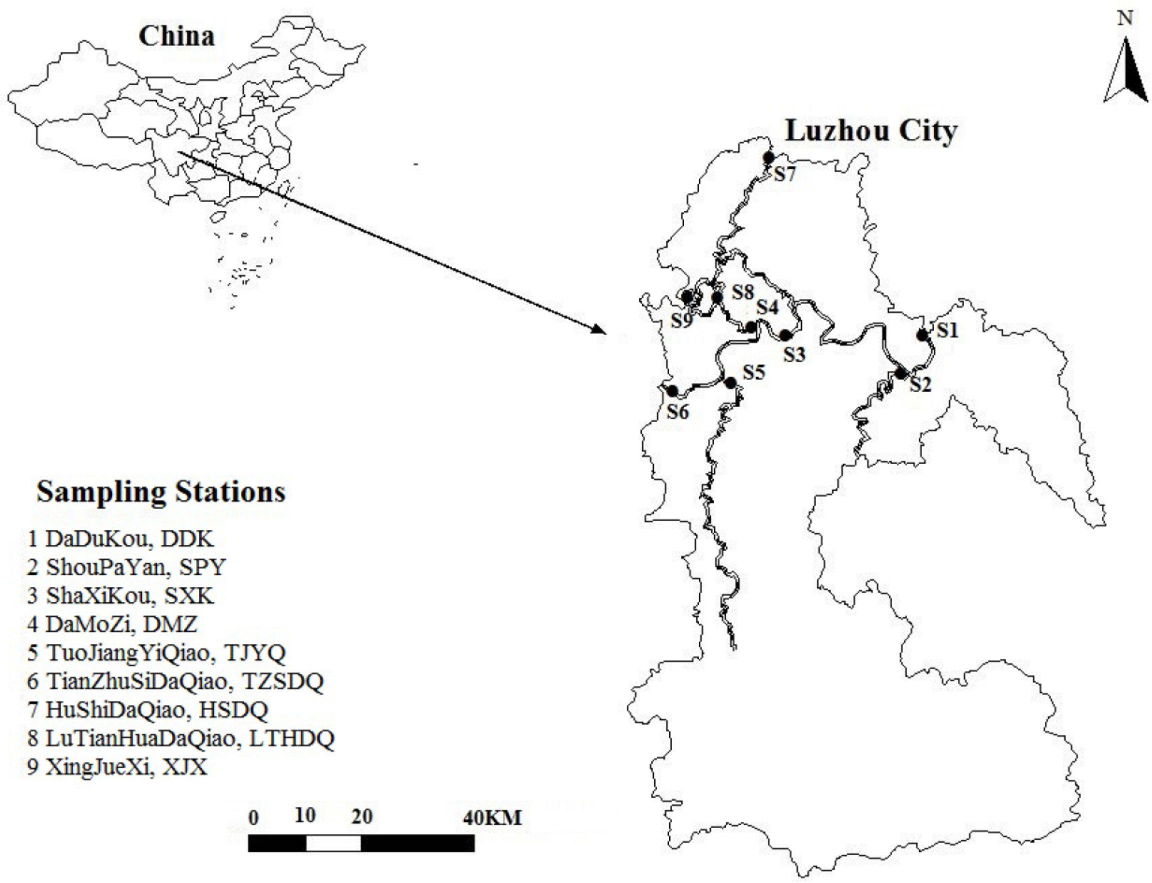

Fig. 1. Map of the study area and surface water quality monitoring stations in Changjiang River Watershed (Luzhou).

phy is high in the south and west and low in the north and east. Luzhou City belongs to the tropical climate in South Asia. The average annual temperature is 17.4°C–19.0°C, with an average annual rainfall of 677–1,262 mm. The spatial and temporal distribution of rainfall is extremely uneven during the year. Moreover, approximately 70–80% of the rainfall is concentrated in May–October, the sunshine duration is 871–1396 h, and the frost-free period is 300–358 d. The rivers in the city are distributed in branches, which are transferred from south to north or vice versa into the Changjiang River. The length of the Luzhou section of Changjiang River is 133 km, the river surface width is 450–800 m, the average annual inflow water volume is 240.8 billion m^3, and the exit water volume is 268 billion m^3 [18]. From January 2011 to August 2016, the Luzhou Environmental Monitoring Center collected water samples every month from nine locations: DaDuKou (DDK), ShouPaYan (SPY), ShaXiKou (SXK), DaMoZi (DMZ), TuoJiangYiQiao (TJYQ), TianZhuSiDaQiao (TZSDQ), HuShiDaQiao (HSDQ), LuTianHuaDaQiao (LTHDQ), and XingJueXi (XJX). DDK, SPY, and SXK are the monitoring points of Changjiang River. DMZ and TJYQ are the monitoring points of Tuojiang River, which is a tributary of Changjiang River. TZSDQ and HSDQ are the monitoring points of Laixi River, which is a tributary of Tuojiang River. LTHDQ and XJX are the monitoring points of Yongning and Chishui Rivers, respectively, which are tributaries of Changjiang River. Tuojiang, Yongning, and Chishui Rivers flow into Changjiang River. LTHDQ and XJX are monitoring points for tributaries flowing into the Changjiang River. DDK, DMZ, and TJYQ are the monitoring points of Luzhou River.

Sixteen parameters were selected on the basis of the sampling continuity of all selected monitoring points. These parameters included water temperature (TEMP), flow rate (Q), pH, electrical conductivity (EC), dissolved oxygen (DO), permanganate index (COD_{Mn}), five-day biochemical oxygen demand (BOD_5), ammonia nitrogen (NH_3–N), oils, biochemical oxygen demand (COD_{Cr}), total nitrogen (TN), total phosphorus (TP), copper (Cu), fluoride (F), arsenic (As), and fecal coliform bacteria (*F. coli*), which were expressed in mg/L except for Q (m^3/s), pH, EC (μS/cm), TEMP(°C), and *F. coli* (cfu/L). The collection, preservation, and analysis of water samples complied with the relevant requirements of the Technical Specification Requirements for Monitoring of Surface Water and Waste Water [19–21]. Table 1 presents the specific analysis method, and Table 2 shows the environmental quality standards for surface water [22].

Table 1
Monitoring methods for water quality parameters

Parameters	Monitoring methods	Method source
TEMP	Thermometer method	GB13195-1991
DO	Electrochemical probe method	HJ 506-2009
EC	Portable conductivity meter method	Water and Wastewater Monitoring and Analysis Methods (Fourth Edition) State Environmental Protection Administration (2002)
pH	Portable pH meter method	Water and Wastewater Monitoring and Analysis Methods (Fourth Edition) State Environmental Protection Administration (2002)
COD_{Mn}	Acid method	GB11892-1989
COD_{Cr}	Dichromate method	GB11914-1989
BOD_5	Dilution and inoculation method	HJ505-2009
NH_3–N	Nessler's reagent spectrophotometry	HJ535-2009
TP	Ammonium molybdate spectrophotometry	GB11893-1989
F	Ion chromatography	HJ/T84-2001
As	Atomic fluorescence method	
Cu	Inductively coupled plasma optical emission spectrometry	HJ776-2015
Oils	Infrared spectrophotometry	HJ 637-2012
F. coli	Multi-tube fermentation method	Water and Wastewater Monitoring and Analysis Methods (Fourth Edition) State Environmental Protection Administration (2002)
Q	Acoustic Doppler flow test specification	SL 337-2006
TN	Alkaline potassium persulfate digestion ultraviolet spectrophotometry	HJ 636-2012

Table 2
Standard of surface water environment quality (GB3838-2002, China)

	DO	COD_{Mn}	BOD_5	NH_3–N	TP	TN	Cu	Zn	F	As	Pb	oils	*F. coli*
I	7.5	2	3	0.15	0.02	0.2	0.01	0.05	1	0.05	0.01	0.05	200
II	6	4	3	0.5	0.1	0.5	1	1	1	0.05	0.05	0.05	2000
III	5	6	4	1	0.2	1	1	1	1	0.05	0.01	0.05	10000

2.2. Analytical methods

Multivariate statistical methods require the water quality indicators to be normal or near normal distribution [23–25]. Therefore, before the CA and DA, the distribution characteristics of water quality indicators must be examined. The methods used in this study were kurtosis and skewness test [13]. When the data structure is particularly deviated from the normal distribution, the water quality index can be approximated to a normal distribution by logarithmic transformation x′ = log10(x), which improves the credibility of the subsequent multivariate statistical method [23,26]. At the same time, in view of the differences in the magnitude and unit of measurement of different water quality indicators, standardizing the data during CA is helpful to improve its credibility [27,28]. All mathematical and statistical calculations in this study were conducted using IBM SPSS Statistics 23.0.

CA is based on the degree of similarity or dissimilarity among research objects to determine the distance between them, thereby closing the objects as a cluster. Objects of different clusters are far from one another [29]. The ratio of the case chain lock distance (D_{link}) to the maximum chain lock distance ($D_{\max}$) is the degree of difference ($\frac{D_{link}}{D_{\max}}$), and the clustering analysis results can be classified according to the degree of difference of 100 times ($\frac{100D_{link}}{D_{\max}}$) [13]. This approach aims to combine objects with the closest properties according to the degree of affinity among variables or samples and form the closest ones until they are grouped together [30,31]. In water quality assessment, CA is often performed according to sampling stations and time to analyze the temporal and spatial variation characteristics of water quality or according to evaluation parameters to analyze the similarity among parameters [1,2,32,33]. In this study, the Euclidean distance method among groups was used to analyze the temporal and spatial similarity of the Luzhou section of the Changjiang River basin by CA. Meanwhile, DA is a multivariate statistical method that classifies the subjects under the conditions of classification and identification, establishes a suitable discriminant function (DF) on the basis of certain discriminant criteria, and discovers the undetermined coefficients in the DF by using substantial raw data [34]. In comparison with CA, DA should initially distinguish the classification of samples. At the same time, the DF can be used to discriminate the sample attribution and identify the prominent pollution parameters. The expression is as follows:

$$f\left(G_i\right) = k_j + \sum\nolimits_{j=1}^{n} w_{ij} p_{ij} \quad (1)$$

where i is the number of group types (G), n is the number of pollution parameters used to classify a set of data into a given group, w_{ij} is the weight coefficient, p_{ij} is the concentration of the main pollution indicator, f is the DF, and k_j is the constant inherent to each group [20]. The discriminant criterion can be used to divide the process into distance discrimination and Fisher discriminant. The verification methods for the effect of DF include self- and external verifications, sample dichotomy, and cross-validation. DA is usually performed on the test data using standard, forward, and backward methods. The results are applied to the spatial analysis of water quality, and the optimal DF and matrix are obtained to verify the results of CA and identify critical pollutants among various sampling stations [35]. In the present study, a step-by-step model was used for DA in manipulating the raw data to confirm the clusters found in CA and evaluate the spatiotemporal variations on the basis of the discriminant variables. The monitoring periods (temporal) and points (spatial) were the grouped variables, and the measured parameters were the independent variables.

3. Results and discussion

3.1. Temporal similarity and period grouping

Temporal CA was used to cluster a dendrogram (Fig. 2) that grouped the months into three clusters with similar physiochemical water quality characteristics. When is ≥2 and <3, the time month is divided into three periods. When is ≥3 and ≤25, the time month is divided into two periods. In this study, the month was divided into three time periods. Periods 1 (December–May), 2 (July–September), and 3 (June, October, and November) corresponded to the dry, wet, and flat seasons, respectively. The results showed that the water quality of Changjiang River Basin was not only subjected to hydrological conditions (i.e., dry and wet seasons) but also by evident seasonal changes [32]. Fig. 2 shows that Period 2 was consistent with the wet season, whereas Periods 1 and 3 were slightly deviated but in line with the actual situation [34]. Therefore, sampling frequency should be appropriately increased for the dry and flat-water seasons to improve the water monitoring quality in the future.

As shown in Table 3, the value of Wilks' lambda for the DF was small (0.178). The chisquare value was high (166.604), and the p level (0.000) was less than 0.05. Therefore, the results of the temporal DA of the study were significant. Tables 4 and 5 present the DFs and classification matrixes (CMs) obtained by temporal DA, respectively. From the tables, stepwise DA only needed four main water

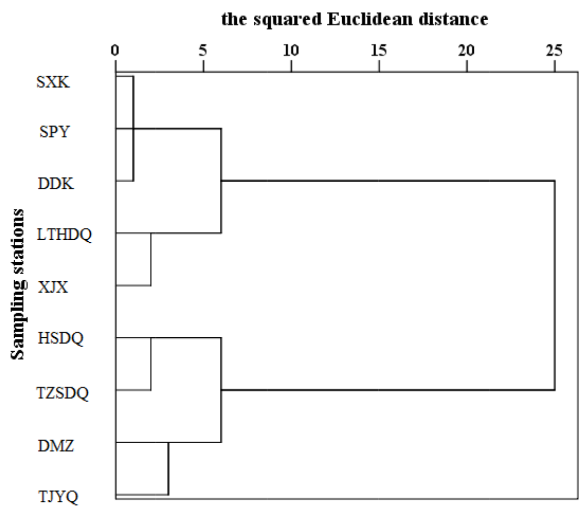

Fig. 2. Dendrogram showing the clustering of monitoring periods in Changjiang River watershed (Luzhou).

Table 3
Wilk's lambda and chisquare values of DA of temporal variations in water quality

	Temporal
Fun. (s)	1
Wilks' lambda	0.178
Chisquare	166.604
Sig.	0.000

Table 5
CM for DA of temporal variations

	Percent correct	Period assigned by DA[a]		
		Period 1	Period 2	Period 3
Period 1	70	317	0	9
Period 2	74.5	0	143	35
Period 3	74.3	136	49	127
Total	71.9	453	192	171

Note: [a]Checked by cross-validation method.

Table 4
Classification function coefficients for DA of temporal variations

Parameters	Period 1	Period 2	Period 3
TEMP	1.569	3.129	2.531
Q	0.001	0.001	0.001
BOD_5	0.269	−0.603	−0.481
F. coli	0	0	0
Constant	−13.802	−48.536	−32.267

quality indicators to construct the DFs. Its discriminating capability would not be significantly reduced, and correct assignments could still be maintained at above 72%. Stepwise DA could show an excellent capability to judge; however, the correct allocation was slightly lower than other reports [35]. Temporal DA showed that TEMP, Q, BOD_5, and *F. coli* were the most important water quality parameters to distinguish Periods 1, 2, and 3 and explained most of the expected changes in water quality time.

Fig. 4 shows the results of temporal DA. The mean TEMP (25.286°C) and Q (7,855.530 m^3/s) in Period 2 were higher than those in Periods 1 (15.062°C, 2,027.179 m^3/s) and 3 (21.204°C,3,831.698 m^3/s; Figs. 4a, 4b) and showed a significant time effect because Period 2 contained warm months and covered the rainy season. BOD_5 refers to the amount of DO consumed by microorganisms to decompose certain oxidizable substances, especially organic ones, in a certain volume of water within five days. It is a comprehensive index the reflects the content of organic pollutants in water [36]. The average BOD_5 in Period 1 (1.656 mg/L) was higher than those in Periods 2 (1.457 mg/L) and 3 (1.313 mg/L; Fig. 4c), because Period 1 included the dry season of the river and the pollutant dilution capability was reduced. The pollution in Period 1 was slightly heavier than the other periods. However, the average value of the

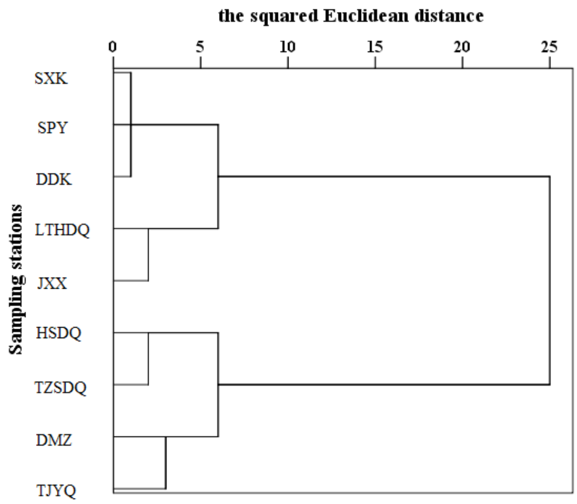

Fig. 3. Dendrogram showing the clustering of monitoring sites in Changjiang River Basin (Luzhou).

three periods was within the first national standard limit (3.000 mg/L, GB3838-2002). The *F. coli* index is one of the most important indicators to evaluate water quality. The number of *F. coli* in Period 2 (21,216.680 cfu/100 mL) was more than those in Periods 1 (12,340.17 cfu/100 mL) and 3 (20,000 cfu/100 mL; Fig. 4d), which exceeded the third national standard limit (10,000 cfu/100 mL, GB3838-2002). The main sources of *F. coli* were domestic sewage and livestock waste water [37,38].

3.2. Spatial similarity and site grouping

The dendrogram in Fig. 3 shows that spatial CA divided the monitoring sites into two main clusters to analyze the spatial characteristics of river water quality. Group A consisted of SXK, SPY, DDK, LTHDQ, and XJX, and Group B comprised DMZ, TJYQ, TZSDQ and HSDQ. The classification of these groups varied with the level of significance, with Groups A and B having similar squared Euclidean distances. In Group A, except for the three monitoring sites in Changjiang River, the remaining sites were all monitoring sites where some tributaries flow into the Changjiang River. The water quality in Group A was mainly Grade II or III, and all the indicators met and remained stable, thereby indicating that it was mildly polluted. Meanwhile, the water quality in Group B was between Grades III and V and showed a fluctuating trend, which indicated that it was moderately polluted. After flowing through Fuji Town in Lu County, Laixi River was affected by industrial wastewater, domestic sewage, and its tributaries, Jiuqu and Maxi Rivers [18]. The main pollution indicators were TP, COD_{Cr}, and COD_{Mn}. The water quality of Tuojiang River was affected by the production and living activities in Luzhou, which were the main pollution indicators for TP, and the concentration of TP remained stable [39,40]. As shown in Table 6, the value of Wilks' lambda for the DF was small (0.134). The chisquare value was high (190.942), and the p level (0.000) was less than 0.05, which indicated that DA had high discriminative power and significance. Tables 7 and 8 present the DFs and

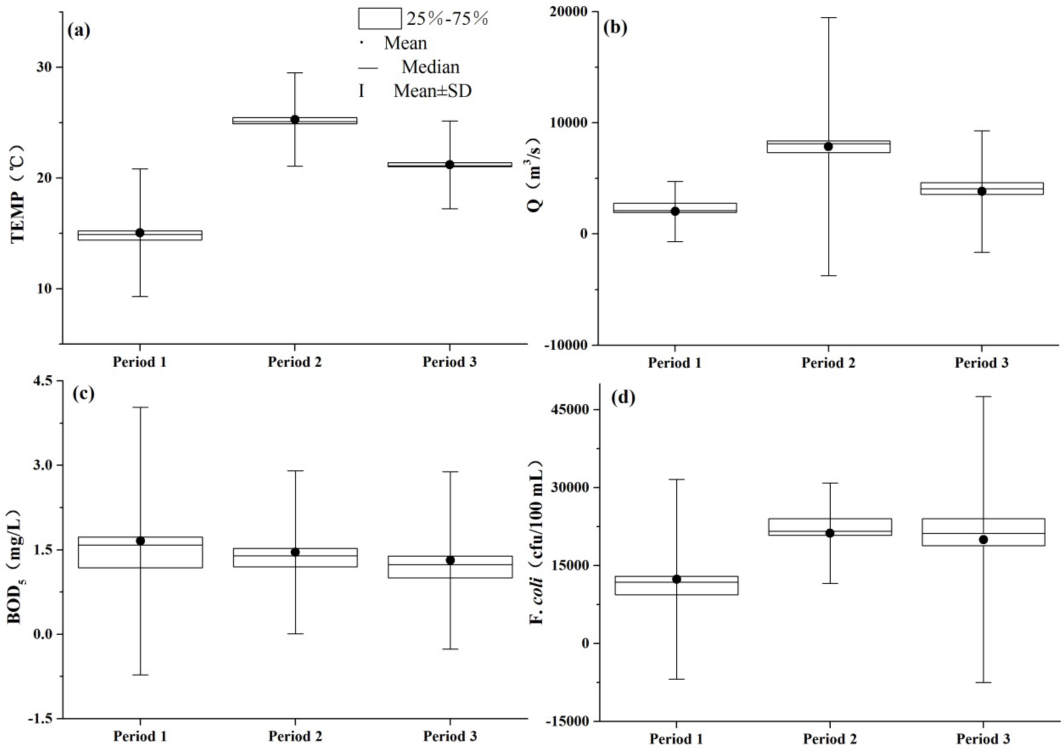

Fig. 4. Temporal variations: (a) temperature, (b) Q, (c) BOD_5, (d) *F. coli* Note: Significance level at 0.05 ($p < 0.05$).

Table 6
Wilk's lambda and chisquare values of DA of spatial variations in water quality

	Spatial
Fun. (s)	1
Wilks' lambda	0.134
Chisquare	190.942
Sig.	0.000

Table 7
Classification function coefficients for DA of spatial variation

Parameters	Group A	Group B
TEMP	0.972	1.553
Q	0	−0.001
EC	0.634	0.888
NH_3–N	−9.626	−18.938
Oils	118.25	172.211
F	31.389	70.122
As	1846.379	3804.762
F. coli	0	5.86E-05
Constant	−28.98	−67.21

CMs obtained by spatial DA, respectively. In comparison with temporal DA, the DFs and CMs generated by spatial DA had a correct discriminating capability of more than 98%, which is slightly higher than other reports [35]. The results of spatial DA showed that the discriminative parameters of Groups A and B were differentiated by TEMP, Q, EC, NH_3–N, oils, F, As, and *F. coli*.

Table 8
CM for DA of spatial variation

	Percent correct	Regions assigned by DA[a]	
		Group A	Group B
Group A	98.7	157	3
Group B	96.9	2	95
Total	98.1	159	98

Note: [a]Checked by cross-validation method

The spatial variability of the river water quality was evaluated by using the discrimination parameters identified by spatial DA (Fig. 5). The average TEMP of Group A (18.526°C) was lower than that of Group B (20.407°C; Fig. 5a); however, the average Q value of Group A (5417.536 m^3/s) was considerably greater than that of Group B (199.959 m^3/s). The water flow was larger than other tributaries because Group A included the Changjiang River or into the Changjiang Estuary monitoring sites. EC is the reciprocal of resistivity that reflects the amount of salt in water, which is a highly important indicator of water quality [41]. The average values of EC and NH_3–N in Group B (58.733 μS/cm, 0.4016 mg/L) were higher than those in Group A (35.214 μS/cm, 0.12436 mg /L). NH_3–N was the main pollutant in the water body of the monitoring

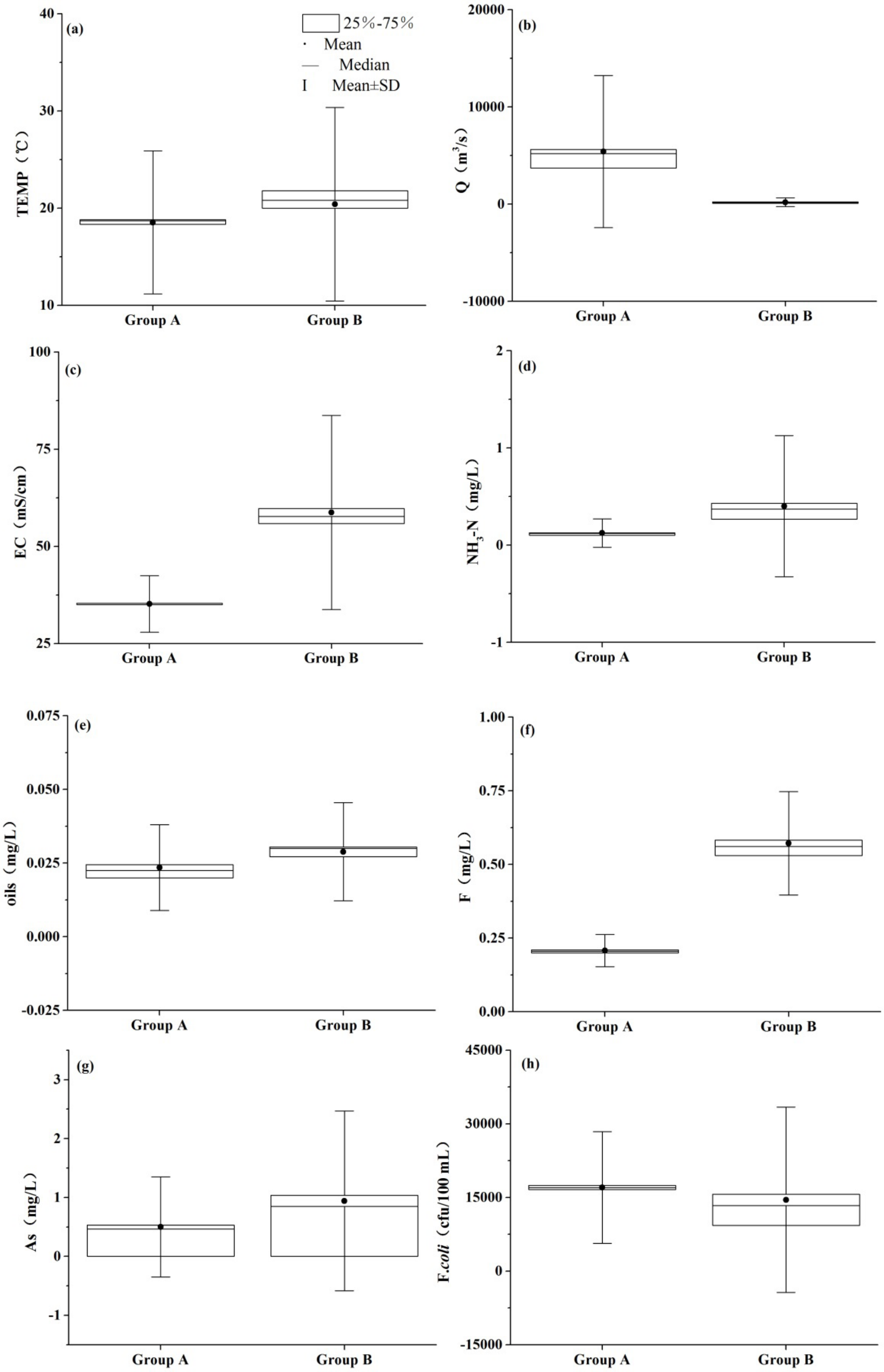

Fig. 5. Spatial variations: (a) temperature, (b) Q, (c) EC, (d) NH_3–N, (e) oils, (f) F, (g) As, and (h) *F. coli*. Note: Significance level at 0.05 ($p < 0.05$).

sites included in Group B. The average concentration of *F. coli* in Group A (17,021.050 cfu/100 mL) was higher than that in Group B (14,510.860 cfu/100 mL, $p = 0.000$), which was higher than the third national standard limit (10,000 cfu/100 mL, GB 3838-2002). These results suggested that human and animal activities had a negative effect on water quality. The concentrations of oils and F were within the second national standard, which were lower than those reported by other authors [42]. The trend of these parameters demonstrated that the average concentrations of oils and F in Group B were higher than those in Group A (FigS. 5e, 5f). Therefore, Group B should strengthen the management of rational drug use and control of oil pollution. As mainly originates from mineral processing, metallurgy, waste treatment, food additives, pesticides, and herbicides, which pollute rivers and cause harm to the human body [43]. The average concentration of As in Group B (0.941 mg/L) was considerably larger than that in Group A (0.499 mg/L), which were markedly larger than the third national standard limit (0.05 mg/L, GB 3838-2002). Therefore, the government should strengthen the treatment of As in wastewater, standardize the operation and waste treatment of the As industry, and increase supervision. Group A was far from pollution sources, and the concentration of pollutants was reduced by river confluence dilution. In comparison with Group A, Group B was more affected by anthropogenic activities. The river sections included in Group B were easily affected by agricultural irrigation, industrial wastewater, and municipal wastewater; and both groups should monitor and control *F. coli*. In addition, the construction and management of many municipal sewers, waste water, and waste treatment plants should also be effectively supervised. The widespread use of agricultural machineries is the source of oils and F. The use of pesticides, herbicides, and animal food additives is the main source of As.

4. Conclusions

The temporal similarity analysis of the Changjiang River Basin showed that the monitoring months were divided into three periods: December–May (Period 1); July–September (Period 2); and June, October, and November (Period 3). TEMP, Q, BOD_5, and *F. coli* were the most important discriminant variables to differentiate the three periods. The spatial similarities demonstrated that the nine monitoring sites could be divided into two clusters; that is, SXK, SPY, DDK, LTHDQ, and XJX (Group A) were mildly polluted areas, whereas HSDQ, TZSDQ, DMZ, and TJYQ (Group B) were moderately polluted areas. In this region, sampling and monitoring were conducted for three types of temporal periods and two typical spatial regions. The representativeness is the clustering relationship; thus, it can reduce the monitoring stations, improve the monitoring efficiency, reduce the cost of large-scale monitoring, and facilitate water quality control. The significant parameters for characterizing temporal and spatial differences using backward DA analysis were TEMP, Q, BOD_5, *F. coli*, EC, NH_3–N, oils, F, and As. Therefore, only the above 10 parameters and DFs were needed to characterize the spatial and temporal differences in the water quality in the Luzhousection of Changjiang River Basin. In future water quality management, strengthening the monitoring of such parameters is necessary.

In brief, the management should focus on monitoring TEMP, Q, BOD_5, and *F. coli* as functions of time and TEMP, Q, EC, NH_3–N, oils, F, As, and *F. coli* as functions of space. The sources of pollution in heavily polluted areas and months can be further explored and the main causes of pollution can be further differentiated by analyzing the spatiotemporal differences of these representative water quality indicators to classify domestic sewage, livestock husbandry pollution, industrial pollution, and surface runoff. On this basis, targeted measures can be taken to control pollution. Monitoring the key pollution indicators during the dry season and Group B areas, such as increasing monitoring frequency, accuracy, and points, is also suggested. This study raises awareness of the temporal and spatial variations of the Luzhou section of Changjiang River Basin.

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References

[1] K.P. Singh, A. Malik, S. Sinha, Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques—a case study, Anal. Chim. Acta, 538 (2005) 355–374.

[2] R.P. Kannel, S. Lee, S.R. Kanel, S.P. Khan, Chemometric application in classification and assessment of monitoring locations of an urban river system, Anal. Chim. Acta, 582(2) 390–399.

[3] S.K. Sundaray, U.C. Panda, B.B. Nayak, D. Bhatta, Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of the Mahanadi river–estuarine system (India) – a case study, Environ. Geochem. Health, 28 (2006) 317–330.

[4] Y. Ouyang, P. Nkedi-Kizza, Q.T. Wu, D. Shinde, C.H. Huang, Assessment of seasonal variations in surface water quality, Water Res., 40 (2006) 3800–3810.

[5] F. Zhou, H. Guo, L. Liu, Quantitative identification and source apportionment of anthropogenic heavy metals in marine sediment of Hong Kong, Environ. Geology, 53 (2007) 295–305.

[6] J. Wang, L. Da, K. Song, B.L. Li, Temporal variations of surface water quality in urban, suburban and rural areas during rapid urbanization in Shanghai, China. Environ. Pollut., 152 (2008) 387–393.

[7] T.M. Qian, Multivariate statistical analysis of water quality in main and tributary stream of Qiantangjiang River in Hangzhou, Environ. Monit. China., 31 (2015) 74–77.

[8] C. Solidoro, R. Pastres, G. Cossarini, S. Ciavatta, Seasonal and spatial variability of water quality parameters in the lagoon of Venice, J. Marine Syst., 51 (2004) 7–18.

[9] V.G. Caccia, J.N. Boyer, Spatial patterning of water quality in Biscayne Bay, Florida as a function of land use and water management, Marine Pollut. Bull., 50 (2005) 1416–1429.

[10] S. Shrestha, F. Kazama, Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. Environ. Model. Software., 22 (2007) 464–475.

[11] H.M. Bu, X.A. Tan, S.Y. Li, Q.F. Zhang, Temporal and spatial variations of water quality in the Jinshui River of the South Qinling Mts. China, Ecotoxicol. Environ. Safety, 73 (2010) 907–913.

[12] Luzhou Environmental Protection Bureau, Luzhou Environmental Quality Report (2011–2015). Luzhou Environmental Protection Bureau, China, 2015.

[13] Y.L. Li, W.X. Zhao, Simulation study of water quality for the three gorges reservoir in Chongqing, J. Chongqing Univ. (Natural Sci. Ed.), 27 (2004) 34–38.

[14] Y.H. Dong, T.Q. Ao, X.D. Li, H.B. Zhang, L.Y. Ma, X. Liu, Comprehensive evaluation on the agricultural non-point source pollution of Laixi River in Lu County, J. Sichuan Agric. Univ., 30 (2012) 456–462.

[15] G.Z. Chen, C.S. Zhu, J.J. Xing, Assessment of water pollution of Laixi River in Luxian County, Sichuan Environ., 28 (2009) 76–80.

[16] Z.Y. Liao, S.N. Zhu, J.H. Hu, The model of evaluation and forecast for Yangtze River's water quality, Technol. Innov., (2017) 75–77.

[17] Q. Li, Construction of water ecological city in Luzhou, China Water Resources., (2017) 31–34.

[18] Luzhou Statistics Intranet. Natural resources of Luzhou, Luzhou Statistics Intranet, http://www.lztjj.gov.cn/Index.aspx. 2010.

[19] SEPA. Technical specifications requirements for monitoring of surface water and wastewater HJ/T 91–2002, Beijing: China Environmental Science Press, 2012, pp. 1–54.

[20] Y.Y. Yao, Water environment monitoring, Chemical Industry Press, China, 2015.

[21] H. Bu, X. Tan, S. Li, Q. Zhang, Water quality assessment of the Jinshui River (China) using multivariate statistical techniques, Environ. Earth Sci., 60 (2010) 1631–1639.

[22] GB3838-2002. Environmental quality standards for surface water, In Inspection and Quarantine of the People's Republic of China, China, 2002.

[23] G. Papatheodorou, G. Demopoulou, N. Lambrakis, A long-term study of temporal hydrochemical data in a shallow lake using multivariate statistical techniques, Ecol. Model., 193 (2006) 759–776.

[24] N. Cliff, Analyzing multivariate data, Technometrics., 46 (2003) 254–255.

[25] R. Johnson, Applied multivariate statistical analysis, Technometrics., 25 (1982) 385–386.

[26] T. Kowalkowski, R. Zbytniewski, J. Szpejna, B. Buszewski,Application of chemometrics in river water classification. Water Res., 40(2006)744–52.

[27] K.P. Singh, A. Malik, V.K. Singh, D. Mohan, S. Sinha, Chemometric analysis of groundwater quality data of alluvial aquifer of Gangetic plain, North India, Anal. Chim. Acta, 550 (2005) 82–91.

[28] W.D. Alberto, D.M. del Pilar, A.M. Valeria, P.S. Fabiana, H.A. Cecilia, B.M. de los Ángeles, Pattern recognition techniques for the evaluation of spatial and temporal variations in water quality. A case study: Suquía River basin (Córdoba–Argentina), Water Resw., 35 (2001) 2881–2894.

[29] H.P. Zhao, W. Chen, Q.X. Li, Y.Z. Sun, Spatio-temporal variation of water quality and pollutant source identification in upper reaches of Zhanghe river, Protect Water., 33 (2017) 47–54.

[30] M. Vega, R. Pardo, E. Barrado, L. Debán, Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis, Water Res., 32 (1998) 358–3592.

[31] K.P. Singh, A. Malik, D. Mohan, S. Sinha, Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of gomti river (india)—a case study, Water Res., 38 (2004) 3980–3992.

[32] F. Zhou, G.H. Huang, H. Guo, W. Zhang, Z. Hao, Spatio-temporal patterns and source apportionment of coastal water pollution in eastern Hong Kong, Water Res., 41 (2007) 3429–3439.

[33] H.M. Zou, L.F. Jiang, F.R. Li, Water quality and cluster analysis of Huaihe River Basin in 2004, Water Resour. Protect., 23 (2007) 60–62.

[34] F. Zhou, Z.J. Hao, H.C. Guo, Temporal and spatial distribution patters of marine water quality in Eastern Hong Kong, Acta Scient. Circums., 27 (2007) 1517–1524.

[35] L.P. Meng, Based on cluster analysis and discriminant analysis method, Environment and Development., (2012) 193–194.

[36] D. Tang, X.J. Zhai, G.R. Zhang, Effects of microorganisms impacting on the determination of biochemical oxygen demand, Environ. Protect. Oil., 27 (2017) 38–39.

[37] G.D. Feng, M.R. Deng, H.H. Zhu, J. Guo, X. Zhang, H.X. Zhu, Microbial source tracking of water fecal pollution: A review, Chinese J. Appl. Ecol., 21 (2010) 3273–3281.

[38] L. Jiang, D.J. Zhu, Y.C. Chen, H. Zhao, Analysis on fecal coliform pollution in surface waters of China, Adv. Sci. Technol. Water Resour., 35 (2015) 11–18.

[39] S.K. Li, Study on water quality evaluation and environmental capacity of Laixi River in Luzhou. Southwest Jiaotong University., (2007).

[40] X.Q. Liu, X.L. Wang, S. Zhang, P. Lei, Improvement of water quality automatic monitoring system of Damozi, Luzhou in Tuojiang River, Sichuan Environment., 25 (2006) 55–56.

[41] W. Jiang, C. Zhou, D.B. JI, D.F. Liu, Y.S. Ren, D. Haffner, D.T. Xie, L. Zhang, Comparison of relationship between conduction and algal bloom in Pengxi River and Modao in Three Gorge Reservoir, Environ. Sci., 38 (2017) 2326–2335.

[42] S. Muangthong, S. Shrestha, Assessment of surface water quality using multivariate statistical techniques: case study of the Nampong River and Songkhram River, Thailand, Environ. Monit. Assess., 187 (2015) 548.

[43] W. Wang, Y.H. Xu, Survey of arsenic pollution and treatment in water body, Studies Trace Elem. Health., 22 (2005) 59–61.