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Research article

Big data analysis of water quality monitoring results from the Xiang River and an impact analysis of pollution management policies

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Abstract: Water pollution prevention and control of the Xiang River has become an issue of great concern to China's central and local governments. To further analyze the effects of central and local governmental policies on water pollution prevention and control for the Xiang River, this study performs a big data analysis of 16 water quality parameters from 42 sections of the mainstream and major tributaries of the Xiang River, Hunan Province, China from 2005 to 2016. This study uses an evidential reasoning-based integrated assessment of water quality and principal component analysis, identifying the spatiotemporal changes in the primary pollutants of the Xiang River and exploring the correlations between potentially relevant factors. The analysis showed that a series of environmental protection policies implemented by Hunan Province since 2008 have had a significant and targeted impact on annual water quality pollutants in the mainstream and tributaries. In addition, regional industrial structures and management policies also have had a significant impact on regional water quality. The results showed that, when examining the changes in water quality and the effects of pollution control policies, a big data analysis of water quality monitoring results can accurately reveal the detailed relationships between management policies and water quality changes in the Xiang River. Compared with policy impact evaluation methods primarily based on econometric models, such a big data analysis has its own advantages and disadvantages, effectively complementing the traditional methods of policy impact evaluations. Policy impact evaluations based on big data analysis can further improve the level of refined management by governments and provide a more specific and targeted reference for improving water pollution management policies for the Xiang River.

Keywords: integrated assessment of water quality; evidential reasoning; principal component analysis; water pollution prevention and control of the Xiang River; big data analysis

1. Introduction

With population growth and social development, water environment issues have become an important global concern. The Xiang River is the mother river of Hunan Province, China and serves as an important foundation for human living and development in Hunan Province. The Xiang River Basin covers 94,660 km^2, with 85,383 km^2 in Hunan Province accounting for 90.2% of the total area. The Xiang River Basin is also the most developed region in Hunan Province, accounting for 40.3% of the total provincial area. The Hunan provincial part of the Xiang River basin begins from Yongzhou City, covering eight cities of Yongzhou, Chenzhou, Hengyang, Loudi, Zhuzhou, Xiangtan, Changsha and Yueyang, including eight major tributaries of the Mi River, Liuyang River, the Lian River, the Lu River, the Xiao River, the Lei River, the Zheng River and the Chongling River. In recent years, rapid economic development and industrialization of the Xiang River Basin has made the basin a major economic belt in Hunan Province. The basin is home to 57.1% of the total provincial population and provides 72.4% of the total provincial GDP and 64.3% of the total provincial industrial added value, ranking first among all regions in the province in terms of economic aggregate and the overall level of industrial development. However, the dense population and developed industry and agriculture have imposed huge pollution risks for the Xiang River Basin. Increasing domestic sewage and industrial/agricultural wastewater make the water pollution issue of the Xiang River Basin increasingly problematic, which restricts sustainable socioeconomic development of the Xiang River Basin, even directly affecting the economic activities and lives of local residents.

Water pollution prevention and control of the Xiang River has aroused great attention from governments. Water quality data lay the foundation for objective evaluations of the effects of water quality management and decision-making. Further, in-depth analysis of the effects of governmental policies on water pollution prevention and control of the Xiang River is important for governments to further improve water pollution prevention and control policies and promote China's sustainable socioeconomic development. This type of analysis can also can provide references for other environmental management policies and corporate emission reductions [1].

In recent years, the new generation of information technology represented by big data is widely used in China. The combination of automatic and manual collection of water quality index data makes the data a certain scale, which has laid the foundation and provides the possibility for the use of big data analysis method to study the water quality and influencing factors of Xiang River. However, most of the research in China and abroad is still about big data concept exploration and application analysis [2–5]. The analysis and evaluation of environmental policy effects are mainly focused on qualitative analysis [6–9] and theoretical model analysis [10–29], where theoretical models are commonly used in econometric models [10–14], Bayesian models [16–19], Poisson regression model [20–23], panel data analysis models [24–27] and game theory models [29]. Most of these studies are based on sample survey data or annual statistics, with a limited number of samples and a relatively small amount of data, which are quite limited in terms of the relevance and timeliness of policy analysis. For this reason, studies have been conducted using big data-related methods for policy research [30–35], in which Ma et al. analyzed the temporal changes and differences of major pollutants based on big data of pollution row monitoring of large thermal power enterprises in Hunan Province, reflecting the overall evolutionary characteristics and regulatory effects of the air pollution control policy system. In this paper, the monitoring big data of the mainstream and main tributaries of Xiang River from 2005 to 2016 by Hunan Provincial Environmental Monitoring Center Station are analyzed at the integrated level of water quality indicators and the level of major pollutants, and a comprehensive evaluation method of time series water quality based on evidence theory is proposed on the analysis at the integrated level.

Chinese *Environmental quality standards for surface water (GB3838-2002)* uses a single-factor evaluation method. It selects the water quality category that has the worst single indicator as the comprehensive water quality category. However, this method cannot scientifically and effectively assess the comprehensive water quality of the water body, and the same water quality category cannot be effectively compared with each other [36–38], which is an obstacle to the analysis of water quality in the main tributaries of Xiang River in this paper. Basin water quality evaluation involves a variety of factors with a phenomenon of missing and incomplete information, which belongs to the uncertainty multi-attribute decision problem. For this type of problem, Dempster and Shafer proposed a theory of imprecise reasoning called evidence theory for dealing with uncertain information or incomplete information in the 1880s. Evidence theory is now widely used in goal identification [39], business decision making [40], performance evaluation [41,42], trend prediction [43,44] and many other fields with uncertain information. Lein [45] classifies land images by an evidential reasoning algorithm to accurately identify agricultural land. Gorin [41] introduces an evidential reasoning approach in student performance assessment to achieve student learning engagement, motivation, learning opportunities, social experiences and other information are integrated and processed.

Given the unique advantages of evidence theory in uncertain information processing and evidence synthesis, scholars have applied it to the field of water quality evaluation and proposed a comprehensive water quality evaluation method based on evidence inference [46–51]: by establishing an identification framework to solve the uncertainty problem of evaluation index division; the Dempster combination rule is invoked to calculate the basic probability of each evidence, which solves the combination processing problem of multiple indicators. However, for the time series of multiple monitoring points, the traditional evidence inference evaluation method uses the mean value of the integrated time series index may lead to information loss. For this reason, this paper proposes a comprehensive evaluation method of time series water quality based on evidence theory, calculating the mass function through sequence summation, introducing the utility function, assigning corresponding utility values to different levels, and realizing the analysis of spatial and temporal characteristics of water quality in the same waters through weighted calculation.

The period from 2005 to 2016 was the most important decade for the management of the Xiang River basin. During this period, the Hunan Provincial Government responded to the central government by issuing a number of policies and regulations related to the management of the Xiang River basin. This study tentatively performs a big data analysis of various water quality parameters monitored at the mainstream and major tributaries of the Xiang River by the Hunan Environmental Monitoring Center Station during 2005–2016 to identify the spatiotemporal characteristics of water quality and pollutants in the Xiang River in terms of an overall water quality index (WQI) and major pollutants. In addition, this study explores the correlation between potentially relevant factors to enrich the methodology and content of policy evaluation, so as to reflect the relationship between the management policies and water quality changes in the Xiang River in a more accurate and detailed manner and provide a more specific and targeted reference for improving pollution management policies of the Xiang River. In the meantime, this study aims to use a big data analysis to improve the level of refined management by governments.

2. Data source and processing

To analyze the effects of environmental protection policies of China's central and Hunan provincial governments on the water quality management of the Xiang River, this study utilized a total of approximately 122,040 data points of 16 water quality parameters monitored from 42 sections (Figure 1) on the mainstream and major tributaries of the Xiang River from 2005 to 2016 by the Hunan Environmental Monitoring Center Station.

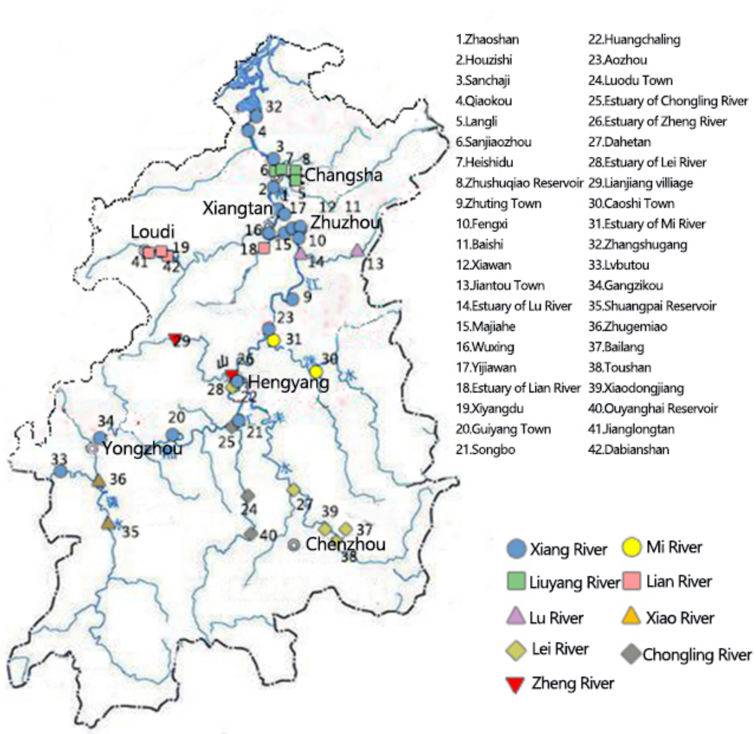


Figure 1. Cross section distribution of the Xiang River basin.

2.1. Selection of water quality parameters

Based on the statistics of the annual mean water quality parameters of Hunan Province, this study focused on industrial wastewater and domestic sewage as the primary pollution sources. In this study, 16 typical parameters related to routine water quality monitoring were also chosen as the primary water quality parameters due to their representativeness and monitoring continuity. These parameters were pH, dissolved oxygen (DO), the permanganate index (CODMn), the five-day biochemical oxygen demand (BOD5), ammonia nitrogen (NH3-N), total phosphorus (TP), copper, zinc, selenium, arsenic, mercury, cadmium, chromium, lead, cyanide and sulfide. In particular, DO is a negative indicator of water pollution. This means that the larger the DO, the less serious the pollution. The other 15 parameters are positive indicators of water pollution; specifically, the larger the indicators, the more serious the pollution. Table 1 presents the criteria limits of the 16 water quality parameters.

Table 1. Criteria limits of the 16 water quality parameters.

No.	parameters/criteria limits		I	II	III	IV	V
1	pH		6-9				
2	DO (mg/L)		7.5	6	5	3	2
3	CODMn (mg/L)	≤	2	4	6	10	15
4	BOD5 (mg/L)	≤	3	3	4	6	10
5	NH3-N (mg/L)	≤	0.15	0.5	1.0	1.5	2.0
6	TP	≤	0.02	0.1	0.2	0.3	0.4
7	Cu (mg/L)	≤	0.01	1.0	1.0	1.0	1.0
8	Zn (mg/L)	≤	0.05	1.0	1.0	2.0	2.0
9	Se (mg/L)	≤	0.01	0.01	0.01	0.02	0.02
10	As (mg/L)	≤	0.05	0.05	0.05	0.1	0.1
11	Hg (mg/L)	≤	0.00005	0.00005	0.0001	0.001	0.001
12	Cd (mg/L)	≤	0.001	0.005	0.005	0.005	0.01
13	Cr (mg/L)	≤	0.01	0.05	0.05	0.05	0.1
14	Pb (mg/L)	≤	0.01	0.01	0.05	0.05	0.1
15	cyanide (mg/L)	≤	0.005	0.05	0.02	0.2	0.2
16	sulfide (mg/L)	≤	0.05	0.1	0.2	0.5	1.0

2.2. Data analysis

2.2.1. Integrated water quality assessment based on evidential reasoning

Evidential reasoning (ER)-based integrated assessment of water quality and spatiotemporal analysis of various water quality parameters were performed. These included: 1) analysis of the multi-year trend in overall water quality and the trend of each water quality parameter in the mainstream of the Xiang River on a yearly scale; 2) analysis of the multi-year trend in the overall water quality in each major tributary and the multi-year trend of each water quality parameter in typical tributaries that were representative of water quality changes on a yearly scale; and 3) analysis of the multi-year trend in the overall water quality and the spatiotemporal trend of each water quality parameter at each section on a yearly scale.

2.2.2. Principal component analysis (PCA)

A PCA was performed to extract the principal components (PCs) of the Xiang River Basin for each year and to obtain the corresponding water quality parameters for each PC loading so as to identify the primary pollutants in the basin in each year. Moreover, the effects of pollution management policies on the water quality of the Xiang River Basin were analyzed according to changes in the primary pollutants in the mainstream and major tributaries of the Xiang River.

The calculation steps of water quality evaluation by principal component analysis are as follows:

1) Standardize the raw data, using $Z = \{z_{l,k}\}$ to denote the standardized data.

2) Calculate the correlation coefficient matrix R of the standardized data Z.

3) Calculate the eigenvectors e_i and eigenvalues λ_i of the correlation coefficient matrix R.

4) Calculate the total contribution of principal components α and determine the number of principal components m:

$$\alpha = \sum_{i=1}^{m} \lambda_i \Big/ \sum \lambda_i$$

5) Select principal components from Step (4), and obtain the score of principal component analysis.

6) Calculate the principal component loadings.

Data analysis was performed in the Python 3.6 software environment using the data analysis packages of numpy, pandas, scipy and sklearn. In this study, Ray, a distributed data processing framework was adopted to improve the big data processing capability.

3. ER-based integrated assessment of water quality

3.1. Evidence combination rules and algorithms

In this subsection, the basic concepts of D-S evidence reasoning theory are briefly discussed [52].

Definition 1 Let Θ be the frame of discernment. If the set function $m: 2^{\Theta} \rightarrow [0,1]$ satisfies:

1) $m(\emptyset) = 0$

2) $\sum_{A \subseteq \Theta} m(A)=1$,

then *m* is referred to as a basic probability assignment (BPA) on *Θ*. It is also known as a mass function, where $\emptyset$ is the empty set and *A* is any subset of *Θ*. For ∀A⊆Θ, if *m* (*A*) > 0, then *A* is defined as a focal element of m.

Definition 2 Let *Θ* be the frame of discernment, and $m: 2^{\Theta} \rightarrow [0,1]$ be the BPA on the frame *Θ*, then:

$$Bel(A) = \sum_{B \subseteq A} m(B) \tag{1}$$

Bel(A) is a belief function that represents the degree of *A* being true, where *A* and *B* are subsets of *Θ*.

The core of evidence theory is Dempster's combination rule as follows:

$m_1, m_2, \ldots, m_n$ are *n* mass functions on the frame of discernment *Θ*, and their orthogonal sum is $m = m_1 \oplus m_2 \oplus \ldots \oplus m_n$. For two mass functions, m_1 and m_2, the Dempster's combination rule is defined as follows:

$$[m_1 \oplus m_2](C) = \begin{cases} 0, c = \emptyset \\ \dfrac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)}, c \neq \emptyset \end{cases} \tag{2}$$

where A and B are both focal elements, $[m_1 \oplus m_2](C)$ is a BPA and the denominator $1 - \sum_{A \cap B = \emptyset} m_1(A)\, m_2(B)$ is denoted as *K* for brevity, which is referred to as a normalization factor. In addition, $\sum_{A \cap B = C} m_1(A)\, m_2(B)$ is called the degree of conflict, which is a metric of the degree of conflict between evidences.

The evidential reasoning-based integrated assessment of water quality was used to identify the spatiotemporal changes of the Xiang River. Methodological flow chart of water quality assessment based on D-S evidential theory is shown in Figure 2.

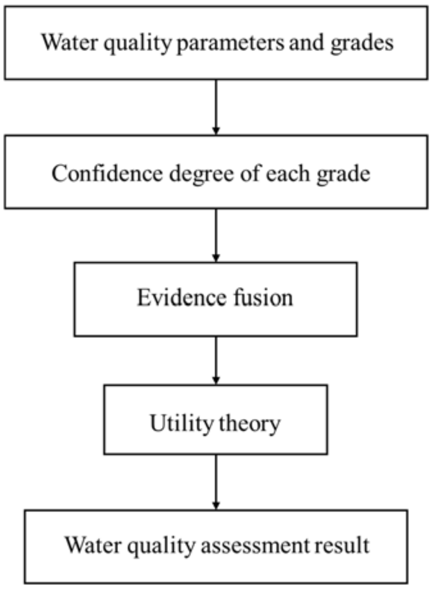


Figure 2. Methodological flow chart.

3.2. Time series-based integrated assessment model of water quality

A water quality assessment involves multiple water quality parameters, each having a different degree of harm to water quality. For the water quality assessment, this study referred to an integrated assessment of water quality of a section or a river (consisting of multiple sections) over a period of time as an assessment scheme. An assessment scheme, *A,* is a time series of sets for a section or for a given length of river over a period of time with *L* time points, expressed as $T = \{E_1, \dots E_L\}$, where, for each section at a given time point, there are *K* water quality parameters to be included in assessment. The set of water quality parameters at a given time point is represented as follows:

$$E_l = \{e_{l,1}, \dots e_{l,K}\} \tag{3}$$

where $e_{l,i}$ represents the monitoring value of the water quality parameter, *I,* at time point, *l,* in the assessment scheme (such as "Xiang River 2015"). As shown in Table 1, according to the Chinese national standard, if there are *N* assessment grades, the set of assessment grade is expressed as follows:

$$H = \{H_1, \dots H_N\} \tag{4}$$

where H_n denotes the assessment grade *n*, with the level H_{n-1} representing better overall water quality than H_n, and h_n representing a limit value of H_n.

3.3. Degree of belief of water quality parameters for water quality assessment grades

In the water quality assessment based on Dempster-Shafer (DS) evidential reasoning, the mass functions are calculated using degrees of beliefs. Using $\beta_n(e_{l,i})$ to denote the degree of belief that the monitoring value, $e_{l,i}$, of a water quality parameter, e_i, at time point, *l,* in an assessment scheme, *A,* suggests the *n*-th assessment grade, H_n, has:

$$S(E_l) = \left\{\left(H_n, \beta_n(e_{l,i})\right), n = 1,2, \dots N, i = 1,2, \dots K\right\} \tag{5}$$

$$where\ \ \beta_n(e_{l,i}) \geq 0, \sum_{n=1}^{N} \beta_n(e_{l,i}) = 1.$$

Given that the water quality parameters included in the assessment are quantitative, they can only fall in a range bounded by two assessment criteria values. More specifically, one water quality parameter supports at most two assessment grades, so $S(E_l)$ represents a complete set of assessments.

Given the monitoring value, $e_{l,i}$, of the indicator $h(e_{l,i})$, the degrees of belief for the n-th assessment grade, H_n, and (n+1)-th assessment grade H_{n+1} satisfy:

$$\beta_n(e_{l,i}) = \frac{h_{n+1} - h(e_{l,i})}{h_{n+1} - h_n}$$

$$\beta_{n+1}(e_{l,i}) = 1 - \beta_n(e_{l,i}) \tag{6}$$

$$\beta_j(e_{l,i}) = 0, j \notin \{n, n+1\},$$

$$where\ \ h_{n+1} \leq h(e_{l,i}) \leq h_n.$$

Because the monitoring values of water quality parameters in the data series will fluctuate, the water quality parameters at different time points of the same section will support the same water quality assessment grade to different degrees. Hence, commonly used averaging approaches for fusion of time series will result in information loss or even cause information bias. Therefore, the series summation method was adopted in this study to fuse the time series of water quality parameters.

Given the monitoring value, $e_{l,i}$, in scheme A, the degrees of belief for the above set H are expressed as follows:

$$B_l = \{\beta_1(e_{l,i}), \ldots, \beta_N(e_{l,i})\} \tag{7}$$

Accordingly, the time-integrated degrees of belief for using the water quality parameter e_i in scheme A to support different assessment grades are:

$$B(e_i) = \sum_{l=1}^{L} B_l = \left\{\sum_{l=1}^{L} \beta_1(e_{l,i}), \ldots, \sum_{l=1}^{L} \beta_N(e_{l,i})\right\} = \{\beta_1(e_i), \ldots, \beta_N(e_i)\} \tag{8}$$

$$To\ ensure\ \ \sum_{n=1}^{N} \sum_{l=1}^{L} \beta_1(e_{l,i}) = 1,$$

$$B(e_i)\, is\ normalized:$$

$$B'(e_i) = \{\beta_1'(e_i), \ldots, \beta_N'(e_i)\} \tag{9}$$

3.4. Basic probability distribution of water quality parameters with respect to water quality assessment grades

The set of relative weights of water quality parameters, e_i, is denoted by $W = (\omega_1, \ldots, \omega_K)$, which was determined by the PCA in this study. If $F = \{f_1, \ldots, f_N\}$ represents the percent variance contributions of the PCs and $C = \begin{Bmatrix} c_{1,1} & \cdots & c_{N,1} \\ \vdots & \ddots & \vdots \\ c_{1,N} & \cdots & c_{N,N} \end{Bmatrix}$ represents the PC loading matrix, then the weight of the water quality parameter, $e_{i,}$ is $\omega_i' = \sum_{n=1}^{N} f_n c_{n,i}$. Normalization is performed to allow W to satisfy $0 \leq \omega_i \leq 1$ and $\sum_{i=1}^{A} \omega_i = 1$.

After the degree of belief based on water quality parameter e_i is obtained for scheme A, evidence fusion is performed following the methods described previously [48,49]:

Let β_n be the degree of belief for the n-th assessment grade, then $\beta_n = f_n(\omega_i \beta_{n,i})$ with $i = 1,2,\ldots N$, where f_n is a non-linear function of $\beta_{n,i}$. If f_n is assumed to behave linearly at a specific point with $\beta_{n,i} = 1$ and $\beta_{j,i} = 0$ for all $j = 1,\ldots,N, j/= n$ and $i = 1,\ldots,L$, β_n can be expressed as a linear combination of $\beta_{n,i}(i = 1,\ldots,L)$ as follows:

$$\beta_n = \sum_{i=1}^{L} \omega_i \beta_{n,i} \tag{10}$$

Let $m_{n,i}$ be a basic probability mass representing the degree to which the i-th basic water quality parameter, e_i, supports the hypothesis that the general attribute, y is assessed to the n-th grade H_n, and $m_{n,i}$ can be obtained as follows:

$$m_{n,I} = \omega_i \beta_{n,I},$$
$$n = 1,2,\ldots\ldots,N \tag{11}$$

Let $m_{H,I}$ be the remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the concerned e_i. It consists of two parts:

$$m_{H,I} = \bar{m}_{H,i} + \widetilde{m}_{H,i} \tag{12}$$

Let $m_{n,I(i)}$ be a combined probability mass representing the degree to which all the first i water quality parameters support the hypothesis that they are assessed to the grade H_n. Let $\widetilde{m}_{H,I(i)}$ and $\bar{m}_{H,I(i)}$ be the two parts of the remaining probability mass unassigned to individual grades after all the first i water quality parameters have been assessed. According to the above definitions, each combined probability mass and its corresponding remaining probability mass, as well as the two parts of the remaining probability mass, can be calculated as summarized below:

$$\{H_n\}: m_{n,I(i+1)} = K_{I(i+1)}\left[m_{n,I(i)} m_{n,i+1} + m_{H,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1}\right], n = 1,2,\ldots\ldots,N \tag{13}$$

$$\{H\}: m_{H,i} = \bar{m}_{H,i} + \widetilde{m}_{H,i} \tag{14}$$

$$\{H\}: \widetilde{m}_{H,I(i+1)} = K_{I(i+1)}\left[\widetilde{m}_{H,I(i)} \widetilde{m}_{H,i+1} + \bar{m}_{H,I(i)} \widetilde{m}_{H,i+1} + \widetilde{m}_{H,I(i)} \bar{m}_{H,i+1}\right], n = 1,2,\ldots\ldots,N \tag{15}$$

$$\{H\}: \bar{m}_{H,I(i+1)} = K_{I(i+1)}\left[\bar{m}_{H,I(i)} \bar{m}_{H,I(i+1)}\right] \tag{16}$$

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} m_{t,I(i)} m_{j,i+1}\right]^{-1} \quad i = 1,2,\ldots\ldots,L-1 \tag{17}$$

After aggregating all L assessments, the combined degree of belief for a given assessment grade, H_n, based on all the water quality parameters can be calculated as follows:

$$\{H_n\}: \beta_n = \frac{m_{n,I(L)}}{1 - \bar{m}_{H,I(L)}}, n = 1,2,\ldots\ldots,N \tag{18}$$

$$\{H\}: \beta_H = \frac{\widetilde{m}_{H,I(L)}}{1 - \bar{m}_{H,I(L)}}, n = 1,2,\ldots\ldots,N \tag{19}$$

3.5. Scheme assessment

The ER-based results provide a decentralized representation of the assessment grades and are difficult to use for scheme assessment and comparison. Therefore, the theory of utility was introduced to transform the distribution results into precise values. Assuming that the utility of the assessment grade, H_n, is $u(H_n)$, the expected utility, $S(A)$, for the integrated assessment of scheme A is expressed as:

$$u\big(S(A)\big) = \sum_{n=1}^{N} b_{H_n} u(H_n) \tag{20}$$

According to the formula above, the result of the integrated water quality assessment of a given assessment scheme, *A,* can be calculated.

4. Big data analysis of water quality monitoring results for the Xiang River, China

4.1. Annual trends of water quality parameters for the mainstream of the Xiang River, China

4.1.1. Annual trends of the ER-based integrated water quality index of the mainstream of the Xiang River, China

The integrated water quality index (IWQI) of the mainstream of the Xiang River between 2005 and 2016 was obtained using the ER method, and the annual trend is shown in Figure 3. The mainstream IWQI increased from 0.9146 in 2005 to 0.9320 in 2016. During China's 11th Five-Year Plan period, the mainstream water quality fluctuated, showing a decreasing trend in 2008 and 2010. However, improvement was shown in other years, with the IWQI, in general, fluctuating near 0.92. Overall, the water quality continued to substantially improve over the 12th Five-Year Plan period.

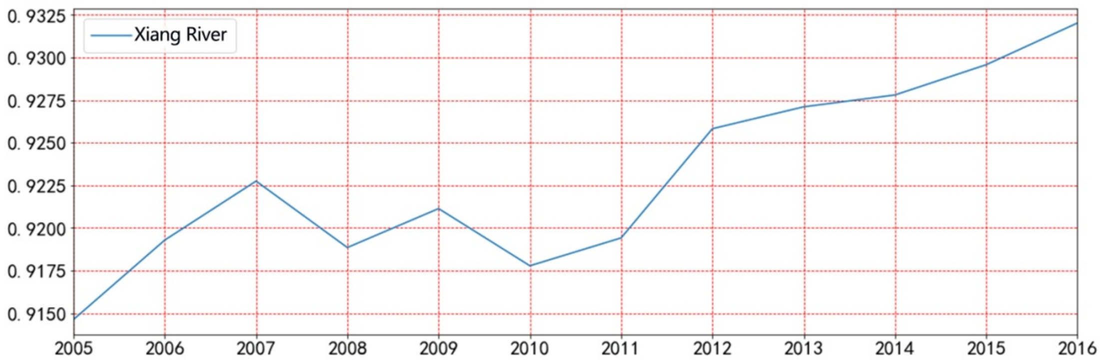


Figure 3. Trend of water quality change in the mainstream of the Xiang River basin.

4.1.2. Annual trends of water quality parameters in the mainstream of the Xiang River, China

The annual trends of various water quality parameters of the mainstream of the Xiang River are presented in Figure 4.

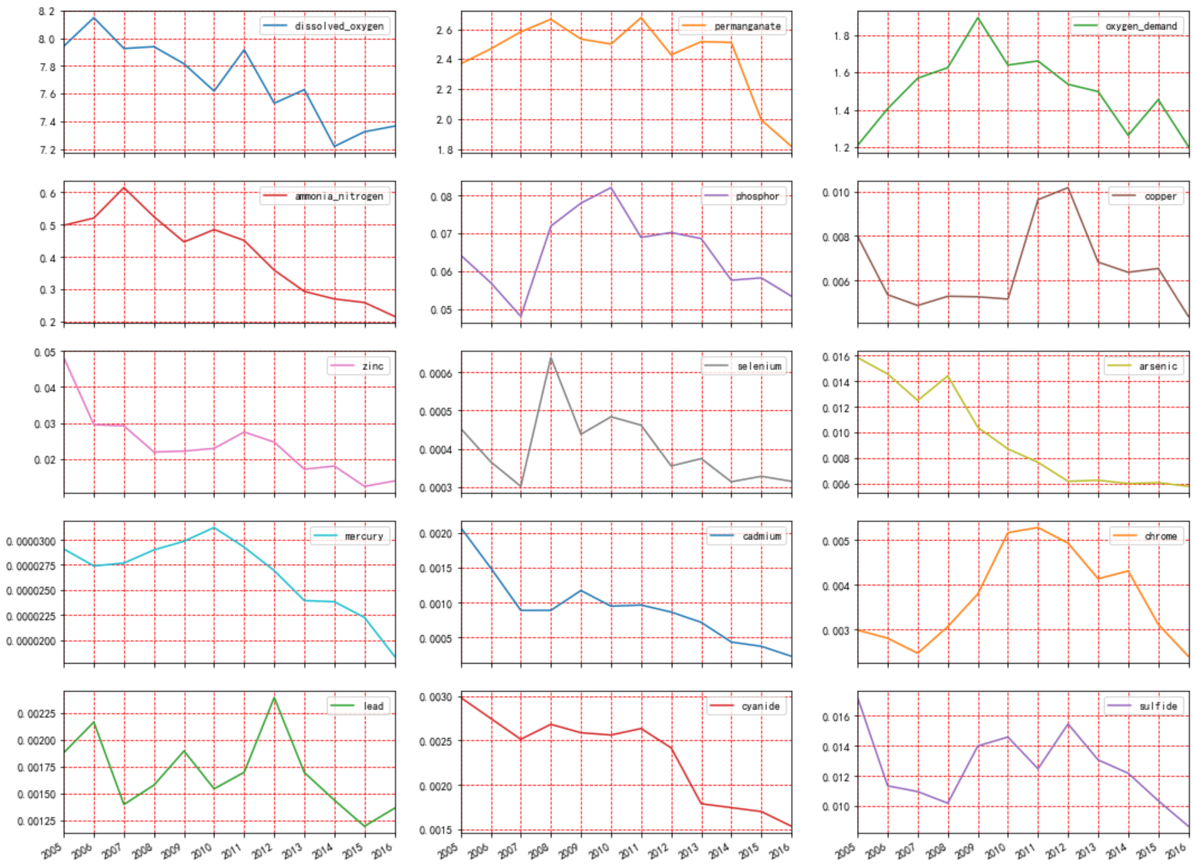


Figure 4. Trends of 16 water quality parameters in the mainstream of the Xiang River.

During 2005–2016, ammonia nitrogen, zinc, arsenic, cadmium and cyanide showed significant, continuous, decreasing trends. In particular, the zinc concentration slightly increased in 2011, but it rapidly decreased from above 0.02 to 0.002 mg/L in 2015. The arsenic concentration showed a significant decreasing trend during the 11th Five-Year Plan period, dropping from 0.016 mg/L in 2005 to 0.006 mg/L in 2012, and after 2012 the concentration tended to be stable at approximately 0.006 mg/L. The cadmium concentration and cyanide concentration showed a similar trend in that there was a dramatic decreasing trend in the early stage of the 11th Five-Year Plan period (2005–2007) (cadmium concentration decreased from 0.002 to 0.001 mg/L and the cyanide concentration decreased from 0.003 to 0.0025 mg/L). In the late stage of the 11th Five-Year Plan period (2007–2011), the decreasing trend tended to be stable, and the concentration was basically the same. After 2011, both cadmium and cyanide showed a significant decreasing trend in the concentration (the cadmium concentration decreased from 0.001 to 0.0001 mg/L, and the cyanide concentration decreased from 0.0026 to 0.0011 mg/L).

CODMn, BOD5, TP, copper, selenium, mercury, chromium, lead and sulfide showed dramatic fluctuations during 2005–2016, but they all showed a decreasing trend during the late stage of this period. In particular, TP, selenium and mercury showed a dramatic decreasing trend since 2010. Chromium showed a dramatic decreasing trend since 2011. Copper, lead, and sulfide showed a dramatic decreasing trend since 2012. CODMn showed a dramatic decreasing trend since 2014.

Most of the water quality parameters of the mainstream of the Xiang River during 2005–2016 showed significant improvements in 2011. Some water quality parameters showed significant improvement since 2011, such as improvements in copper, lead and sulfide since 2012, and an improvement in CODMn since 2014.

4.2. Annual trends of water quality parameters in the tributaries of the Xiang River, China

4.2.1. Annual trends of the ER-based IWQI in the tributaries of the Xiang River, China

The annual trends of the ER-based IWQI in the tributaries of the Xiang River are presented in Figure 5. In terms of the IWQI, the tributaries were divided into four types. The Xiao River, Lei River and Chongling River tributaries always had better water quality than the mainstream, and the water quality slightly improved. The Zheng River and Liuyang tributaries differed significantly from the mainstream in water quality and even affected the latter water quality. Prior to 2007, there was a water quality decreasing trend in the two tributaries, and after 2007, the water quality tended to improve in general, especially in 2011, when there was dramatic water quality improvement. However, overall, the water quality was still significantly worse than that of the mainstream. The water quality of the Lian River tributary was not dramatically different from that of the mainstream and showed slight fluctuations, with its water quality gradually improving and approaching that of the mainstream since 2011. The Lu River and Mi River tributaries had similar water qualities as the mainstream, but since 2011, the two have slightly worsened as compared to the mainstream.

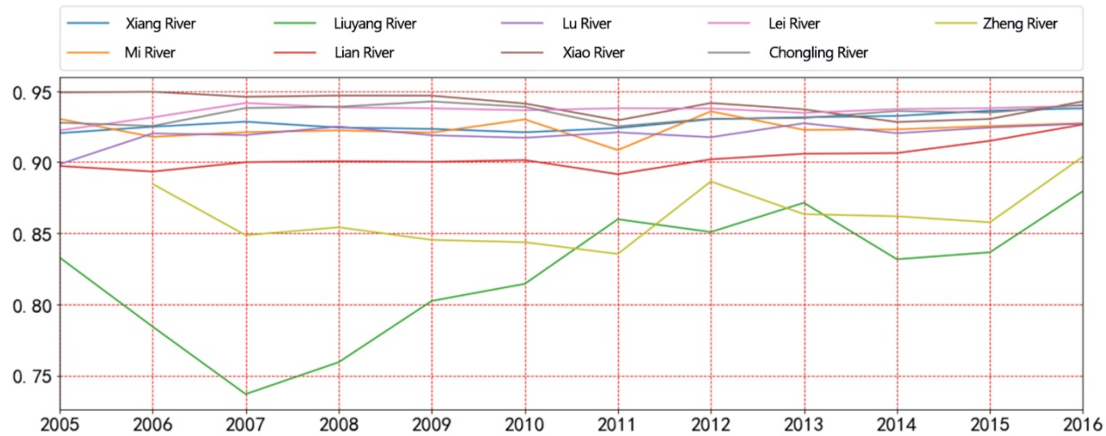


Figure 5. Trend of water quality change in the tributaries of the Xiang River basin.

4.2.2. Annual trends of water quality parameters in the tributaries of the Xiang River, China

Considering the characteristics of the tributaries, the Lian River, Liuyang River and Mi River tributaries were selected as representatives of the three types of tributaries with worse water qualities relative to the mainstream for the water quality analysis. The annual trends of water quality parameters in the Mi River are presented in Figure 6.

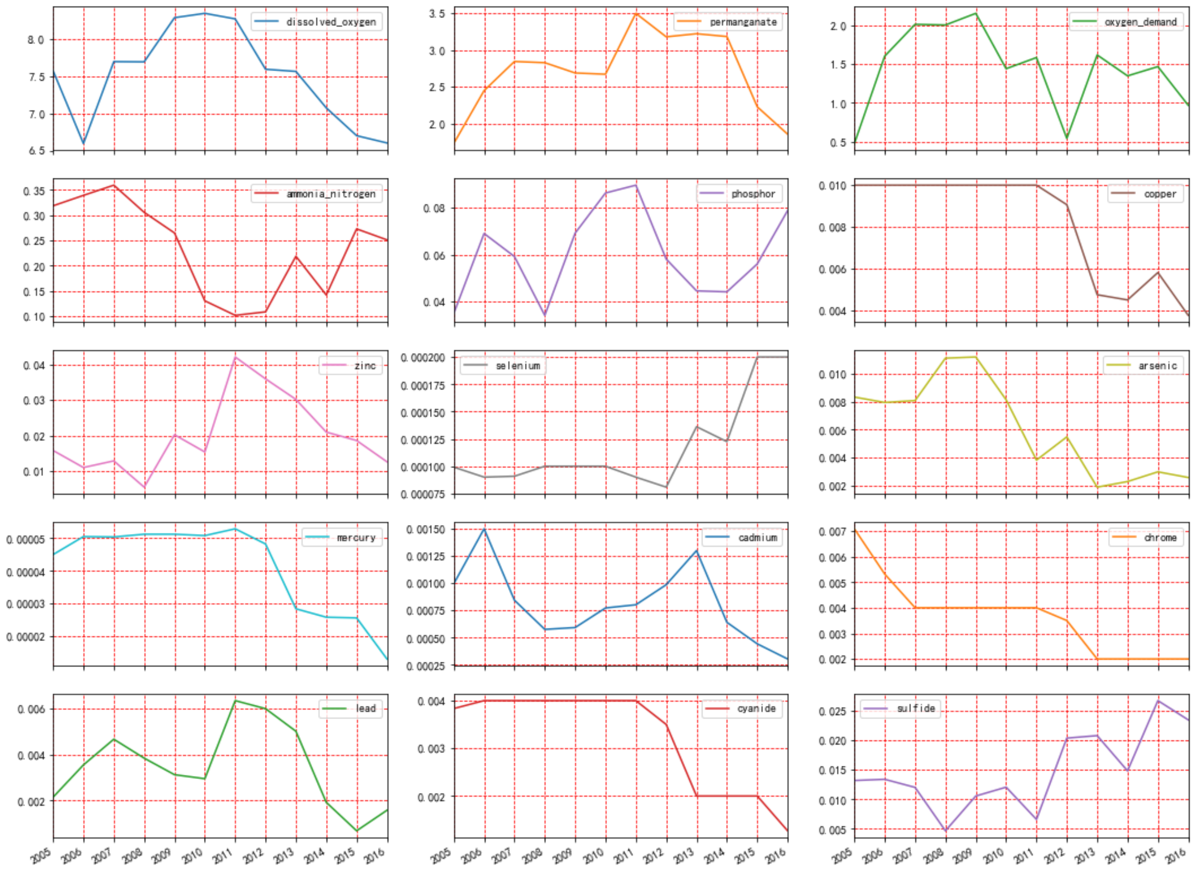


Figure 6. Trends of 16 water quality parameters in the mainstream of the Mi River.

During 2005–2016, the concentration of copper, mercury and cyanide remained basically stable from 2005 to 2011, but showed a significant decreasing trend since 2011.

Between 2005 and 2016, DO, CODMn, zinc, lead and other water quality parameters first showed an increasing trend and then a decreasing trend, all reaching their maximum concentration in 2011 followed by an obvious continuous decreasing trend afterwards. Between 2005 and 2016, BOD5 and ammonia nitrogen first showed an increasing trend and then a decreasing trend followed by another increasing trend. In particular, BOD5 rose to the maximum in 2009 and dropped to the minimum in 2012. Ammonia nitrogen rose to the maximum in 2007 and dropped to the minimum in 2011. Selenium and sulfide showed a fluctuating, increasing trend throughout the period of 2005–2016.

As shown above, during 2005–2016, some water quality parameters of the Mi River tended to improve after 2011, but some failed to meet the pre-set goal for water pollution prevention and control, and instead showed an increasing trend. This was the primary cause of the worse water quality in the Mi River in general compared with the mainstream since 2011.

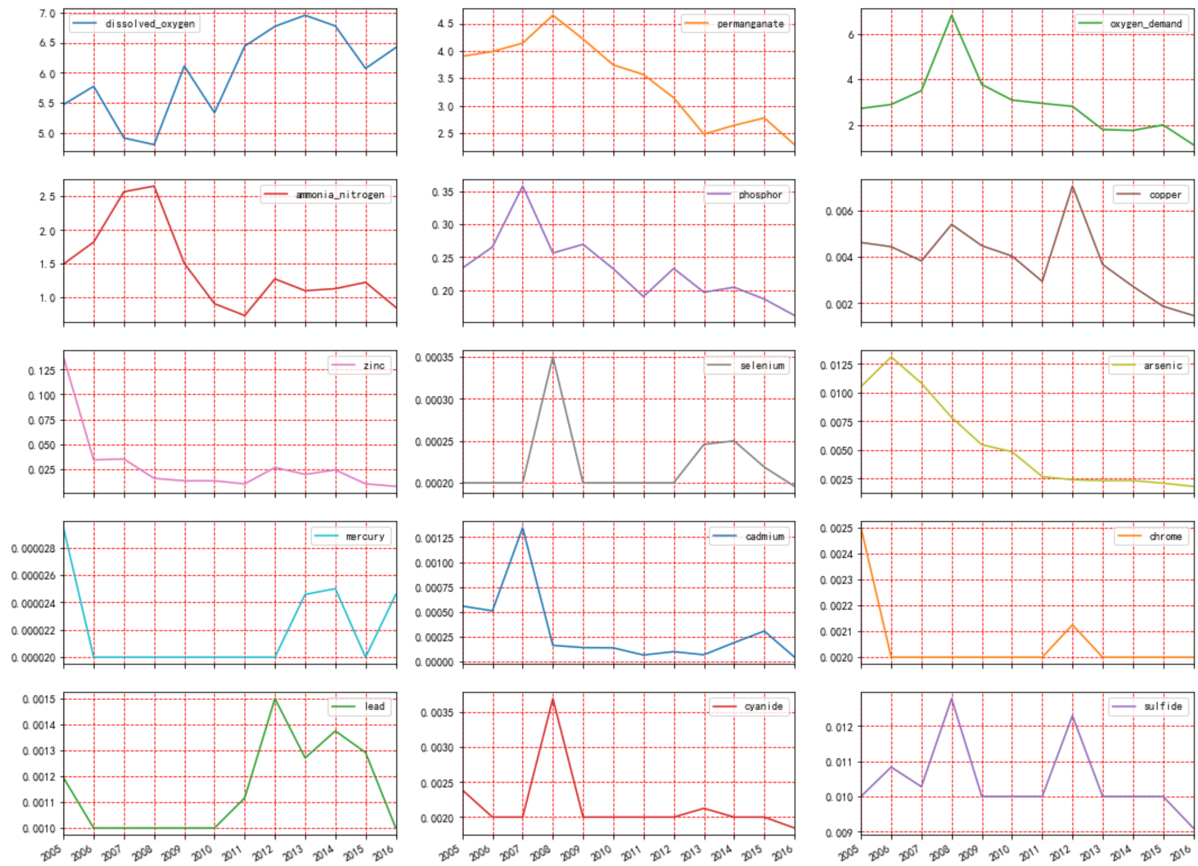


Figure 7. Trends of 16 water quality parameters in the mainstream of the Liuyang River.

The annual trends of water quality parameters for the Liuyang River are presented in Figure 7. During 2005–2016, CODMn, BOD5, ammonia nitrogen, TP, copper, zinc, arsenic, mercury, CODMn, BOD5, ammonia nitrogen and cyanide rose to maximums in 2008. TP and cadmium rose to the maximum in 2007. Copper and lead rose to the maximum in 2012.

The annual trends in water quality parameters in the Lian River are presented in Figure 8. BOD5, ammonia nitrogen, copper, mercury, cadmium, chromium, lead, cyanide and sulfide first showed an increasing trend and then a decreasing trend followed by another increasing trend during 2005–2016, all reaching their maximum levels during 2010–2012. After this they decreased to some extent, but the levels were still similar to those in 2005.

Most of the water quality parameters of the Lian River between 2005 and 2016 reached their maximum levels during 2010–2012. Afterwards, there was a decreasing trend, but the levels were basically similar to those in 2005, which was the primary cause of the worse water quality of the Lian River in general compared with the mainstream.

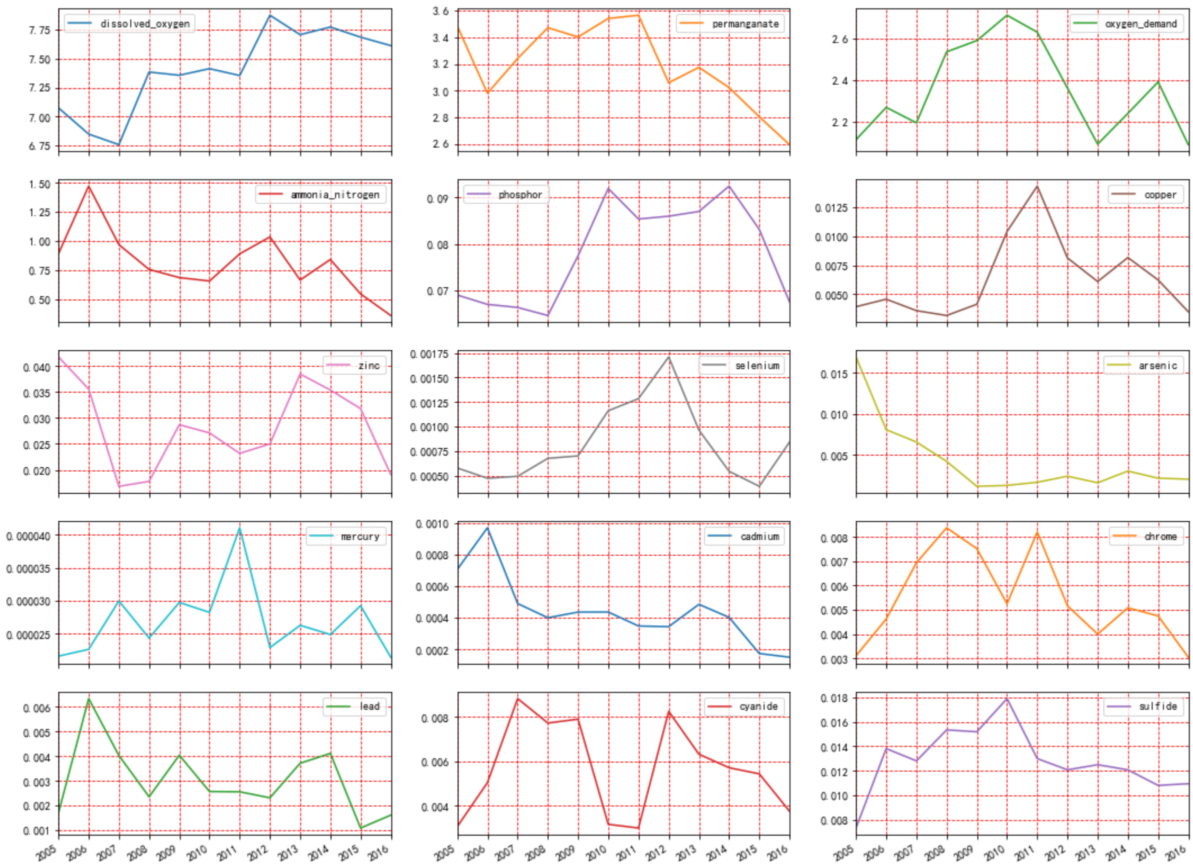


Figure 8. Trends of 16 water quality parameters in the mainstream of the Lian River.

4.3. Figure/image and caption

Figure 9 shows the spatial trends of water quality parameters in the mainstream of the Xiang River, where the monitoring sections are listed on the abscissa axis from left to right in the direction from the upstream to the downstream.

Table 2. Urban distribution of each section of Xiang River.

Urban	Section of Xiang River
Yongzhou	Lvbutou, Gangzikou, Guiyang Town
Hengyang	Songbo, Huangchaling, Aozhou, Zhuting Town
Zhuzhou	Fengxi, Baishi, Xiawan, Majiahe
Xiangtan	Yijiawan, Wuxing, Zhaoshan
Changsha	Houzishi, Sanchaji, Qiaokou
Yueyang	Zhangshugang

According to the urban locations of the sections (Table 2) and the regional trends of water quality parameters in the mainstream of the Xiang River (Figure 9), it can be seen that the IWQI of each of the sections was the best in the cities of Yongzhou and Zhuzhou and relatively poor in the cities of Hengyang, Xiangtan and Changsha. In particular, Yongzhou City, which is located in the upstream of the Xiang River, had a relatively high IWQI with slight fluctuations. The IWQI showed a decreasing trend in Hengyang City, but it rapidly improved when water flowed to the junction (town) between Hengyang City and Zhuzhou City. The IWQI was the best at the Fengxi-Xiawan section in the middle reaches of the Xiang River. After the Xiang River entered the downstream cities of Xiangtan and Changsha, the IWQI began to deteriorate again.

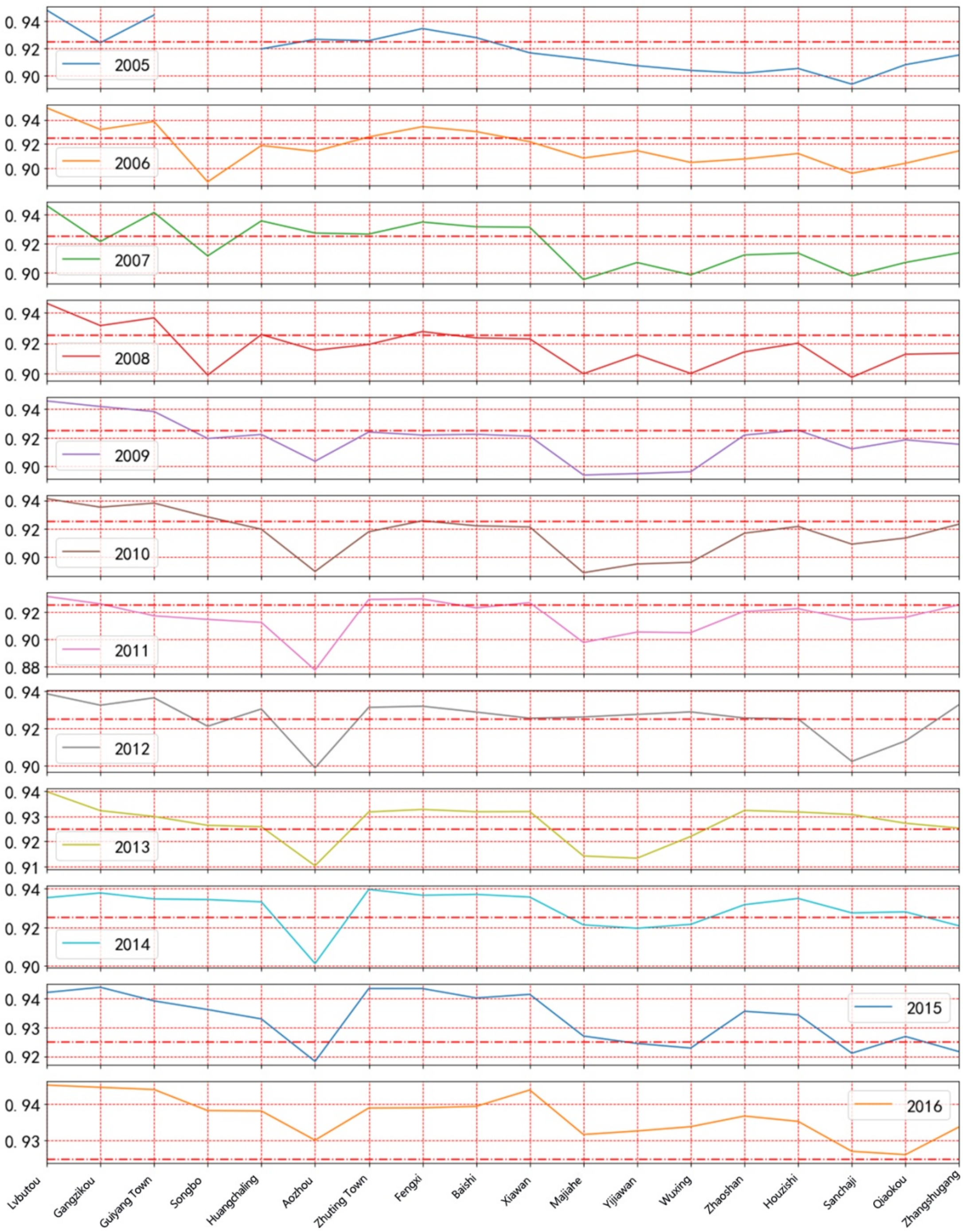


Figure 9. Spatial trends of water quality parameters in the mainstream of the Xiang River

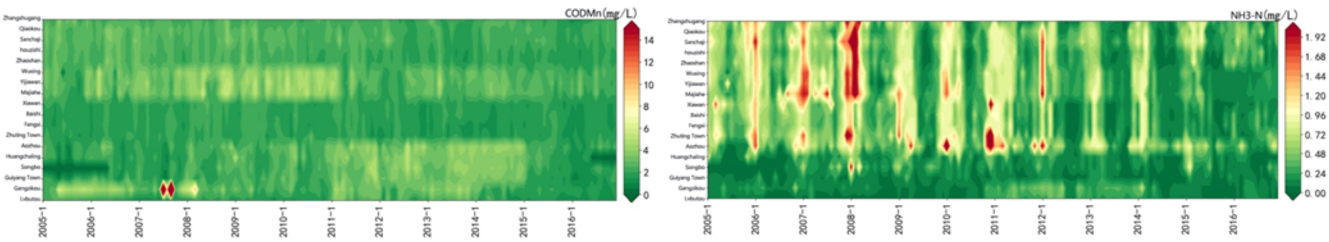
With respect to the distribution of the IWQI at various sections, the upstream of the Aozhou section showed obvious differences before and after 2009. Before 2009, the IWQI was relatively stable and even showed an increasing trend. After 2009, as the Aozhou section showed the lowest IWQI among all the sections, the upstream of the Aozhou section showed an obvious decreasing trend. As shown by the geographical locations of the sections of the Xiang River, two major tributaries of poor water quality, namely, the Zheng River and the Mi River, merged into the Xiang River in front of the Aozhou section. This resulted in the sudden deterioration of the IWQI at the Aozhou section.

After the Aozhou section, the IWQI improved significantly at the Zhuting Town section, and it became the best of all sections in the mainstream of the Xiang River. After the Zhuting Town section, the IWQI did not undergo large changes at the Fengxi, Baishi and Xiawan sections, with the sections showing good water quality. In the downstream of Zhuzhou City, however, the IWQI showed a dramatic decline at the Majiahe section, after which the IWQI remained relatively stable at other sections. Downstream of the Sanchaji section, the IWQI showed a decreasing trend, which was attributed to the fact that the nearby tributary, the Liuyang River, merges into the Xiang River. At the Zhangshugang section, which is the last mainstream section prior to the Xiang River enters Dongting Lake, the IWQI improved significantly.

In general, the geographical distribution of the IWQI at the mainstream sections of the Xiang River did not show large annual variation after 2009. That is, the Aozhou, Majiahe, and Sanchaji sections showed the worst water quality. The middle reaches of the mainstream of the Xiang River (at the Zhuting Town, Fengxi, Baishi and Xiawan sections) had excellent water quality. In the middle and lower reaches of the Xiang River mainstream, which ranges from the Majiahe section to the Sanchaji section, the IWQI was relatively stable. At the Zhangshugang section, where the mainstream of the Xiang River enters the Dongting Lake, the water quality recovered.

To account for the water quality changes, a spatiotemporal trend analysis was performed on each water quality parameter in the mainstream of the Xiang River, as shown in Figure 9. Pollutants in the mainstream were primarily CODMn, ammonia nitrogen and TP originating from the discharge of domestic sewage or agricultural waste, followed by heavy metals, such as selenium, arsenic, cadmium and hexavalent chromium. These pollutants showed obvious seasonal changes and regional characteristics.

As shown in Figure 10, CODMn was high throughout the mainstream, especially in the upstream from the Lvbutou section to the Aozhou section and at the Majiahe, Yijiawan and Wuxing sections in the middle reaches. Ammonia nitrogen pollution was primarily distributed in the middle and lower reaches of the mainstream, with obvious seasonal dependence and high pollution primarily occurring around January. In general, ammonia nitrogen pollution was evenly distributed in the mainstream.



(a)

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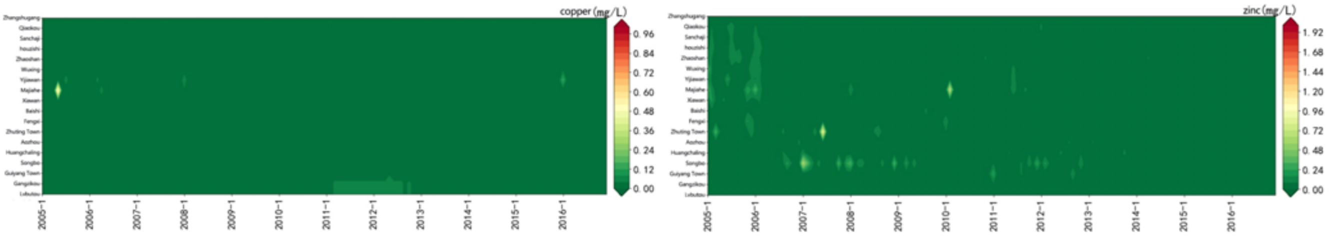

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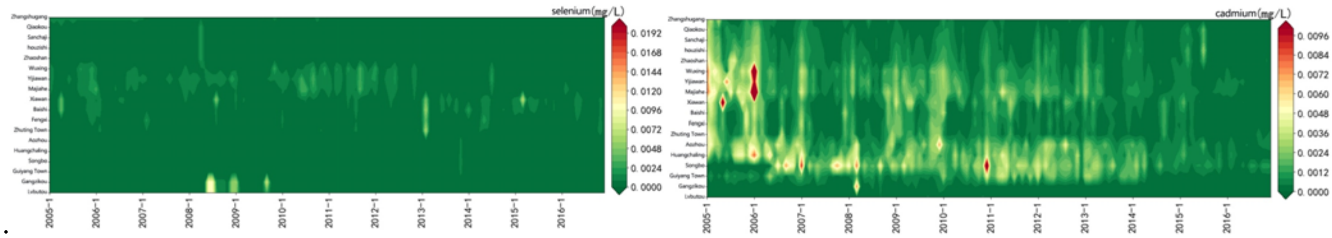

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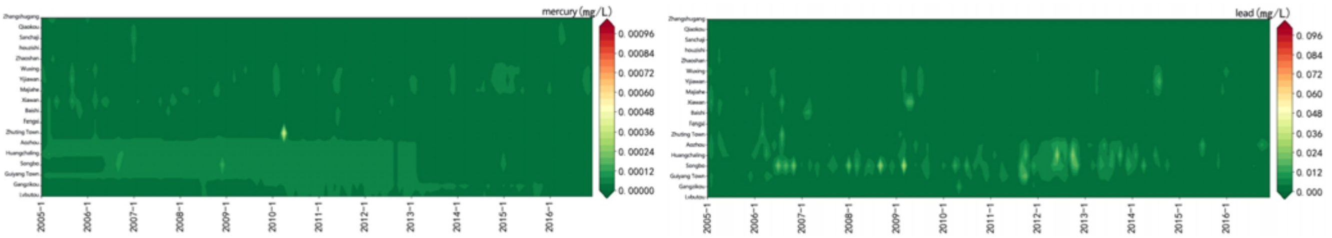

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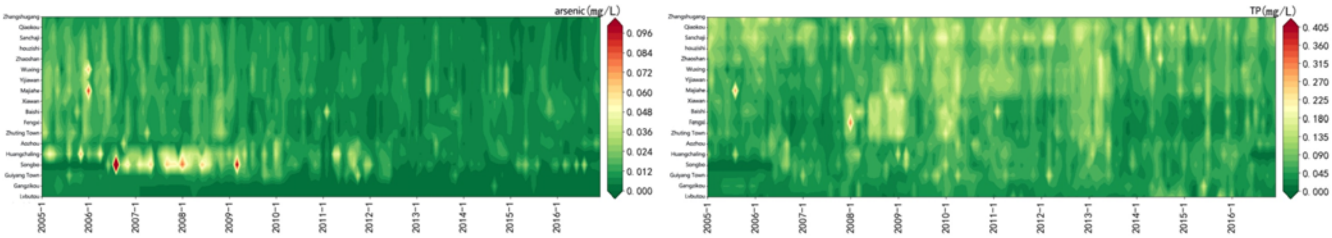

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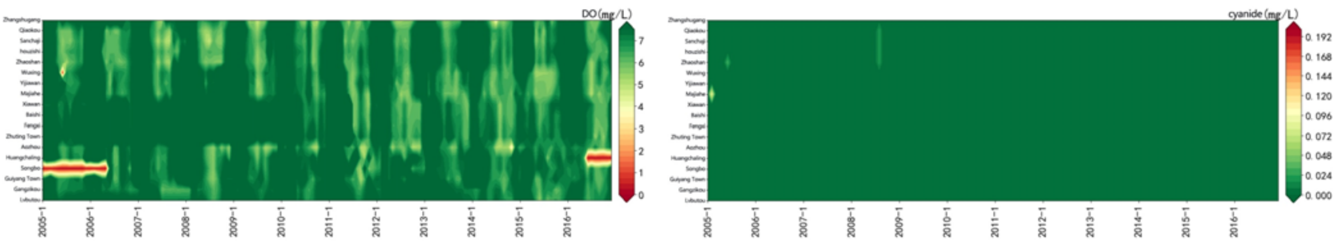

(f)

Figure 10. (a) Spatial trends of CODMn and NH3-N;(b) Spatial trends of copper and zinc; (c) Spatial trends of selenium and cadmium; (d) Spatial trends of mercury and lead; (e) Spatial trends of arsenic and TP; (f) Spatial trends of DO and cyanide.

There was sporadic, mild pollution of copper and zinc. Selenium was primarily concentrated in the middle reaches, but the level of pollution was relatively low. Cadmium was concentrated in the upper and middle reaches of the mainstream and improved significantly after 2015. Mercury and lead pollution were primarily distributed in the upstream, but the level was relatively low. Moreover, there was almost no obvious pollution at the end of 2016. Arsenic pollution was similar to TP pollution in that they were evenly distributed in the mainstream, but the level of pollution was relatively serious in the upstream. In particular, as shown in Figures 9 and 10, the primary water quality parameters that affected the Songbo section prior to 2009 were DO, arsenic, while cadmium. In addition, the primary water quality parameters that affected the Aozhou section after 2009 were CODMn, ammonia nitrogen and cadmium, with ammonia nitrogen and TP being the main water quality parameters that affected the Sanchaji section. In general, all of the water quality parameters, especially the heavy metals, improved significantly, but CODMn and TP did not improve.

4.4. Change analysis of pollutant PCs in the Xiang River Basin, China

PCA was performed on the annual water quality parameters of the Xiang River Basin to explore the evolution of main pollutants in the basin. This was done to analyze the effects of environmental management on water quality in the basin. In this study, six PCs were extracted in each year according to the rule that PCs should have eigenvalues greater than one. Due to the space limitation in this article, only the first three PCs of the years 2007, 2010, 2013, and 2016 are listed in Table 3.

Table 3. Factor loadings after Varimax rotation

parameters	2007			2010			2013			2016		
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
DO	-0.712	0.100	0.255	0.328	-0.169	-0.377	0.254	-0.322	0.058	0.387	-0.134	-0.346
CODMn	0.519	-0.028	-0.037	-0.675	-0.224	0.477	-0.812	-0.063	-0.089	-0.741	0.099	-0.114
BOD5	0.757	0.370	0.135	-0.699	-0.050	0.328	-0.580	0.280	0.285	-0.486	-0.053	-0.420
NH3-N	0.799	0.080	0.166	-0.345	-0.237	0.184	-0.580	0.362	0.530	-0.831	-0.046	0.037
TP	0.846	0.060	0.157	-0.661	0.076	0.348	-0.539	0.476	0.440	-0.843	0.072	0.087
Cu	-0.013	0.529	-0.051	-0.287	-0.583	0.015	-0.115	-0.704	0.369	0.051	0.142	-0.490
Zn	-0.103	0.408	0.250	0.338	-0.216	0.369	-0.410	-0.262	0.108	0.074	0.198	-0.487
Se	0.049	-0.358	0.332	-0.076	0.161	0.447	0.052	0.157	0.244	-0.024	-0.296	-0.545
As	-0.025	0.661	0.144	-0.251	-0.347	-0.561	-0.112	0.102	-0.519	0.125	0.683	-0.036
Hg	-0.146	0.711	-0.315	0.136	-0.662	-0.079	-0.387	-0.515	0.034	-0.226	-0.333	-0.082
Cd	-0.102	0.652	0.322	-0.163	-0.389	-0.302	-0.449	-0.111	-0.495	0.118	0.676	-0.313
Cr	-0.002	0.265	-0.653	0.669	-0.222	0.441	0.127	-0.725	0.475	0.174	-0.379	-0.473
Pb	-0.187	0.341	0.253	-0.056	-0.558	-0.111	-0.534	-0.135	-0.464	-0.144	0.685	-0.282
cyanide	0.081	0.094	-0.539	0.140	-0.806	0.192	-0.270	-0.137	0.291	-0.094	-0.443	-0.547
sulfide	0.136	-0.002	-0.573	0.587	-0.127	0.645	-0.593	-0.353	-0.338	-0.058	0.422	-0.182
Eigenvalue	2.809	2.296	1.645	2.733	2.291	2.034	2.962	2.108	1.930	2.487	2.207	1.834
Variability	18.73	15.30	10.96	18.22	15.27	13.56	19.75	14.05	12.87	16.58	14.71	12.23
Cumulative	66.75			67.75			70.95			65.73		

The first six PCs were not significantly different from one another in terms of percent contribution, with them cumulatively accounting for approximately 70% of the total variance in the water quality. According to the selection criterion of water quality parameters, the loading should be greater than 0.4. Hence, the water quality parameters relevant to the first PC (PC1) in 2007 were determined to be DO, CODMn, BOD5, ammonia nitrogen and TP, which are primarily indicative of domestic sewage pollution. The water quality parameters relevant to the second PC (PC2) were copper, zinc, arsenic, mercury and cadmium, indicative of heavy metal pollution. The water quality parameters relevant to the third PC (PC3) were chromium, cyanide and sulfide, with chromium originating from the upstream pollution inputs.

In 2010, the PC1-relevant water quality parameters were CODMn, BOD5, TP, chromium and sulfide. The PC2-relevant water quality parameters were copper, mercury, lead and cyanide. The PC3-relevant water quality parameters were CODMn, selenium, arsenic, chromium and sulfide. In 2013, PC1-relevant water quality parameters were CODMn, BOD5, ammonia nitrogen, TP, zinc, cadmium, lead and sulfide. The PC2-relevant water quality parameters were TP, copper, mercury and chromium. The PC3-relevant water quality parameters were ammonia nitrogen, TP, arsenic, cadmium, chromium and lead. Unlike in 2007, the water quality parameters of each PC in 2010 and 2013 did not represent a single type of pollution (e.g., domestic sewage pollution versus heavy metal pollution).

In 2016, the PC1-relevant water quality parameters were CODMn, BOD5, ammonia nitrogen and TP, primarily originating from domestic sewage pollution. The PC2-relevant water quality parameters were arsenic, cadmium, lead, cyanide and sulfide, indicative of heavy metal pollution. The PC3-relevant water quality parameters were BOD5, copper, zinc, selenium, chromium and cyanide.

For the annual trend of the PCs, each PC began to fail to represent a single type of pollution since 2010 due to the environmental management of the Xiang River Basin, indicating that governmental intervention began to generate positive effects. In 2015 and 2016, PC1 began to represent domestic sewage pollution and PC2 heavy metal pollution again, which indicated that pollution management had entered a stable stage, and the next stage will focus on management of domestic sewage pollution.

5. Impact analysis of management policies of the Xiang River, China

5.1. Impacts of environmental protection policies on the annual trends of water quality parameters

Since 2008, the national government has issued a series of management policies for the Xiang River. The promulgation and implementation of these policies have had significant impacts on the annual levels of water quality parameters in the Xiang River.

1) **The comprehensive management plan implemented in 2008 achieved some results, but more targeted measures are needed**. In 2008, the Hunan Provincial Government issued the Implementation Plan for the Comprehensive Management of Water Pollution in the Xiang River Basin.

The annual trend of the mainstream IWQI of the Xiang River (Figure 3) indicates that between 2008–2011, the mainstream IWQI fluctuated near 0.92, indicating that the water quality of the mainstream of the Xiang River improved to some extent. However, this period was the initial stage of the management of the Xiang River Basin, so the policy impacts were not stable. In addition, the annual trends of the tributary IWQI (Figure 5) indicate that the Liuyang River showed a clear increasing trend, while other tributaries showed fluctuating water quality or even worsening water quality with small change magnitudes. These annual trends suggest that the implementation plan had a certain promotional effect on the management of the Xiang River Basin by local municipal governments.

The annual trends of the primary water quality parameters in the mainstream (Figures 4 and 10) indicate that most of the pollutants first showed an increasing trend and then a decreasing trend, or showed a continuous decreasing trend, while only some heavy metal pollutants showed an increasing trend or fluctuated. This suggests that the implementation plan had effectively prevented the water environment from continuous deterioration, and the water environment had been initially improved.

However, this also suggests that some pollutants need to be controlled through more targeted management programs.

2) **The heavy metal pollution control plan implemented since 2009 has significantly reduced heavy metal pollution in the river basin**. In November 2009, the Implementation Plan for Research and Comprehensive Demonstration of Key Remediation Technologies of Heavy Metal Pollution in the Water Environment of the Xiang River was included in the National Science and Technology Major Project for Water Pollution Control and Treatment. In 2010, the central government invested 520 million yuan in 46 projects for the management of heavy metal pollution in the Xiang River Basin. In 2011, the State Council approved the Twelfth Five-Year Plan for Comprehensive Prevention and Control of Heavy Metal Pollution that indicated for the first time in China the inclusion of heavy metal pollution prevention and control in a national plan. In March 2011, the Hunan Provincial Government issued the Implementation Plan for the Management of Heavy Metal Pollution in the Xiang River Basin, taking the lead in promoting heavy metal pollution management in the Xiang River Basin.

The annual trend of the mainstream IWQI of the Xiang River (Figure 3) indicates that the mainstream water quality of the Xiang River Basin showed an obvious improvement trend from 2010 to 2013, and the overall water quality improved significantly. The annual trends of water quality parameters in the mainstream (Figures 4 and 10) indicate that since the start of heavy metal pollution management in the Xiang River in 2009, arsenic and cadmium were the first to show pollution improvements in response to the implementation. This was followed by selenium and mercury, that have shown dramatic declines in pollution levels since 2010. In 2011, the Hunan Provincial Government released the Implementation Plan for the Management of Heavy Metal Pollution in the Xiang River Basin, and made significant progress in the pollution management of zinc and chromium since 2011. The annual trends of the tributary IWQI (Figure 5) indicates that the poor water quality of the Lian River, the Zheng River, and the Liuyang River began to improve significantly since 2011. As shown in Figures 6–8, heavy metal such as copper, mercury, zinc and lead showed significant decreasing trends after 2011. Copper and lead in the Liuyang River decreased significantly after 2012. In addition, in the Lian River there was an obvious decreasing trend in copper, mercury and chromium after 2011, selenium and cadmium after 2012 and zinc after 2013.

As shown by the annual trends of the water quality parameters in the mainstream and three tributaries with poor water quality, the change trend of heavy metal pollution during specific time periods coincided with the time when relevant policies were issued. Therefore, this provides a micro-perspective that reflects the effectiveness of heavy metal pollution management in the Xiang River.

3) **Since 2013, the No. 1 Key Project led to obvious positive effects on the control of pollution sources**. The Regulations for the Protection of the Xiang River in Hunan Province came into effect on April 1, 2013. On September 22, 2013, the Hunan Provincial Government listed the protection and management of the Xiang River as the No. 1 Key Project. On December 25, 2013, the implementation plan of the above regulations was issued, which was an addition to the guiding documents for the implementation of the No. 1 Key Project.

The annual trend of the mainstream in the IWQI of the Xiang River (Figure 3) indicates that the mainstream water quality improved steadily from 2013 to 2014. In addition, it showed a new, obvious rising trend since 2014. The annual trends of the mainstream water quality parameters (Figures 4 and 10) indicate that since 2013, in addition to heavy metals, other water quality parameters of CODMn, TP, cyanide and sulfide also showed significant decreasing trends. This confirms that since its first implementation in 2013, the No. 1 Key Project has achieved good results in controlling pollution sources.

The annual trends of PCs (Table 3) indicate that since 2010, each annual PC failed to represent a single type of pollution, indicating that the management had played a positive role in pollution management to some extent. However, PC1 represented domestic sewage pollution and PC2 heavy metal pollution in 2015 and 2016. This indicated that pollution management entered a stable stage, and the No. 1 Key Project had generated positive effects on the control of pollution sources.

5.2. Impacts of regional industrial structures and management policies on regional water quality

The annual trends in the IWQI and water quality parameters at the junction sections between cities (Figures 9 and 10) showed that water quality was relatively good in the mainstream downstream of the cities of Yongzhou, Hengyang and Xiangtan. This is indicative of the effectiveness of water quality management in these cities, especially Hengyang City that showed the most significant effectiveness. Hengyang City included the implementation of the first Three-year Action Plan into the No. 1 project of the municipal government, and the city invested nearly 200 million yuan dedicated to management of its drinking water source protection zone, where 34 original sewage outlets were shut down. In addition, Xiangtan City accelerated the overall withdrawal of heavily polluting enterprises in the Zhubu area, shutting down 28 enterprises since 2013 while simultaneously relocating enterprises in an environmentally friendly manner and promoting regional transformation and upgrading. Yongzhou City strictly implemented pollution source management by launching a Regional Restrictions scheme for prefectures and counties where environmental pollution was beyond the environmental capacity, pollution discharge was beyond the pollution quota, or reduction of excessive production capacities was not sufficient.

As shown in Figures 9 and 10, the water quality in the downstream of Zhuzhou City showed a dramatic decline, resulting in poor overall water quality in the mainstream entering into Xiangtan City. This phenomenon may be attributed to the fact that Zhuzhou City, which is dominated by heavy manufacturing industries, conducted the concentrated discharge of industrial waste water in the downstream. However, all local governments took actions in accordance with the Implementation Plan for the Management of Heavy Metal Pollution in the Xiang River Basin. For example, all chemical enterprises in seven key areas of heavy metal pollution, such as the Qingshuitang and Zhubugang areas, were relocated to other areas. As of June 2013, a total of 756 heavy metal enterprises had been shut down. This explains why the mainstream with poor water quality in the downstream of Zhuzhou and Changsha showed water quality improvement since 2014 (Figure 8). Based on the above analysis and the spatiotemporal trends of water quality parameters in the mainstream of the Xiang River in Figure 10, it can be seen that the implementation of targeted management policies in these areas had obvious promotional effects on regional water quality.

5.3. Changes in water quality management priorities since the start of policy implementation

Spatiotemporal trend analysis and PCA of water quality parameters in the Xiang River Basin (Figures 4, 6–8, 10 and Table 3) indicate that through the two five-year plans of pollution management, water quality parameters, in particular heavy metals, showed obvious improvements for the entire Xiang River Basin, as well as in each tributary and local city. Through the two five-year plans of pollution management, various water quality parameters, especially heavy metal related indicators, improved significantly. The priorities of water quality management were shifted from comprehensive water quality management in 2008 to heavy metal pollution management in 2011. The priorities were then shifted to water quality maintenance and improvement in 2013, achieving the expected results. However, there were no improvements in CODMn and TP, and further improvements will be the focus of the next stage of pollution control in the Xiang River Basin.

6. Conclusions and policy recommendations

This study evaluated the impacts of pollution control policies using a big data analysis of water quality monitoring results. This study provides an objective reflection of the water quality characteristics of the Xiang River, as well as policy impacts. To overcome the drawbacks of conventional ER-based assessment methods that rely on a time series of means that are subject to information loss and index assessment methods that are subject to subjective bias in the determination of weights, this study proposed an ER-based integrated assessment method for a time series of water quality parameters. Based on this new method in conjunction with PCA, this study conducted an integrated water quality assessment for the mainstream and major tributaries between 2005 and 2016 and analyzed the spatiotemporal trends of the IWQI and water quality parameters. The results showed that: 1) A series of environmental protection policies issued by Hunan Province since 2008 had significant and targeted impacts on water pollutants in the main stream and tributaries during each year, and, in particular, the heavy metal pollution in the river basin was significantly alleviated. 2) The regional industrial structures and management policies had region-specific impacts on water quality, but generally they all led to significant improvements in the relevant water quality parameters in each region, thereby improving the overall regional water quality. 3) Finally, due to the two five-year plans of pollution management, water quality parameters and especially heavy metals in the Xiang River Basin improved significantly, but there were no improvements for CODMn and TP.

In view of the changes in the pollution monitoring data of the Xiang River, the following policy recommendations are being made for the relevant administrative departments. 1) It is necessary to improve the ecological environment supervision system of the Xiang River and maintain the current achievements in water quality management. It is desirable to improve the ecological environment supervision system by establishing an evaluation system for the green performance of local governments, constructing a modern intelligent monitoring system for the ecological environment, and promoting the formation of an accountability system for ecological environmental damage. 2) It is necessary to focus on resolving prominent environmental concerns in the Xiang River Basin. Currently, the primary water pollution in the Xiang River Basin is mainly dominated by CODMn and TP originating from domestic sewage and agricultural production. It is recommended to improve the comprehensive urban and rural sewage treatment system in the river basin and establish a resource recycling base for urban and rural domestic waste so as to ensure healthy development of the overall environment in the Xiang River basin. 3) It is necessary to strengthen ecological management and restoration in key areas of the Xiang River Basin. It is also recommended to construct key ecological function zones, strengthen small watershed management, promote the connectivity of rivers, lakes and reservoirs, and conduct coordinated planning of shoreline resources of the Xiang River. In addition, the protection and restoration of important ecological function zones and natural reserves within the geographical ranges of the Xiang River should be strengthened.

Policy impact research based on big data analysis of water quality monitoring results is complementary to an econometric model-based policy impact assessment. This study offered a multi-perspective and intuitive representation of water quality characteristics of the Xiang River and provided new directions for policy assessments in the future. However, due to limitations in data collection, this study only explored water quality characteristics of the Xiang River, while failing to perform a correlation analysis on related data, such as meteorological changes and corporate emissions. In the future, it will be necessary to collect a wider data set and combine them with empirical strategies (such as PSM-DID) and big data methods to quantitatively identify the impacts of national pollution management policies on water quality so as to identify the causal effects of policies.

Acknowledgments

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Conflict of interest

The authors declare there is no conflict of interest.

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