

Spatio-Temporal Variation Characteristics of Water Quality and Its Response to Climate: A Case Study in Yihe River Basin

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ABSTRACT. Spatial-temporal patterns of river water quality, the identification of pollution sources and contaminated areas are crucial to water environment protection and sustainable development of the river basin. In this study, spatial-temporal characteristics of river water quality in the Yihe river basin were investigated through multivariate analysis methods, including principal component analysis (PCA), cluster analysis (CA), discriminant analysis (DA), and one-way ANOVA. The water quality indicators (Hydrogen ion concentration (pH), electric conductivity (EC), dissolved oxygen (DO), turbidity, chemical oxygen demand (COD), total phosphorus (TP), and ammonia nitrogen (NH₄⁺-N)) were investigated at 17 sampling sites in three periods (i.e., high-, mean-, low flow period) during 2016 ~ 2017. The results show that: (1) PCA served to extract and recognize the most significant indicators affecting water quality in the Yihe river basin, i.e., pH, EC, COD, and NH₄⁺-N. (2) CA divided the Yihe river basin into three groups with similar water quality features, namely the upper, middle, and lower reaches. (3) DA demonstrated strong dimensionality reduction ability with the accuracy of clustering was 94.1%, and only a few indicators (i.e., DO, EC, turbidity, NH₄⁺-N, and TP) could reflect the spatial variations in water quality. (4) One-way ANOVA indicated that the water quality was the worst in the lower reach of Yihe river basin during the mean-flow period, followed by which in the upper and middle reaches during the high-flow period. (5) The spatiotemporal characteristics of water quality were mainly restrained by human factors (e.g., the construction of highway and agricultural activities), climate change (e.g., precipitation and temperature), and natural environments (e.g., topography).

Keywords: river water quality, spatial-temporal characteristics, multivariate statistical analysis, Yihe River Basin, climate change

1. Introduction

Rivers are the most important water bodies on land (Oki and Kanae, 2006; Vörösmarty et al., 2010), and most ancient civilizations in the world are originated in large river basins (Mir and Gani, 2019). Excellent water quality and adequate water quantity are critical to human health (Pejman et al., 2009; Zhang et al., 2012) and the sustainable development of the economy in the river basin (Ravindra et al., 2003; Wu et al., 2018). Humans have made the best use of water resources through industrialization, irrigation, and engineering measures (e.g., dams, reservoirs and water transfer across river basins) (Oki and Kanae, 2006; Wang et al., 2016). However, the demand for high-quality water resources is growing consistently, nearly 80% of the world's population still faces serious water security threats (Oki and Kanae, 2006; Vörösmarty et al., 2010). River is the most vul-

nerable water body to contain pollution from agricultural runoff, domestic and industrial sewage (Singh et al., 2005; Varol et al., 2012; Wang et al., 2013; Liu et al., 2019; Chaudhuri et al., 2020) under the multiple effects of natural processes (e.g., climate change, soil erosion, and weathering of bedrock) (Vega et al., 1998; Oke-tola et al., 2013; Shrestha and Wang, 2020), human activities (e.g., agricultural, urban and industrial activities) (Vitousek et al., 1997; Paul and Meyer, 2001; Sickman et al., 2007; Zhang et al., 2018; Yu et al., 2020), and increasing water demand (Vörösmarty et al., 2010). With the increasing degradation of river water quality, including eutrophication, organic matter, and heavy metal pollution (Vitousek et al., 1997; Carpenter et al., 1998), its disastrous impacts on drinking water safety, industrial and agricultural production, and aquatic biodiversity have attracted wide attention (Carpenter et al., 1998; Wang et al., 2017). Consequently, it is particularly important to control river pollution and prevent the degradation of river water quality. Moreover, previous study revealed that water quality is apparently spacetime dependence, thus it is necessary to monitor and evaluate the river water quality in the river basin in different periods (Strobl et al., 2008; Pérez et al., 2017; Sinha et al.,

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2019). Climate change also impacts water quality directly or indirectly, such as associated changes in precipitation patterns (i.e., precipitation amount, intensity, and frequency) affect the amount of nitrogen transported to downstream water bodies (Sinha and Michalak, 2016; Sinha et al., 2019). To help the provincial government protect the river water environment and control river pollution, it is very crucial to conduct a thorough examination of the spatio-temporal characteristics of water quality and the associated influencing factors based on monitoring data.

Previously, a number of efforts about water quality in river basins have been made in many countries and regions, through which the spatiotemporal similarities and differences of various water quality indicators were analyzed at different sampling points over multiple periods (Vitousek et al., 1997; Ravindra et al., 2003; Bellos and Sawidis, 2005; Singh et al., 2005; Kannel et al., 2007; Sickman et al., 2007; Varol et al., 2012; Wang et al., 2013; Putro et al., 2016; Rigi et al., 2019). Multivariate statistical analysis methods are reliable tools for water quality assessment and water pollution problem treatment (Singh et al., 2004, 2005; Igibah and Tanko, 2019). Due to their excellent performance in reducing the data dimension, extracting potential information, and verifying the spatial and temporal changes in water quality, multivariate statistical tools such as principal component analysis (PCA), factor analysis (FA), cluster analysis (CA), discriminant analysis (DA) and one-way analysis of variance (ANOVA) have been widely used to handle the massive and complex water quality data that generated through the water environment monitoring projects. Numbers of studies were devoted to identify the spatiotemporal variation of river water quality (Simeonov et al., 2003; Singh et al., 2005; Sundaray et al., 2006; Shrestha and Kazama, 2007; Varol et al., 2012; Li et al., 2017; Zhu et al., 2018; Mir and Gani, 2019; Sun et al., 2019) and the water environment assessment of groundwater (Andrade et al., 2008; Zhang et al., 2012), coastal water body (Zhou et al., 2007), and lakes (Pejman et al., 2009; Wu et al., 2018).

The Yiluo River is the combined name of Yihe River and Luohe River, which is the largest tributary below the Yellow River Sanmenxia Reservoir. The water quality directly affects the sustainable development of economy and society of the Yihe River Basin. However, in most of the previous studies, several related studies in Yiluo River Basin were mainly focused on heavy metal pollution (Yan et al., 2016), relationships between aquatic organisms and water environment factors (Lin et al., 2019), and effects of landscape spatial heterogeneity on water quality (Yu et al., 2014; Liu et al., 2019). There has been no report in studying the spatiotemporal characteristics of water quality in typical small watersheds in the Yihe River Basin. Furthermore, only a handful of studies have surveyed the combined effects of land use variation and climate change on water quality, and these have only been conducted in individual river basins (Tu, 2009).

Therefore, as the extension of previous studies, the objective of this study is to analyze the spatiotemporal characteristics of water quality in the Yihe River Basin through multiple statistical methods, as well as the potential causes of pollution. In detail, (1) measuring the water quality data targeting on six indicators (i.e., pH, EC, DO, COD, TP and $\text{NH}_4^+\text{-N}$) that monitored in 17 typical sub-basins in Yihe River Basin during three

water periods (i.e., high-, mean-, low flow period) from 2016 to 2017; (2) analyzing the spatiotemporal characteristics of water quality through four multiple statistical methods (i.e., PCA, CA, DA and ANOVA); (3) investigating the potential factors that effecting the water quality of the Yihe River Basin (such as human activities, climate change and natural environment). The results are expected to provide a scientific basis for water resource management, utilization, and ecological environment protection in the Yihe River Basin.

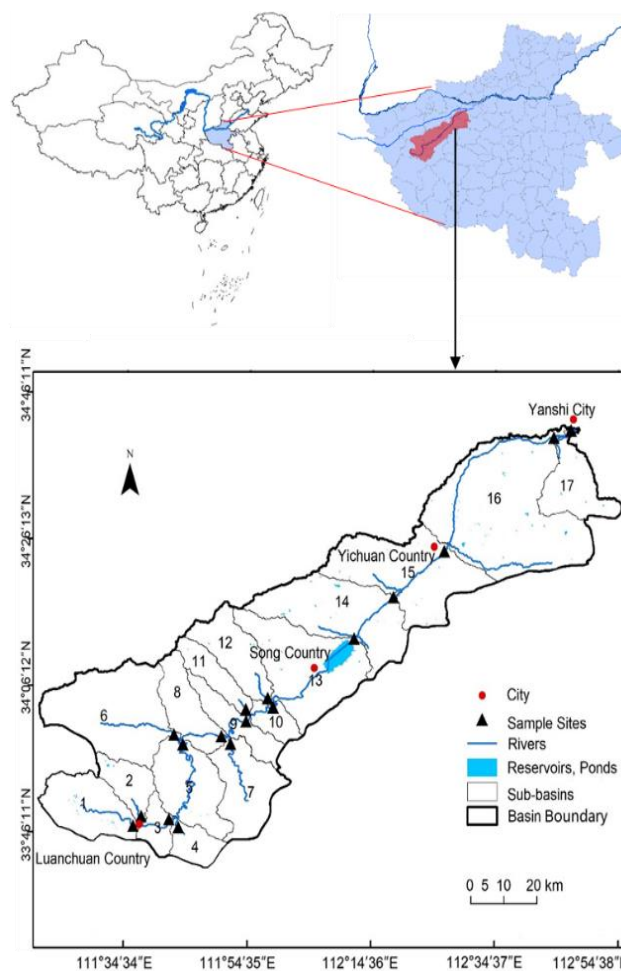


Figure 1. Location of sampling sites and sub-basins in Yihe River basin.

2. Overview of the Study Area

The Yihe River Basin is one of the major regions in the Yellow River Basin over China ($33^{\circ}39' \sim 34^{\circ}41' \text{N}$, $111^{\circ}19' \sim 112^{\circ}54' \text{E}$) (Figure 1). The extent of the Yihe River Basin and 17 typical sub-basins were extracted through the Arc SWAT hydrological analysis module (Ren, 2018). These extracted basins were based on the digital elevation model (DEM) data with a precision of 30 m (<http://henu.geodata.cn>), river network and terrain features (e.g., slope and altitude). Yihe River Basin is a transitional section of China's topography ladder from the second step to the third one, with an elevation from 109 to 2159 m,

Table 1. Statistical Description of Water Quality Indicators in the Yihe River Basin

	Low-Flow Period				Mean-Flow Period				High-Flow Period				Units
	Max	Min	Mean	Std.	Max	Min	Mean	Std.	Max	Min	Mean	Std.	
pH	8.55	7.14	7.89	0.31	8.45	7.00	8.00	0.40	8.50	6.14	7.88	0.57	—
EC	840.50	209.50	577.32	154.44	916.00	354.50	604.82	160.92	816.00	383.00	599.51	132.04	μs•cm ⁻¹
DO	13.38	4.43	9.51	2.09	12.44	7.36	9.26	1.33	11.96	4.42	8.35	1.72	mg•L ⁻¹
Turbidity	28.35	0.42	13.17	9.57	20.00	0.77	13.69	6.88	19.91	3.33	10.36	5.15	NTU
COD	71.47	7.91	37.46	19.78	33.50	2.70	18.68	9.81	25.75	4.45	12.56	5.92	mg•L ⁻¹
NH ₄ ⁺ -N	4.72	0.11	0.73	1.06	19.72	0.55	4.69	4.87	3.09	0.06	0.41	0.74	mg•L ⁻¹
TP	0.15	0.00	0.03	0.03	0.10	0.01	0.03	0.03	0.14	0.00	0.02	0.03	mg•L ⁻¹

Table 2. Single Sample K-S Inspection

		pH	EC	DO	TUR	COD	NH ₄ ⁺ -N	TP
Normal Indicators ^{a,b}	Mean	7.92	596.54	9.16	12.41	22.90	1.94	0.02
	Standard deviation	0.35	111.81	1.15	5.27	8.40	1.89	0.03
Most Extreme Difference	Absolute value	0.26	0.17	0.19	0.15	0.13	0.28	0.28
	Positive	0.10	0.17	0.19	0.11	0.13	0.28	0.25
	Negative	-0.26	-0.11	-0.09	-0.15	-0.11	-0.21	-0.28
Kolmogorov-Smirnov Z		1.06	0.70	0.77	0.60	0.52	1.17	1.15
progressive significance (both sides)		0.22	0.71	0.59	0.86	0.95	0.13	0.14

a. The test distribution is normally distributed; b. Calculated based on data.

Table 3. Principal Component Loading Matrix of Low-, Mean-, and High-Flow in Yihe River Basin

Indicators	Low-Flow Period			Mean-Flow Period		High-Flow Period		
	PC1	PC2	PC3	PC1	PC2	PC1	PC2	PC3
pH	-0.803	0.179	0.164	0.894	0.060	0.939	-0.051	-0.006
EC	0.849	0.304	-0.046	0.379	0.707	0.840	-0.084	0.238
DO	-0.458	-0.078	0.393	0.142	0.633	-0.123	-0.030	0.864
Turbidity	0.048	0.262	0.836	0.320	-0.696	0.939	-0.070	-0.188
COD	0.022	0.897	0.170	0.322	0.755	0.078	0.889	0.010
NH ₄ ⁺ -N	0.731	0.045	0.099	0.857	0.235	-0.253	0.806	-0.123
TP	0.163	0.608	-0.654	0.741	0.113	0.493	-0.122	0.563
Eigenvalue	2.363	1.327	1.173	2.989	1.492	2.947	1.426	1.076
Variance contribution rate (%)	30.569	19.644	19.266	35.042	28.970	40.137	20.989	16.710
Accumulating contribution rate (%)	30.569	50.213	69.479	35.042	64.012	40.137	61.126	77.837

with an area of 5.54×10^3 km². The mountainous area accounts for 53.4%, the hilly area accounts for 35%, and plains and the river valley account for 11.6% (Ren, 2018). Therefore, the main landscape of the Yihe River Basin is the mountain landscape. Yihe River originates from Menton Ridge, Sanhe Village, Taowan Town, Luanchuan County, south of Xiong'er Mountain, and locates in Luoyang City, Henan Province, China. The river flows from the southwest to the northeast, and through Song Country, Yichuan country, and Luoyang City from the source, and finally injects into Luohe River in Yang Village, Yanshi Country. The length of the main river is 2.68×10^2 km, and the annual average run-off volume is 1.27×10^9 m³. Yihe River Basin locates in a temperate continental monsoon climate zone, which have cold-dry winters and hot-humid summers. The annual average temperature varies from 12.4 °C (southwest) to 15.2 °C (northeast) (Ren et al., 2017). The annual average precipitation ranges 700 (northeast) to 900 mm (southwestern), approximately 50% of which is concentrated in July to September. Rainstorms were often occurred during summer, which would trigger disasters such as floods and mudslides (Liu et al., 2019). Cinnamon soil, brown soil, adamic earth and skeletal soil are the main soil types of Yihe River Basin.

2.1. Water Quality and Climate Change Data

Given the operability of sampling and the representativeness of the output of sampling points in the sub-basin, the exits of these 17 sub-basins are exactly the planned sampling sites. A total of six times samples were taken from December 2016 to August 2017 according to the hydrological regularity and the characteristics of multi-year precipitation in the Yihe River Basin: Twice during the low-flow period (December 2016 to January 2017), twice during the mean-flow period (April to May 2017), and twice during high-flow period (July to August 2017). These samples were taken once a month. Following previous studies (GonzalesInca et al., 2015; Li et al., 2017; Zhang et al., 2018) and the main landuse types, seven river water quality indicators were selected in the Yihe River Basin, including pH, EC, DO, turbidity, COD, NH₄⁺-N, and TP, Table 1 presents their specific statistical descriptions. Water samples at each sampling point in the sub-basin were collected in a pretreated polyethylene bottle and stored in a sampling box at 4 °C. The values of pH, EC and DO were measured on-site with the SX713 portable measuring instrument (Runsun Instruments Inc., Chengdu, China). Turbidity was measured on-site using the portable GZ-

20B turbidimeter (Fenglin Technology Inc., Shanghai, China). The location of the sampling point and the peripheral environment were also recorded at the same time. The residual three indicators (i.e., COD, NH₄⁺-N and TP) were examined through the 5B-6 (C) triple-parameter measuring instrument (Lianhua Technology Inc., Beijing, China) as soon as possible after all water samples have been brought back to the laboratory within 24 hours.

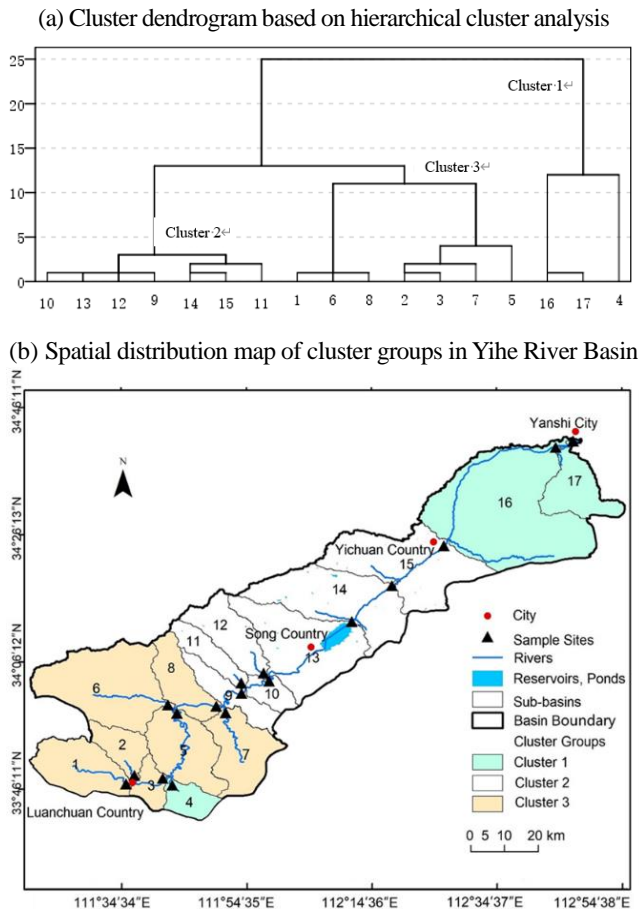


Figure 2. Cluster dendrogram of the sampling sites based on water quality indicators.

From our previous studies (Liu et al., 2017), climate change had close direct or indirect associations with the investigated water quality. This study focused on analyzing the spatio-temporal associations between river water quality and potential influencing factors of water pollution, such as climate changes (i.e., precipitation and temperature) in Yihe River Basin. To do this, the observed monthly precipitation and temperature data at four weather stations (i.e., Luanchuan Country, Song Country, Yichuan Country, and Yanshi city) from 1998 to 2017 were collected in the Statistical Yearbook (Luoyang Statistical Yearbook).

2.2. Multivariate Statistical Analysis Methods

In this study, PCA, CA, DA and ANOVA were used to evaluate the spatiotemporal characteristics of water quality in Yihe

River Basin. Multivariate statistical analysis requires that the pollution indicators have a normal or near-normal distribution (Sun et al., 2013; Mavukkandy et al., 2014). The single-sample Kolmogorov-Smirnov test method (Liu et al., 2003; Rigi et al., 2019) was used to analyze the distribution characteristics of pollutant concentrations in the water samples. When $\alpha = 0.05$ and $\alpha = 0.01$, the cutoff values of Kolmogorov-Smirnov (K-S) test statistic Z (Kolmogorov-Smirnov Z) were 1.36 and 1.63, respectively. When the bilateral asymptotic significance probability $Sig < \alpha$, reject the null hypothesis, otherwise accept.

The PCA performance well on the dimensionality reduction of complex data. Several comprehensive factors that reflect the majority of original data could be examined through linear transformation. It also has a significant ability in identifying the types and sources of major pollutants in different study periods (Vega et al., 1998; Simeonov et al., 2003). There are six key steps: normalizing the original data, constructing the correlation coefficient matrix, acquiring the eigenvalues and eigen-vectors, identifying the principal component contribution rate and cumulative contribution ratio, calculating the principal component load, and examining the score of each principal component (Ma et al., 2015).

CA is an unsupervised pattern recognition technology, which can quantitatively determine the kinship relationship between a batch of samples without prior assumptions (Vega et al., 1998; Varol et al., 2012). Hierarchical cluster analysis (HCA) is one of the most general CA to classify water quality indicators into cluster groups according to their similarity or nearness (Igbah and Tanko, 2019). HCA has two forms, there are Q-type clustering (i.e., classifying samples) and R-type clustering (i.e., classifying observed variables of the research object). In this study, Q-type clustering method was used to measure the distance between samples and generate the clustering tree diagram. The method is based on the squared Euclidean distance and the Ward algorithm (Strobl et al., 2008).

DA can be used to distinguish cluster analysis results and determine primary pollution indicators. There are three main types: standard, forward and backward. Among them, the backward discriminant analysis method has a better ability to reduce the dimension and discriminate of the indicators. As a result, the backward discriminant analysis method was used to analyze the spatial difference of water quality in the Yihe River Basin, and the cross-validation method was chosen to test its discriminative ability.

ANOVA is a very useful tool for analyzing datasets, which can be classified into two categories one-way and multiway ANOVA. The controlling factors of water quality changes in the Yihe River Basin are mainly time and space. A one-way analysis of variance can be performed. The significance test formula as follows:

$$F = \frac{SSA / (k - 1)}{SSE / (n - k)} \quad (1)$$

where k is the number of levels, n is the number of samples, SSA is the sum of squared spreads between groups, and SSE is the

sum of squared deviations within groups. The F statistic obeys the F distribution with degrees of freedom ($k - 1, n - k$). When the corresponding associated probability value is less than the significance level α (usually 0.05), the null hypothesis is rejected, indicating that the population means have significant differences at different levels of the control variable. Otherwise, there are no significant differences. The above analysis was done collaboratively using Microsoft Excel 2007 and SPSS 20.0.

3. Results

3.1. Evaluation of Water Quality

Table 2 shows the result of the sample K-S test for each water quality indicator. Progressive significance values (both sides) for each indicator are greater than 0.05, indicating that overall river water quality indicators in 17 typical sub-basins over the Yihe River Basin conforms to the normal distribution. Thus, the monitored river water quality data can be used for multivariate statistical analysis.

3.2. Temporal Variation Characteristics of River Water Quality in Yihe River Basin

Temporal variation characteristics of seven river water quality indicators in 17 typical sub-basins were analyzed through the PCA (Table 3). KMO and Bartlett Spheroid tests showed that the principal component analysis was effective ($df = 21, P < 0.01$).

The extracted principal components could reflect the basic situation of the original data (Liu et al., 2003; Simeonov et al., 2003). Three principal components (PCs) were extracted during the low- and high-flow period, and two PCs were extracted during the mean-flow period according to the principle (i.e., eigenvalue is greater than 1). Based on previous studies (Liu et al., 2003; Hussain et al., 2021), the absolute value of PCs that above 0.70 in this study was used as a criterion for determining high-load values (Table 3, Bold font). Then, the water quality variations during different water periods in the Yihe River Basin can be explained and discussed as follows. The absolute values of the PCs load of COD, $\text{NH}_4^+\text{-N}$, EC and pH were greater than 0.7 in the three periods (Table 3). It indicated that COD, $\text{NH}_4^+\text{-N}$, EC and pH were the most notable factors which affecting water quality throughout the study period in the Yihe River Basin. However, during low- and high-flow period, turbidity has a relatively higher PC load value. TP and DO have a strong correlation with the PC load value during the mean- and high-flow period, respectively.

During the low-flow period, the PC1 explained 30.57% of the water quality variation, which was much larger than the contribution rates of the variance of PC2 (19.64%) and PC3 (19.27%). EC and $\text{NH}_4^+\text{-N}$ showed a strong positive correlation (correlation coefficient > 0.7) with the PC1, while pH and DO have a negative correlation with the PC1. EC is a comprehensive indicator of the degree of ion activity in water and the evaluation of ion quality (Zhang et al., 2012), which mainly reflects the impact of human activities and geological sediments in the water environment (Bellos and Sawidis, 2005; Yang et al., 2007; Xie et al., 2020). Generally, the value of pH in river water is

weakly alkaline, which is mainly affected by external pollution sources and aquatic biological activities, and the pH can control the redox reaction of river water to a certain extent (Li et al., 2017). The pH load value was negative, indicating that it was lower during the low-flow period. The content of DO is generally saturated in natural water, but it will decrease rapidly with the increase of biomass (Chang, 2005). When DO is less than 2 mg L^{-1} , most fish cannot survive (Russo et al., 1981). The water quality indicator that strongly related to the PC2 was COD, while TP was generally weaker associated. COD characterizes the level of organic pollution in water bodies and is closely associated with wastewater discharge from urban, industrial, and agricultural activities (Bellos and Sawidis, 2005; Li et al., 2017). TP related to the input of pesticides, industrial wastewater, and agricultural activities (Kannel et al., 2007). The high values of COD and TP in the water would reduce the DO concentration and induce the deterioration of surface water quality (Kannel et al., 2007; Zhang et al., 2012; Li et al., 2017). Fang et al. (2013) have emphasized that agricultural non-point source pollution was relatively small during the low-flow period compared to point source pollution. Therefore, during the low-flow period, various pollutants that entered the Yihe River have formed the organic pollution, such as domestic sewage and industrial wastewater discharge. The decomposition process may consume a large amount of oxygen (the value of DO is negative, Table 3) and generate ammonia (higher $\text{NH}_4^+\text{-N}$ value, Table 3), organic acids and carbon dioxide. The hydrolysis of these acidic substances led to a decrease in pH, which was consistent with previous findings (Vega et al., 1998; Shrestha and Kazama, 2007). Consequently, the PC1 and PC2 can be classified as the combined effects of natural changes in the water environment and human activities (e.g., domestic and industrial wastewater discharge). Turbidity indicates the degree of resistance of suspended matter and colloids in water (such as soil, silt, and plankton) to light transmission (Wu et al., 2018). Turbidity has a strong positive correlation with PC3, which may be related to a large number of sand mining operations in the basin during the low-flow period.

When it comes to the mean-flow period, the variance contribution rate of the PC1 was 35.04%, of which the larger factor loads were mainly occupied by pH, $\text{NH}_4^+\text{-N}$ and TP. River water quality at sub-basin scale was largely affected by the dual effects of natural processes and human activities (Oketola et al., 2013; Zhang et al., 2018; Mir and Gani, 2019). For example, short-term surface runoff from rainfall will bring non-point source pollution and domestic sewage that generated through agricultural activities into rivers, causing nitrogen and phosphorus pollution in the water body. Field investigations have found that spring cultivation in the Yihe River Basin was carried out from March to April every year. The chemical fertilizers (e.g., phosphorus and organic fertilizers) that were used in the cultivation of crops (e.g., peanuts, cotton, tobacco, and vegetables) would directly pollute rivers due to the erosion of rainfall and runoff. In addition, the denitrification of pathogenic microorganisms such as *E. coli* carried in organic fertilizers (e.g., livestock and poultry manure) and bacteria produced in the process of returning straw to the field also have

contributed to nitrogen and phosphorus pollution in water (Jia and Zhang, 2015; Li et al., 2018; Wang et al., 2020; Yao et al., 2020). The variance contribution rate of PC2 is 28.97%, which is primarily related to EC and COD and can be classified as the common impact of natural and human activities.

In terms of the high-flow period, pH, turbidity and EC were the main influence factors of the PC1. In the process of high-intensity rainfall during the high-flow period, a large number of terrestrial materials that produced by agricultural activities and soil erosion will migrate into the river water body with rainwater and the surface runoff, polluting the surface water. Turbidity represents pollution that induced by rainfall events during the high-flow period, such as Erosion. The variance contribution rate of the PC1 was 40.14% (Table 3), which is much larger than the variance contribution rates of PC2 (0.99%) and PC3 (16.71%), indicating that the river water quality during the high-flow period was greatly affected by the combined effects of non-point source pollution and rainfall events. The load values of COD, $\text{NH}_4^+\text{-N}$ of the PC2 was increased obviously in the high-flow period than the other two periods. During the high-flow period, not only the precipitation increased significantly, but also the farmers applied large amounts of fertilizer to crops, especially corn. Nitrogen that cannot be effectively used by the plants would finally enter river with rainfall-runoff or groundwater infiltration, resulting in an increasing of nitrogen content in river water bodies. Besides, the $\text{NH}_4^+\text{-N}$ content that discharged into surface water was also much higher, which usually came from the manure of free ranges livestock and poultry in rural areas, domestic and industrial sewage. Thus, with the increase of water temperature in summer, bacteria and other microorganisms in the river will increase nitrification, reflecting the degree of nitrogen and organic pollution in water. The PC3 has a strong positive correlation with DO (Table 3). In addition, the average value of DO during the high-flow period was as low as 8.35 (Table 1). This might be due to the fact that the water body received large amounts of untreated domestic, industrial wastewater, and other sources of pollution, resulting in higher concentrations of pollutants in the water and higher microbial activity. These biological processes may further consume lots of oxygen in the water, such as the metabolic activities of microorganisms and the decay of aquatic organisms.

Water quality indicators that have a significant impact on river water quality in one period may have reduced influence in another period. In general, the main water quality indicators of the three water periods in the Yihe River Basin reflect the dual influences of human activities and the natural environment characteristics on water quality: the main polluted factors in the low-flow period were organic pollution and the variations of natural environment, followed by nitrogen pollution. Nitrogen was the leading factor in river water pollution during the mean-flow period, followed by organic and phosphorus pollution. Organic pollution and nitrogen were the main factors affecting river water quality in the high-flow period. At the same time, comparing the statistical description of the water quality indicators of the Yihe River Basin during the three periods (i.e., low-, mean- and high-flow period) (Table 1), it can be found that: the average values of pH in the three water periods were

slightly alkaline, and the change range during the entire study period from 6.13 to 8.9, which was basically within the range (6.5 ~ 9.0) which aquatic organisms can maintain their natural processes (Chang et al., 2012). The lowest value of pH (6.14) was appeared in the high-flow period, which might be caused by the decomposition of organic matter in wastewater discharge. Seasonal changes in pH did not show much difference. The maximum values of DO and COD were appeared in the low-flow period, while these of EC, turbidity and $\text{NH}_4^+\text{-N}$ were distributed in the mean-flow period. The mean value of TP was higher in the low-flow and the mean-flow period relative to these in the high-flow period, which is consistent with previous research (Li et al., 2018). These might be due to the decreased of precipitation and runoff in these two periods, and the hydraulic erosion which affected the concentration of TP in river water to a certain extent.

3.3. Spatial Distribution Characteristics of River Water Quality in Yihe River Basin

3.3.1. Spatial Cluster Analysis

Based on the monitored water quality indicators of the Yihe River Basin from 2016 to 2017, hierarchical cluster analysis was performed on the 17 typical sub-basins. After recalibrated the distance based on the cluster, the threshold 13 was selected to divide the sample points into three groups (Figure 2). The spatial similarity analysis of the sample points was operated to capture the spatial distribution characteristics of river water quality in the Yihe River Basin. The samples that included in each group were as follows: Cluster 1 (i.e., C1) {4, 16, and 17}; Cluster 2 (i.e., C2) {9, 10, 11, 12, 13, 14, and 15}; Cluster 3 (i.e., C3) {1, 2, 3, 5, 6, 7, and 8}.

According to the river network map, sub-basins division map, field investigation, and sampling in the Yihe River Basin, it can be inferred that the water quality of the same cluster group was affected by similar pollution sources and natural backgrounds, and thus has similar characteristics: in detail, samples 16 and 17 included in C1 were mainly distributed in the lower plain rivers. The rivers in this group (C1) flow through agriculture area, are close to the urban area, and are more scattered in space than the other two groups. In recent years, with the reduction of cultivated land, the continuous increase of construction land (Ren et al., 2017), and the accumulation of pollution in the upper and middle reaches of rivers, the water quality in C1 has been seriously polluted by agriculture, industry, and domestic discharge. Affected by the domestic sewage and industrial wastewater of Luanchuan County and its tributaries, the water quality of sample 4 (C1) located in upstream was also poor. The C2 samples mainly flows through farmlands and towns in the middle reaches of the Yihe river. Along with the increase in construction and forest land in C2, and the decrease of cultivated land and grassland (Ren et al., 2017), the water quality in this region was affected by both urbanization and agricultural activities. The sample points of C3 were belong to the upper reaches of the forest area and located at the southern foot of the Xiong'er Mountain. There was less human disturbance in this area, so the river was clean. The water quality of the above three groups (i.e., C1, C2, and C3) was all subject to human interference to varying degrees.

Table 4. Eigenvalues of the Spatial Discriminant Analysis

Typical Discriminant Function	Eigenvalues	Variance (%)	Accumulation (%)	Canonical Correlation Coefficient
1	22.817	93.4	93.4	0.979
2	1.606	6.6	100.0	0.785

Table 5. The Structure Matrix of the Characteristic Function of the Spatial Discriminant Analysis

Water Quality Indicators	Discriminant Function	
	1	2
TP	0.274*	-0.172
DO	0.134*	-0.074
NH ₄ ⁺ -N	0.123*	-0.094
COD ^(a)	0.061*	0.008
EC	0.248	0.525*
Turbidity	0.085	0.415*
pH ^(a)	0.037	-0.085*

Note: * represents the largest absolute correlation between a variable and a discriminant function; (a) indicates that the variable was not utilized in the analysis.

Table 6. Wilks' λ, Chi-Sqr, and Test of the Spatial Discriminant Analysis

Function Test	Wilks' λ	Chi-Sqr	df	Significant
1 to 2	0.016	45.410	14	0.000
2	0.384	10.535	6	0.104

3.3.2. Discriminant Analysis

To identify the water quality indicators that induced significant variations between groups, and to further verified the results of the above-mentioned spatial cluster analysis, the spatial characteristics of the three groups of water quality indicators were analyzed through DA (Tables 4, 5, and 6). The eigenvalues of the spatial discriminant analysis (Table 4) showed that the first discriminant function could explain almost all the variables (93.4%). TP, DO, NH₄⁺-N, and COD contribute higher to discriminant function 1 than other indicators (i.e., EC, turbidity and pH). However, EC, turbidity, and pH contributed higher for the discriminant function 2 (Table 5). The value of Wilks' λ and chi-square coefficient were 0.016 ~ 0.384 and 10.535 ~ 45.41 (Table 6), respectively. The significance test values (0.000) of two discriminant functions were both less than 0.01, indicating that the spatial clustering analysis was reliable; the Wilks' λ significance test value of discriminant function 2 is 0.104 > 0.05, which also showed the validity of discriminant functions of 1 and 2.

Table 7 exhibited the verification matrix of the discriminant analysis classification. The diagonal represented the number and proportion of samples that were predicted correctly, while the remainder denoted the number and proportion of samples which were incorrectly predicted. The overall accuracy of the grouping results of the clustering analysis was 94.1%, indicating that it was reasonable to explore the characteristics of the spatial variation of water quality based on the clustering groups.

Table 8 showed the classification function coefficients of the linear discriminant function of Fisher. Based on Tables 4 and 8, it can be inferred that the construction of the discriminant function involved five water quality indicators, including DO, EC, turbidity, NH₄⁺-N, and TP. These five water quality indicators not only implied that the discriminant function have a

better ability to reduce the dimension of the indicators, but also showed that they have significant variations between there cluster groups (i.e., C1, C2, and C3). Therefore, the above five water quality indicators and discriminant functions could be used to characterize the spatial differences of water quality in the Yihe River Basin. The monitoring of such indicators needs to be strengthened in the future.

Table 7. Validation Matrix of the Classification by Means of Discriminatory Analysis

Primitive Group	Forecast Group		
	C1	C2	C3
C1	3 (100%)	0	0
C2	0	7 (100%)	0
C3	0	1 (14.3%)	6 (85.7%)

"C1" represents the sample points 4, 16, and 17; "C2" represents the sample points 9, 10, 11, 12, 13, 14, and 15; "C3" represents the sample points 1, 2, 3, 5, 6, 7, and 8.

Table 8. Classification Function Coefficients of DA

	Clustering Groups		
	1	2	3
DO	56.816	41.795	44.387
EC	1.591	1.392	1.358
Turbidity	-7.758	-6.375	-6.782
NH ₄ ⁺ -N	14.764	14.837	15.416
TP	1552.138	260.377	471.095
(Constant)	-2265.599	-1723.768	-1690.270

3.4. Spatiotemporal Variation Characteristics of Water Quality in Yihe River Basin

The one-factor ANOVA analysis was performed for the

water quality indicators during three time periods (i.e., low-, mean-, and high-flow period) and different space scales (i.e., C1, C2, and C3). Figure 3 presented the average value of water quality during the three periods under the three clustering groups in the Yihe River Basin. It can be found that EC, DO, turbidity, $\text{NH}_4^+\text{-N}$, and TP revealed significant spatial and temporal differences, except for the two indicators of pH and COD (Figure 3). This verified the results of discriminant analysis to some extent, which also further confirmed that there were significant differences among clusters.

According to the variations of the water quality indicators during the three monitoring periods, it was interesting to find that: DO and $\text{NH}_4^+\text{-N}$ were significantly different in the high-flow period, respectively; turbidity presented notable difference in the mean-flow period; EC revealed an apparent difference between the low-flow period and mean-flow period; TP showed significant differences in the three periods of low-, mean-, and high-flow. The averaged values of water quality indicators in most clusters (C1: EC, turbidity and TP; C2: DO and $\text{NH}_4^+\text{-N}$, C3: turbidity, $\text{NH}_4^+\text{-N}$ and TP) showed a trend of mean-flow period > low-flow period > high-flow period; the averaged values of DO-C1, DO-C3, turbidity-C2, ($\text{NH}_4^+\text{-N}$)-C1 and TP-C2 presented a trend of low-flow period > mean-flow period > high-flow period; the averaged value of EC-C3 showed a trend in the low-flow period > high-flow period > mean-flow period; the averaged value of EC-C2 revealed a trend of high-flow period > mean-flow period > low-flow period. Among the seven monitoring river water indicators, the maximum averaged value of four indicators (i.e., EC, turbidity, $\text{NH}_4^+\text{-N}$, and TP) were appeared in the mean-flow period; and these of two indicators (COD and DO) were distributed in the low-flow period; only the maximum value of the averaged pH was monitored during the high-flow period. In general, river water pollution was the most serious during the meanflow period, followed by the low-flow period, and the water quality was best in the high-flow period.

The variation of the mean values of the seven water quality indicators (i.e., pH, EC, DO, turbidity, COD, $\text{NH}_4^+\text{-N}$ and TP) during the same period in different spatial clusters (i.e., C1, C2 and C3) indicated that the water quality of the Yihe River Basin displayed a gradual decline trend from upstream to downstream. Moreover, the water quality characteristics of the three clustering groups were closely related to their spatial location. The maximum averaged values of the EC, TP, DO and turbidity were occurred in C1, which flows through agriculture land and urban area in the lower reaches of the river basin. Besides, EC, TP in C1 showed significant differences with the other two groups. The averaged value of TP in C1 was higher than the other two groups, and the difference between C2 and C3 was not significant. The DO and turbidity in C1 were significantly different from the other two groups in the high-flow and low-flow periods, respectively. The minimum value of the mean concentration of $\text{NH}_4^+\text{-N}$ was appeared in C2, which was significantly different from C1 in the high-flow period. The water quality indicators (except TP) in the upper reaches of the forest area (C3) were lower than those of the other two groups, indicating that C3 was less subjected to human interference and the water quality

was better. Therefore, the regions with relatively severe pollution could be identified based on the average concentration of the above five water quality indicators and their spatial difference. For instance, the averaged values of EC, TP, DO and turbidity were much higher in C1, and they also have significant differences with the water quality in the middle and upper reaches (C2, C3). The poor water quality in C1 may be induced by industrial pollution and agriculture non-point source pollution in the area, as well as the accumulation pollution from the middle and upper reaches (C2, C3).

4. Discussion

4.1. Temporal Variation Characteristics and Its Response to Climate Change

Generally, river water quality was the worst in the low-flow period and was better in the high-flow period (Yang et al., 2007). However, the overall water quality of the Yihe River Basin was the worst in the mean-flow period, followed by the low-flow period, while it was the best in the high-flow period. The river water quality may be significantly affected when the peripheral land-use type changed from natural to urban land (Tu and Xia, 2006; Shen et al., 2011; Putro et al., 2016). The construction of the highway from Luanchuan Country to Lushi Country highway in the upstream reaches was started during the low-flow period (Henan Government, 2017), and the land-use changes caused by which might be one of the main influencing factors of the poor water quality during this period. Luanchuan County is a mountainous landform, the roads, farmland, and residential areas of which were mainly distributed along the river valley. The development of the highway construction project has promoted the conversion of land-use types such as cultivated land and residential areas along with the river reserves to roads. This process would not only cause soil erosion but also directly affect the water quality of the adjacent river. The bare soil produced by this project would be washed into the river water body through surface runoff. Besides, the highway in this area mainly constructed in the form of high subgrades. Construction waste (e.g., waste slag, magma, and silt), road runoff, and flying dust that generated in the process of subgrades filling would easily enter the river. Thus, the turbidity of the river water was apparently increased, and finally induce the reduction of the quality in river water. At the same time, the aquatic ecological control project was carried out in the Song Country urban area and the Yichuan Country in the middle reaches during the mean-flow period. The project promoted the input of pollutants into the Yihe River, which made the concentration values of turbidity, $\text{NH}_4^+\text{-N}$ and TP of C3 and C1 were much higher during the mean-flow period than those in low- and high-flow period and affected the river water quality.

During the low-flow period, the water quality of the Yihe River Basin was also relatively poor. Previously, precipitation was widely regarded as one of the most powerful meteorological inputs in hydrological and water quality (Sajjad et al., 2018; Solakian et al., 2019). Figure 4 shows the averaged values of the monthly precipitation and temperature at four weather stations (i.e., Luanchuan Country, Song Country, Yichuan Country

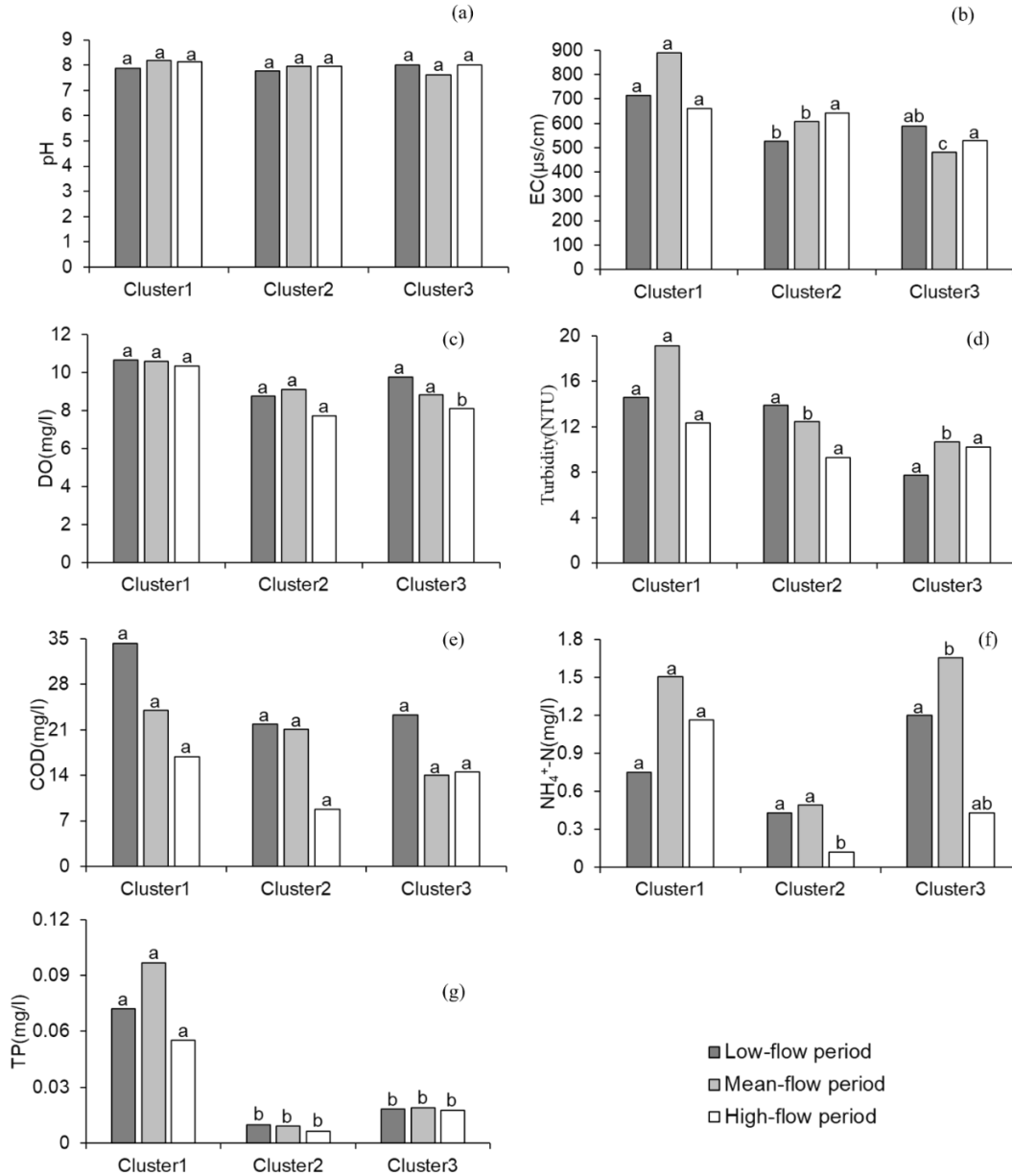


Figure 3. Spatial variations of discriminant indicators from spatial DA. Different letters (i.e., a, b, and c) of each water quality indicator in the same period represent significant differences among groups, $P < 0.05$.

and Yanshi city) from 1998 to 2017. The results showed that during the low-flow period (i.e., December and January), the upper reaches (i.e., Luanchuan Country) only received 15.9 mm precipitation, much less than that in other regions. The river flow would also decrease owing to the decrease in precipitation during the low-flow period. Moreover, some river tributaries of the upper reaches (C3) were restricted by the mountainous terrain, and rivers were small and narrow, which increases the difficulty of pollutants diffusing in the river water. The lowest values of temperature were presented in the low-flow period, ranging from -0.17 to 2.98 °C (Figure 4). The temperature of the river water was also relatively low during this period, which affects the metabolism rate of the microorganisms that decompose pol-

lutants. Thus, a large amount of pollution load would stay in the river water, resulting in pollution enrichment. In addition, during the investigation, we also noted that the domestic sewerage was not fully integrated into the sewerage treatment system in the upper reaches of the Yihe River Basin. Therefore, the direct discharge of domestic sewage was another major factor of severe pollution during the low-flow period in the area. Finally, in the low-flow period, active sand mining activities were also one of the causes of river water pollution. Most of the precipitation in the Yihe River Basin was concentrated in summer and has a higher river runoff. Thus, pollutants (e.g., $\text{NH}_4^+\text{-N}$ and TP) were diluted, and resulting in lower values of water quality monitored indicators during the high-flow period.

4.2. Spatial Variation Characteristics of Water Quality and Potential Pollute Source

The gradient of urbanization is increasing from the upstream to the downstream in the Yihe River Basin. Land-use variations and land management methods that caused by human activities and urbanization development have significant effects on water quality changes (Varol et al., 2012; Wu et al., 2018). The water quality of the middle and upstream reaches of the Yihe river was superior to that of downstream reaches. Forest land has a pretty good weakening effect on water quality deterioration, and the roots and litter of vegetation have a strong retention and absorption effect of pollutants (Ji et al., 2015). Most of the mainstream (C2) belongs to hilly landforms. More than half of the rivers, canals and reservoirs in the study area were distributed on C2. Due to their strong capacity to purify pollutants, most of the water quality indicators monitored at C2 showed smaller averaged concentration values during the low- and high-flow periods. The lower reaches of the Yihe river flows through Yichuan Country and Yanshi Country (C1), its urbanization level was relatively higher than the middle and upper reaches. Therefore, in addition to the increase in point source pollution leading to the deterioration of river water quality, an increase in the proportion of impervious surfaces in the sub-basins would also endanger aquatic ecosystems and river water quality, which was consistent with previous study (Paul and Meyer, 2001). In urban areas, short-term heavy rainfall can promote contaminates matters to enter rivers through impervious surfaces. The underground drainage system in the city would further increase the peak flood flow and shorten the time for pollutants to enter the river. Besides, the accumulation of upstream pollutants leads to the deterioration of the water quality of downstream rivers after passing through the city. These reflect the impact of human socioeconomic activities and natural processes (e.g., precipitation) on river water quality. Therefore, in addition to the high pollution load of TP and $\text{NH}_4^+\text{-N}$ in the water body due to the construction of the high-way in the upper reaches of the Yihe river during the mean-flow period, the water quality in the upper reaches (C3) and the midstream (e.g., Lulun Reservoir in C2) of the Yihe River Basin was better than the lower reaches (C1) during the low-flow and high-flow period (Figures 2b and 3).

Consequently, the temporal and spatial changes in water quality in the Yihe River Basin were affected by both human activities and natural factors. In addition to the effects of the construction of the high-way, the aquatic ecological control project, and cultivation, the temporal variation in water quality was also affected by climate change (e.g., precipitation and temperature), the variation in space was also restricted by natural environment characteristics such as topography.

4.3. Representations of Spatial-Temporal Changes of the River Water Quality

In terms of the representation of spatiotemporal changes in water quality in a river basin, the quantity and quality of monitoring water data in space were mostly presented through the discrete graphics (e.g., histogram, scatter diagram, and line chart) (Ravindra et al., 2003; Sundaray et al., 2006; Sun et al.,

2013; Wu et al., 2018). However, methods such as spatial interpolation were rarely used to draw contour maps on a two-dimensional plane to simulate the spatial difference in water quality (Wang et al., 2013). And little or no studies have used three-dimensional (i.e., 3D) surface maps to describe the quantity, quality, density, and correlation of river water quality data at different sampling points. Rivers are 3D geographical things (Liu et al., 2019). Three-dimensional simulation of the spatial characteristics of river water quality data at different sampling points will be more visual, intuitive and more in line with people's habits of daily observation. The 3D kernel density surface graph can appropriately exaggerate the difference between the high and low values and can effectively highlight the differences between hot spots and regions, thereby making the display of thematic information more intuitive and diverse (Lu et al., 2017). In the future, related theories and techniques that expressed in three-dimensional such as kernel density estimation are desired to be explored and applied to the spatial mapping of river water quality. These are expected to provide more intuitive and scientific tools for river water environmental protection and water quality improvement.

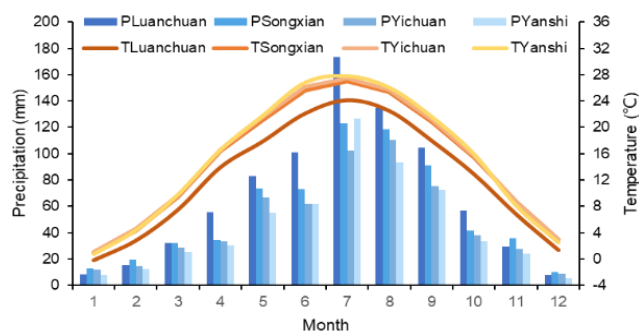


Figure 4. The monthly average precipitation (i.e., P) and temperature (i.e., T) of four weather stations (i.e., Luanchuan Country, Song Country, Yichuan Country, and Yanshi city) in Yihe River Basin from 1998 to 2017.

5. Conclusions

In this study, the spatiotemporal characteristics of river water quality were analyzed in 17 sub-basins in Yihe River Basin during low-, mean- and high-flow period based on the multivariate analysis methods. The potential pollution sources and contaminated areas were also identified according to the socioeconomic activities, meteorological data and the field investigations data in the Yihe River Basin in China. The results showed that: (1) PCA shows that the water quality in the Yihe River Basin was dominated by organic pollution during the low-flow period, followed by nitrogen pollution; nitrogen pollution was the influential indicators during mean-flow period, followed by phosphorus and organic pollution; nitrogen and organic was the main pollution during the high-flow period, respectively. (2) CA divides the sampling points of the Yihe River Basin from upstream to downstream into three categories (i.e., C1, C2 and C3). The results of DA verified that the accuracy of the CA was 94.1%. It also showed good dimensionality reduction ability, that is,

only five key water quality indicators (i.e., DO, EC, turbidity, TP and $\text{NH}_4^+\text{-N}$) could reasonably reflect the water quality status in the Yihe River Basin. This can lessen the cost and number of recurring sampling indicators to optimize the sampling strategy. (3) Water pollution was most severe in the mean-flow period, followed by the low-flow period, and water quality in the high-flow period was the best. The water quality shows a declining trend from upstream to downstream, and the water pollution located downstream (C1) was relatively severe. (4) The spatial and temporal variations of water quality were affected by human activities (e.g., the construction of the high-way, the aquatic ecological control project and cultivation), natural processes (e.g., precipitation and temperature) and natural environment characteristics (e.g., topography). Besides, related techniques of three-dimensional expressions such as nuclear density estimation can be used for the spatial mapping of river water quality in the future.

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