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Original Research

The Spatial-Temporal Pattern and Source Apportionment of Water Pollution in a Trans-Urban River

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Abstract

Deteriorating water quality in urban areas has drawn wide interest in China. In our study, water quality was monitored monthly during December 2009-November 2011 from 16 sites located in a trans-urban river. The spatial pattern showed that the concentrations of EC, Ca^{2+}, Mg^{2+}, BOD_5, COD_{cr}, TP, and NH_4^+-N were higher midstream and downstream than upstream, while measured pH and DO upstream were higher than measurements midstream and downstream. The temporal pattern showed that the concentrations of EC, TP, BOD_5, NH_4^+-N, Mg^{2+}, and Ca^{2+} in the wet season were lower than in the dry season, while the concentrations of COD_{cr} in the wet season were higher than in the dry season. Receptor-based source apportionment revealed that most of the variables were influenced by domestic sewage, cropland, and woodland runoff pollution. Therefore, the best method to prevent water quality degradation is to manage the domestic sewage, cropland, and woodland runoff.

Keywords: water quality, urban river, spatial and temporal pattern of water quality, water pollution source apportionment

Introduction

A critical step toward effectively controlling river pollution is the development of water quality monitoring programs to track environmental conditions and determine spatio-temporal trends. But such monitoring systems result in voluminous data, which are difficult to analyze and interpret because of the latent interrelationships between the parameters and monitoring sites [1-2]. Thus the application of advanced statistical methods to these datasets is required to interpret spatial and temporal patterns, to identify significant parameters and potential pollution sources, and to quantify source contributions.

In recent years, multivariate statistical methods such as cluster analysis (CA), factor analysis (FA), principal component analysis (PCA), and multivariate linear regression (MLR) have been effectively applied to the

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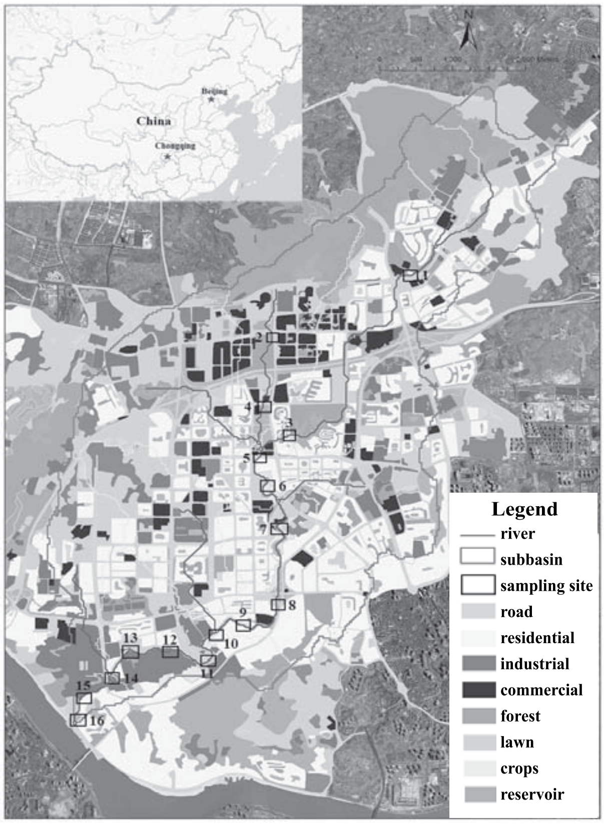

Fig. 1. The study area and water quality monitoring sites.

assessment of surface water quality, evaluation of spatial or temporal variations in groundwater and coastal water, as well as identification of the latent pollution sources in marine sediments. For instance, Zhou et al., Ouyang et al., and Simeonov et al. classified the sampling sites by CA and identified the main pollution sources by PCA [3-6]. Su et al. determined the significant variables affecting temporal and spatial variations in the Qiantang River (China) by DA [7]. Simeonov et al., Huang et al. and Huang et al., quantified source contributions using APCS-MLR [6, 8-9]. Yesilirmak analyzed the temporal and spatial variations in Buyuk Menderes River by using statistical methods [10]. Multivariate analyses are sensitive to outliers and the non-normal distributions of geochemical datasets; thus, appropriate data pretreatment, including estimation of missing data, examination of normal distributions, and data transformation should be taken into consideration. This is a principle often ignored in most environmental studies [4].

The main aim of this study is to apply multivariate methods (CA, PCA, FA and APCS-MLR) to evaluate spatial and temporal patterns in trans-urban river water quality and to apportion river water pollution in Chong Qing. Specifically, CA was used to determine the similar or dissimilar relationships between sampling sites; PCA and FA were used to identify underlying pollution sources and their continuous spatial and temporal impacts for the entire study area over different periods, and APCS-MLR was introduced to further estimate source distributions for each pollution variable.

Materials and Methods

Study Area and Sampling Sites

The Panxi River Basin is located in northern Chongqing, China (Fig. 1). It is an area of approximately 35 km^2 (from 29°34′11.22″ to 29°37′54.08″N and 106°28′26.75″ to 106°31′45.68″ E) and has a population of 0.2 million. It belongs to a subtropical monsoon climate with a mean annual temperature of 17.5~18.7ºC, and a mean annual precipitation of 1100~1300 mm. Most of the precipitation occurs during the period between April and July, and the highest temperature occurring during the period between July and September (Fig. 2). Land use within the basin largely consists of residential, commercial, industrial, lawns, crops, and water (Fig. 1).

To accurately represent the water quality of the river systems, a sampling strategy was designed to cover a wide range of determinants at the key sites. In the present study, a total of 16 sampling sites were selected (Fig. 1).

Sampling and Chemical Analysis

In our study, water samples were collected twice a month during December 2009-November 2011 from 16 monitoring stations (Fig. 1). The following

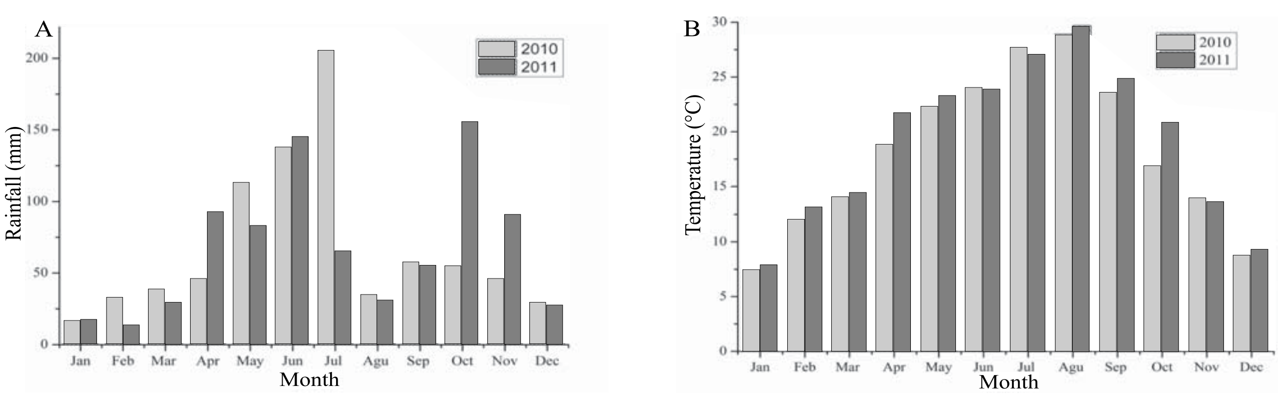

Fig. 2. Temporal variations of rainfall and temperature for 2010-11.

Table 1. Water quality parameters.

Parameters	Abbreviation	Analytical method and equipment
pH	pH	pH meter (Hach, USA, Sension 156)
Electrical conductivity	EC	Electrometric method (Hach, USA, Sension 156)
Dissolved oxygen	DO	Electrochemical probe method (Hach, USA, Sension 156)
Biochemical oxygen demand after 5 days	BOD_5	Dilution and seeding method (Thermo Scientific Orion, USA, 850A+)
Chemical oxygen demand	COD_{cr}	Rapid digestion and spectrophotometric method (Hach, USA, DRB200, Shimadzum, Japan, UV-1700)
Total phosphorus	TP	Persulfate digestion spectrophotometric method (Shimadzum, Japan, UV-1700)
Ammonia nitrogen	NH_4^+-N	Spectrophotometric method with Nessler's reagent (Shimadzum, Japan, UV-1700)
Nitrate nitrogen	NO_3^--N	Spectrophotometric method with phenol disulfonic acid (Shimadzum, Japan, UV-1700)
Calcium	Ca^{2+}	Inductively Coupled Plasma Optical Emission Spectrometer (ICP-OES) (Leemans, USA, Prodigy)
Magnesium	Mg^{2+}	Inductively Coupled Plasma Optical Emission Spectrometer (ICP-OES) (Leemans, USA, Prodigy)
Sulphate	SO_4^{2-}	Ion chromatograph (Dionex, USA, ICS-1000)

11 physiochemical parameters were analyzed: pH, conductivity (EC), dissolved oxygen (DO), five day biochemical oxygen demand (BOD_5), chemical oxygen demand (COD_{cr}), total phosphorus (TP), ammonia nitrogen (NH_4^+-N), nitrate-nitrogen (NO_3^--N), sulfate (SO_4^{2-}), calcium (Ca^{2+}), and magnesium (Mg^{2+}).

At each site water was sampled from a bridge over the river using a stainless steel bucket and a plastic bottle. Buckets and bottles were rinsed three times with river water before samples were collected. The water pH, EC and DO were measured by a portable water quality analyzer (Hach, USA, Sension 156) in situ. Immediately after collection, samples were brought to the laboratory for analyses of the other water quality parameters. The analysis methods followed national quality standards for surface waters, China [11], and the specific method used is presented in Table 1.

Data Pretreatment

The values of kurtosis and skewness beyond the range of −2 to +2 suggested significant departures from normality [12].The statistical analysis of data showed that the kurtosis and skewness values were −0.57 to 1.08 and −0.97 to 1.28, respectively. Therefore, all variables were normally distributed. For CA and PCA/FA, all variables were further z-scale standardized (mean = 0, variance = 1) to avoid misclassification due to wide differences in data dimensionality.

Multivariate Statistical Methods

River water quality data sets were subjected to five multivariate techniques: cluster analysis (CA), principal component analysis (PCA), factor analysis (FA), and absolute principal component score-multiple linear regression (APCS-MLR). All mathematical and statistical computations were made using Microsoft Office Excel 2003 and SPSS 19.0.

Cluster Analysis

CA is a group of multivariate techniques whose primary purpose is to assemble objects based on the characteristics they possess. CA is used to develop meaningful aggregations, or groups, of entities based on a large number of interdependent variables [13]. Hierarchical agglomerative clustering is the most common approach, which provides intuitive similarity relationships between any one sample and the entire data set, and is typically illustrated by a dendrogram (tree diagram). In the study, hierarchical agglomerative CA was performed based on the normalized dataset (mean of observations over the whole period) by means of Ward's method using squared Euclidean distances as a measure of similarity [14]. The spatial and temporal variations in water quality were determined from hierarchical CA using linkage distance.

Principlal Component Analysis /Factor Analysis

Factor analysis, which includes PCA, is a very powerful technique applied to reduce the dimensionality of a dataset consisting of a large number of interrelated variables, while retaining as much as possible the variability presented in the dataset. PCA includes correlated variables with the purpose of reducing the numbers of variables and explaining the same amount of variance with fewer variables (principal components). Factor analysis attempts

Table 2. Water quality parameters and summary basic statistics of the Panxi River between 2009-12 and 2011-11.

Parameters	Mean	S. D.	Min	Max	Standard	Below standards for all sites (%)	Units
pH	8.16	0.371	7.53	9.13	6 ~ 9	6.0	pH units
EC	545.11	117.151	300.00	772.75	—	—	µs/cm
DO	5.80	2.487	1.82	15.02	≥2	7.0	mg/L
BOD_5	12.05	5.190	2.89	28.35	≤10	51.6	mg/L
COD_{cr}	62.28	24.680	5.57	138.27	≤40	79.2	mg/L
TP	0.82	0.338	0.10	1.79	≤0.4	82.3	mg/L
NH_4^+-N	7.25	4.226	0.14	17.00	≤2.0	85.2	mg/L
NO_3^--N	1.64	0.914	0.04	4.85	—	—	mg/L
Ca^{2+}	60.21	11.977	28.48	80.97	—	—	mg/L
Mg^{2+}	10.89	2.509	5.98	16.34	—	—	mg/L
SO_4^{2-}	77.52	12.410	42.87	107.61	≤250	0	mg/L

Mean: average value; S.D: standard deviation; Min: minimum value; Max: maximum value. Standard is Class V surface water standard developed by China (GB3838-2002) (SEPB 2002b)

to explain the correlations between the observations in terms of the underlying factors, which are not directly observable [15].

Principal component analysis extracts eigenvalues and related loadings from the covariance matrix of original variables to produce new orthogonal variables through Varimax rotation, which are linear combinations of the original variables [16]. Using PCA we can identify the unobserved latent pollution sources [17]. In our study, PCA of the normalized variables (water quality dataset) was performed to extract the significant principal components and to further reduce the contribution of variables with a minor significance. These PCs were subjected to varimax rotation (raw) generating original variables. Following Pekey et al. eigenvalues>1 were selected as the new orthogonal variables [18]. According to Liu et al. the factor loadings as "strong," "moderate," and "weak" correspond to absolute loading values of >0.75, 0.75-0.50, and 0.50-0.30, respectively [19].

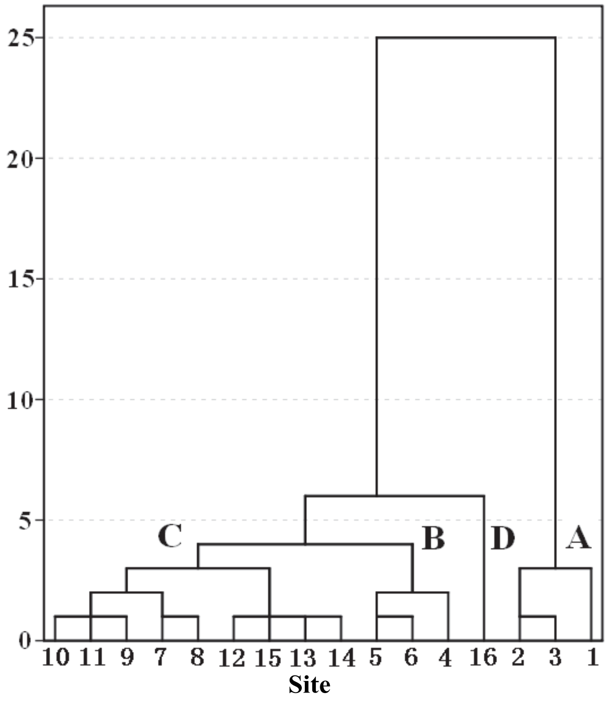

Fig. 3. Dendrogram showing spatial similarities of monitoring sites produced by CA.

Absolute Principal Component Score-Multiple Linear Regression (APCS-MLR)

Absolute principle component score, a proven approach to effectively supply quantitative information regarding the contributions of each source type [4, 18], was applied to calculate source contributions after determining the number and characteristics of possible sources by PCA. After determination of the number and identity of possible sources influencing the river water quality in Panxi River using PCA, source contributions were computed through the APCS-MLR technique in this paper.

Results and Discussions

Water Quality Properties of Panxi River

As shown in Table 2, the mean water pH and DO were 8.16 and 5.80 mg/L, respectively, 6.0% of pH and 7.0% of DO samples exceeded the Grade V for pH (6-9) and DO (2.0 mg/L) when compared to the national quality standards for surface waters, China [20]. The mean water NO_3^--N, NH_4^+-N, and TP were 1.64, 7.25, and 0.82 mg/L, respectively, 85.2% of NH_4^+-N and 82.3% of TP samples exceeded Grade V for NH_4^+-N (2.0 mg/L) and TP

(0.4 mg/L) when compared to the national quality standards for surface waters in China [20]. The mean water BOD_5 and COD_{cr} were 12.05 and 62.28mg/L, respectively. 51.6% of BOD_5 and 79.2% of COD_{cr} samples exceeded Grade V for BOD_5 (10 mg/L) and COD_{cr} (40 mg/L) when compared to chinese national quality standards for surface waters [20]. Mean water EC, Ca^{2+}, and Mg^{2+} were 545.11µs/cm, 60.21 mg/L, and 10.89 mg/L, respectively. There are no stated limits by the State Environmental Protection Bureau of China [20] for EC, Ca^{2+}, and Mg^{2+}. The mean water SO_4^{2-} was 77.52 mg/L, with all SO_4^{2-} samples meeting the drinking water standard limit value of 250 mg/L [20]. Based on the above results, the water quality of the trans-urban river indicated that it was seriously polluted by organic pollutants (BOD_5 and COD_{cr}) and nutrient-related impacts (TP and NH_4^+-N), which indicated that the water quality was affected by human activity. This result was similar to earlier studies, such as Suthar et al., who reported that the Buyuk Menderes River was polluted by BOD_5 (37.02mg/L) and COD_{cr} (170.21 mg/L) [21]. Zhou et al. (2007) found that the Hong Kong River (China) was seriously polluted by BOD_5 (19.68mg/L), COD_{cr} (34.83 mg/L), TP (1.92 mg/L), and NH_4^+-N (7.12 mg/L) [22].

The Spatial Variation of Water Quality

Spatial Similarities and Grouping

CA produced a dendrogram grouping the 16 monitoring stations into four clusters (Fig. 3). Group A (sites 1-3) were located in the upstream section of the Panxi River in an area that has extensive forest cover and fewer human activities, thus the water quality was relatively less polluted. Group

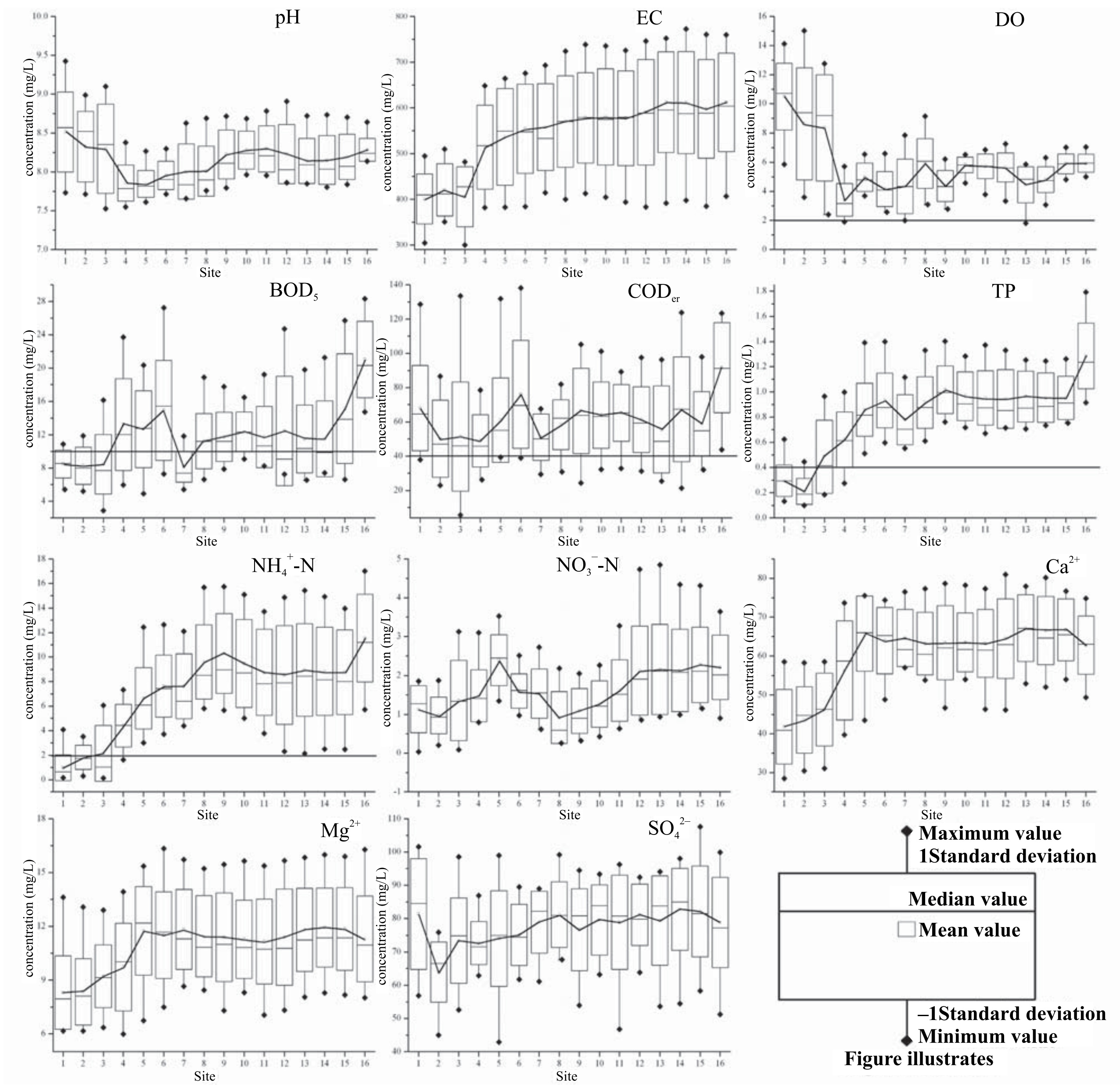

Fig. 4. Spatial variations of 11 water parameters in the Panxi River.

Table 3. Loadings of 11 selected variables on varimax rotated factors in the Panxi River.

Variables	Factors		
	PC1	PC2	PC3
NH_4^+-N	0.938	-0.038	-0.098
EC	0.911	-0.183	-0.187
TP	0.890	-0.032	0.231
Ca^{2+}	0.856	-0.230	0.009
Mg^{2+}	0.811	-0.190	-0.259
BOD_5	0.670	0.151	0.326
pH	-0.069	0.858	0.045
DO	-0.394	0.677	-0.134
SO_4^{2-}	0.019	-0.318	0.008
NO_3^--N	-0.162	-0.337	0.730
COD_{cr}	0.149	0.524	0.673
Eigenvalue	4.71	1.73	1.21
% Total variance	42.83	15.77	11.03
Cumulative %	42.83	58.60	69.63

B (sites 4-6) were located in the midstream section of the Panxi where the river received pollutants from municipal wastewater, which represented moderately polluted parts of the river. Groups C (sites 7-15) and D (site 16), located in the downstream section of the river, were strongly influenced by untreated domestic and cropland wastewater runoff and represented highly polluted parts. In addition, the accumulating pollutants from upstream and midstream combined with the discharge of domestic sewage along the downstream river further aggravated the impact on water quality in the downstream river.

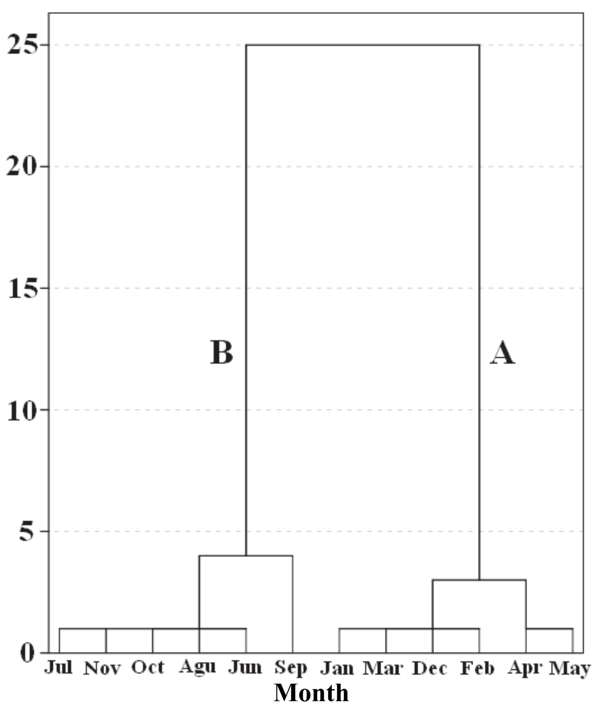

Fig. 5. Dendrogram showing temporal similarities of monitoring periods produced by CA.

Table 4. Source contribution (in %) to each variable in the Panxi River.

Parameters	S1	S2	S3	US	R^2
PH	—	42.10	—	57.90	0.735
EC	50.37	22.08	2.11	25.44	0.898
DO	15.79	59.35	1.10	23.76	0.632
BOD_5	40.58	19.98	4.03	35.41	0.678
COD_{cr}	6.40	5.91	49.21	38.47	0.750
TP	64.77	—	3.42	31.80	0.845
NH_4^+-N	61.19	—	1.31	37.50	0.889
NO_3^--N	7.41	6.81	33.68	52.11	0.672
Ca^{2+}	42.36	24.85	—	32.79	0.785
Mg^{2+}	44.98	23.03	2.93	29.06	0.762
SO_4^{2-}	—	26.21	—	73.79	0.301

The spatial distribution of different pollution zones was the same as the majority of earlier studies. Shrestha and Kazama found that in the Fuji River basin (Japan), less polluted areas were situated mainly at the upstream sites and higher levels of pollution were mainly situated at the downstream sites [14]. Zhou et al. found that in eastern Hong Kong (China) the relatively high-pollution zones were adjacent to the coastline and the relatively low-pollution zones were far from human impact [4].

The Spatial Variation of Water Quality

The curves for NH_4^+-N and TP showed the increasing trend from upstream to downstream (Fig. 4). One explanation for this effect is that upstream of the Panxi River is mainly covered by woodland and lawn. However, in the midstream and downstream sections of Panxi River the surrounding land is mainly covered by residential, commercial, and cropland. An increased amount of sewage discharge leads to a significantly increased concentration of pollutants. High concentrations of NH_4^+-N and P were also reported from wastewater by Almeida et al. [23], and agricultural activities by Singh et al. [24]. NO_3^--N concentrations were higher at site 5, increased from site 8 to site 16, and were related to the large domestic wastewater discharge into the river at site 5 and downstream sites. Nestler et al. reported that the nitrate nitrogen in the surface water of an urban ecosystem may be derived from sewage [25].

The BOD_5 and COD_{cr} concentrations showed an increasing trend from upstream to downstream (Fig. 4), mainly due to high population density, and commercial and agricultural activity. Our results are also consistent with earlier research showing that the organic pollution was mainly from domestic wastewater and nonpoint source pollution [23, 26].

The pH and DO were both higher upstream than in the midstream and downstream (Fig. 4). It is understandable that high levels of dissolved organic matter consume large amounts of oxygen, leading to anaerobic fermentation processes and the formation of ammonia and organic acids. Hydrolysis of these acidic materials causes a decrease of water pH value [27]. Therefore, the average pH value is higher upstream than in the midstream and downstream. With increasing organic matter decomposition, DO decreased upstream to midstream and downstream. Boyle and Fraleigh and Kirchner et al. have reported that the DO decrease was mainly caused by the decomposition of organic compounds [28-29].

The EC, SO_4^{2-}, Ca^{2+}, and Mg^{2+} increased upstream to downstream (Fig. 4) mainly because of the constant influx of forest and cropland runoff. Boyacioglu and Boyacioglu found that the high concentrations of Mg^{2+}, Ca^{2+}, and EC usually originate from local parent rock and agricultural pollution [30].

The Temporal Variation of Water Quality

Temporal Similarities and Grouping

As an exploratory method, temporal CA produced a dendrogram grouping the 12 months into two clusters (Fig. 5). Group A consisted of the months January-May and December, corresponding to the local hydrological conditions for dry periods, and with relatively high

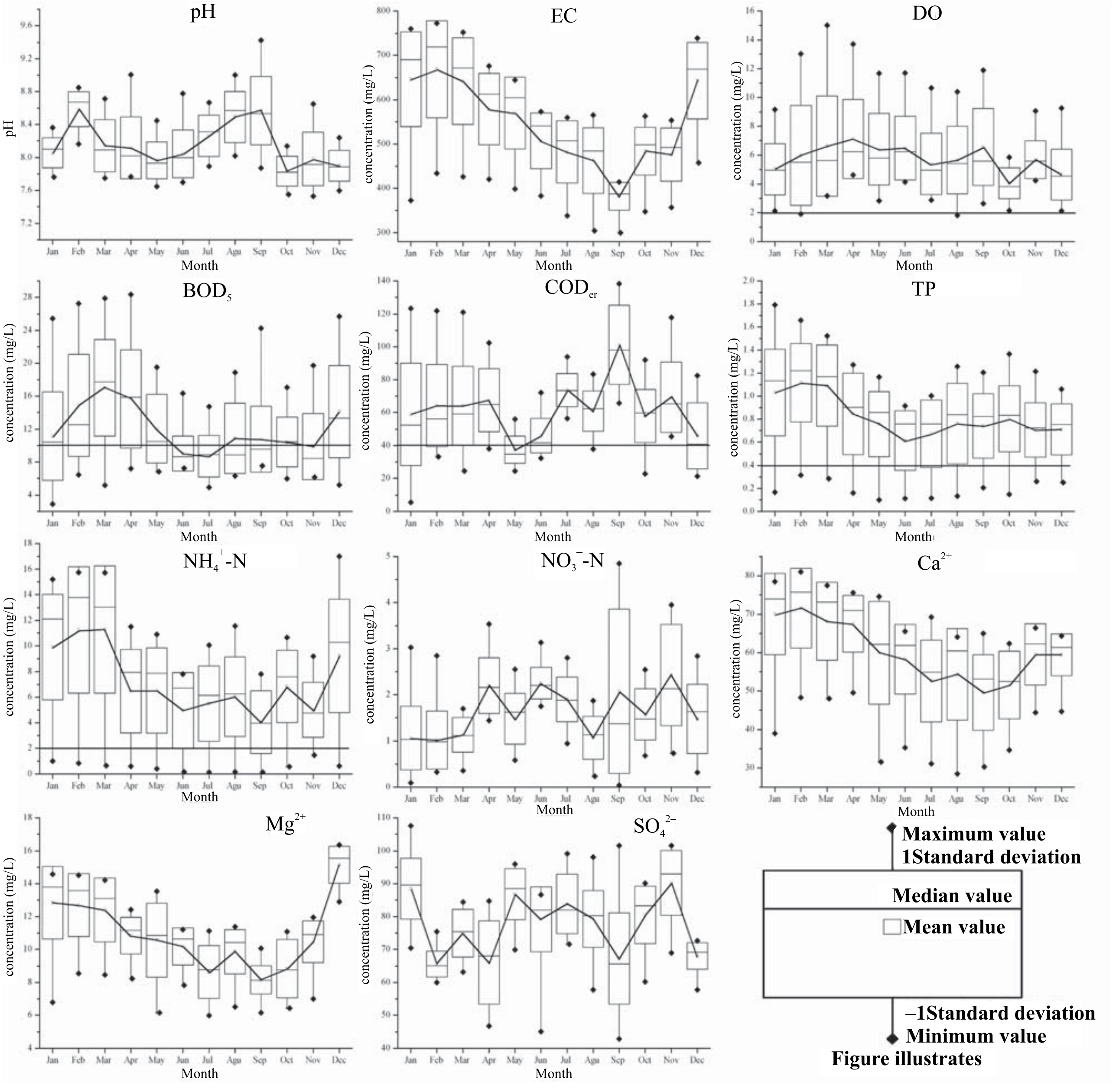

Fig. 6. Temporal variations of 11 water parameters in the Panxi River.

water pollution. Group B consisted of June-November, corresponding to the local hydrological conditions for wet periods with less polluted water due to rainfall dilution. This result is consistent with the studies of Varol and Sen for the Behrimaz Stream (Turkey), and Varol et al. for the Tigris River (Turkey) [31-32]. They distinguished the seasonal variation of water quality into wet and dry periods.

The Temporal Variation of Water Quality

Seasonal variation in the water quality of rivers is largely determined by natural processes (precipitation rate, weathering process) and anthropogenic influences (urban, industrial, and agricultural activities and increasing exploitation of water resources) [33-34]. Results from the Kolmogorov-Smirnov tests showed significant seasonal differences ($P<0.05$) for TP, BOD_5, NH_4^+-N, EC, Mg^{2+} and Ca^{2+} between the dry and wet seasons, the remaining parameters saw no significant seasonal differences ($P>0.05$). As shown in Fig. 6, the concentrations of TP, BOD_5, NH_4^+-N, EC, Mg^{2+}, and Ca^{2+} in the wet season were significanly lower than those in the dry season (Fig. 6). This is mainly because the pollutants were diluted by rainfall runoff in the wet season. Although the COD_{cr} showed no significant seasonal differences ($P>0.05$), the concentrations of COD_{cr} in the wet season were higher than those in the dry season. This might be influenced by pollution from urban stormwater runoff [35]. The concentrations of pH and DO were higher in August and September. This is probably ascribed to higher temperatures during August and September. Kannel et al. found that the DO concentration in the river was temperature-dependent due to its easy saturation in the warmer water [36].

Identification of Potential Pollution Sources

PCA was performed to identify the characteristics of water quality variables in three clusters, and the factor loading matrix is listed in Table 3. The results of Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity test were 0.747 and 1499.673 (P<0.05), respectively, indicating that PCA would be useful for providing significant reductions in dimensionality. Based on eigenvalues >1, FA evolved three varifactors (VFs) comprising 69.63% of the total variance.

The first varifactor (VF1) accounted for 42.83% of the total variance, had strong and positive loadings on NH_4^+-N, EC, TP Ca^{2+}, and Mg^{2+}, and a moderately positive loading on BOD_5. Thus the VF1 was named as the nutrient and ionic pollution. In our study, the land uses are mainly woodland and lawn in the upstream and agricultural and residential in the downstream. Therefore, PC1 may be identified as a domestic sewage and agricultural and woodland runoff source.

The second varifactor (VF2), accounting for 15.77% of the total variance, had strong and positive loadings on pH and a moderately positive loading on DO and COD_{cr}. In our study, the DO concentration was higher in March to September than other months. Kannel et al. found that the DO concentration in the river was temperature-dependent due to its easy saturation in warmer water [36]. Simeonov et al. reported that the pH, DO, and EC was attributed to the "physicochemical" source of the variability [6]. Zhou et al. thought that the pH and TEMP represents the "physicochemical" source of the variability [4]. Therefore, PC2 may be identified as the "physicochemical" source.

For VF3, accounting for 11.03% of the total variance, it had moderate and positive loadings of NO_3^--N and COD_{cr}. In general, stormwater runoff could also carry solid substances that usually had high concentrations of organic pollution. In our study, the COD_{cr} concentration was higher in July to September than other months, indicating the polluting effect of urban stormwater on river water quality during the rainy season. Therefore, PC3 may be identified as an urban runoff source.

The pollution sources in the river system can be identified by representation of the factor scores in the factor analysis [37-38]. The high factor scores corresponded to a high influence of the factor [39]. As shown in Fig. 7A, a factor score 1 was significant to the condition of sites 13-16 and 9, which were polluted by domestic sewage and cropland runoff. The increasing trend in factor scores 1 along the trans-urban river indicated the impact of human activities on the river. Factor score 2 was significant to the condition of sites 1-3, which are three reservoirs, located

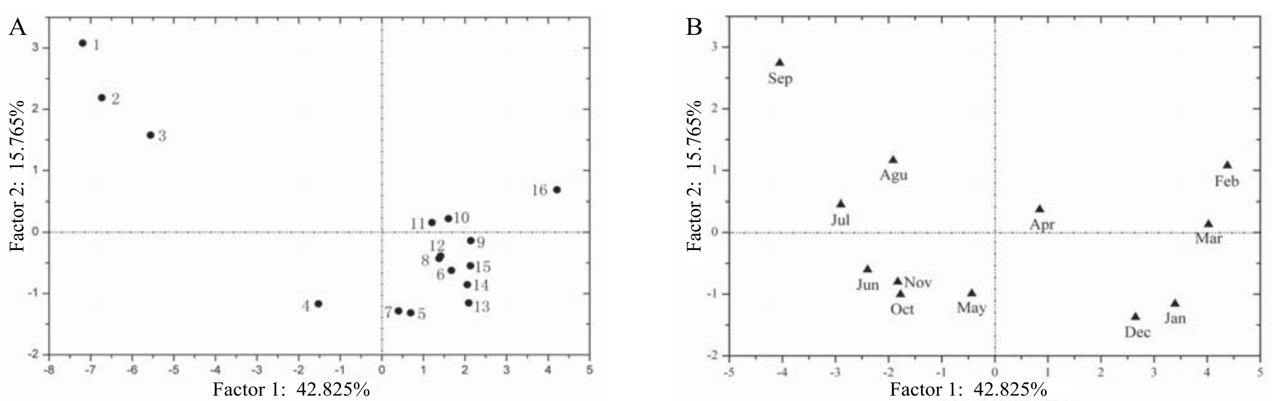

Fig. 7. Scatter plot of the first two factor scores for the 16 sampling sites and 12 months.

in the upper reaches of the Panxi River with higher pH and DO, reflecting the influences of the internal factor of the river. As shown in Fig. 7B, a factor score of 1 distinguished the months January-March and December from the other months. Due to December-March being in the dry season (Fig. 2A), pollutants are not diluted by rainfall; therefore, the concentrations of pollutants were higher than for other months. Factor score 2 mainly influenced the water quality in August and September. Due to higher temperatures in August and September (Fig. 2B), the internal reaction in the river is relatively fast. In short, the integrated factor scores recognized sites 13-16 and 9, and the months January-March and December as sites and periods of high pollution, respectively.

Source Contribution Based on APCS-MLR

After determining the number and characteristics of possible sources by PCA, source contributions were then assessed using APCS-MLR. The results (Table 4) indicated that APCS-MLR was relatively accurate, based on correlation coefficients (R^2), except for SO_4^{2} (0.301). Most variables were primarily influenced by domestic sewage, cropland, and woodland runoff pollution (accounting for 50.37%, 40.58%, 64.77%, 61.19%, 42.36%, and 44.98% of the variations in EC, BOD_5, TP, NH_4^+-N, Ca^{2+}, and Mg^{2+} concentrations, respectively), "physicochemical" source pollution (42.10% and 59.35% of pH and DO, respectively) and urban runoff pollution (49.21% and 33.68% of COD_{cr} and NO_3^--N, respectively). The unidentified sources (US) in Panxi River, attributed to river water pollution for most of the water quality variables (23.76-73.79%). Zhou et al. found that in eastern Hong Kong (China), most variables were primarily influenced by soil weathering and organic pollution, nutrient pollution (or cropland runoff), and mineral pollution. Unidentified sources (US) in both areas attributed to coastal water pollution for most of the water quality variables (2.6-36.9%) [4]. Su et al. found that in the Qiantang River (China), most variables were primarily influenced by domestic sewage and agricultural pollution, industrial wastewater discharge, vehicle exhaust and sand mining, and mineral weathering. The unidentified sources (US) in all groups, contributed to pollution in Qiantang River for most of the water quality variables (1.4-29.4%) [40]. In our study, the unidentified sources were significantly higher than other studies, mainly because the pollutants in urban rivers were typically from mixed sources and it was difficult for the multivariate method, such as APCS-MLR, to clearly identify the detailed sources. Because the unidentified sources account for a large proportion of sources, further study is necessary to identify these unknown sources.

Conclusions

Based on two years of monitoring, more than 50% of the samples exceeded Grade V of the Chinese National Quality Standards for Surface Waters (GB 3838-2002, 2002) for NH_4^+-N, TP, BOD_5, and COD_{cr} concentrations – indicating that water quality was seriously polluted by organic pollutants (BOD_5 and COD_{cr}) and nutrient-related impacts (TP and NH_4^+-N).

The Panxi River is characterized by high spatial and temporal variations in water quality. The concentrations of EC, Ca^{2+}, Mg^{2+}, BOD_5, COD_{cr}, TP, and NH_4^+-N were significantly higher midstream and downstream than upstream; however, the concentrations of pH and DO were higher upstream than midstream and downstream. The seasonal variation of the water quality of rivers is largely determined by hydrological conditions (dry and wet seasons). The concentrations of TP, BOD_5, NH_4^+-N, EC, Mg^{2+}, and Ca^{2+} in the wet season were lower than the dry season, but the concentrations of COD_{cr} in the wet season were higher than the dry season.

The PCA and APCS-MLR were applied to identified pollution source and source apportionment. Results from the PCA showed that domestic sewage and cropland and woodland runoff pollution, "physicochemical" source pollution, and urban runoff pollution could explain 69.63% of the total variances in water quality in the Panxi. Receptor-based source apportionment through APCS-MLR revealed that most variables were primarily influenced by domestic sewage and cropland and woodland runoff pollution in the trans-urban river. However, the significant contributions of unidentified sources in the Panxi for most of the water quality variables indicated other latent sources or complicated processes.

Discharge of domestic sewage into the river is still an important contributor to water pollution, so it is necessary for the local government to rebuild sewage pipelines for collecting domestic sewage in order to restore the degraded water quality. In addition, because of the unidentified sources accounting for a large proportion of sources, further investigation is needed to identify these unknown sources.

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