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Water quality analysis using the CCME-WQI method with time series analysis in a water supply reservoir

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ABSTRACT

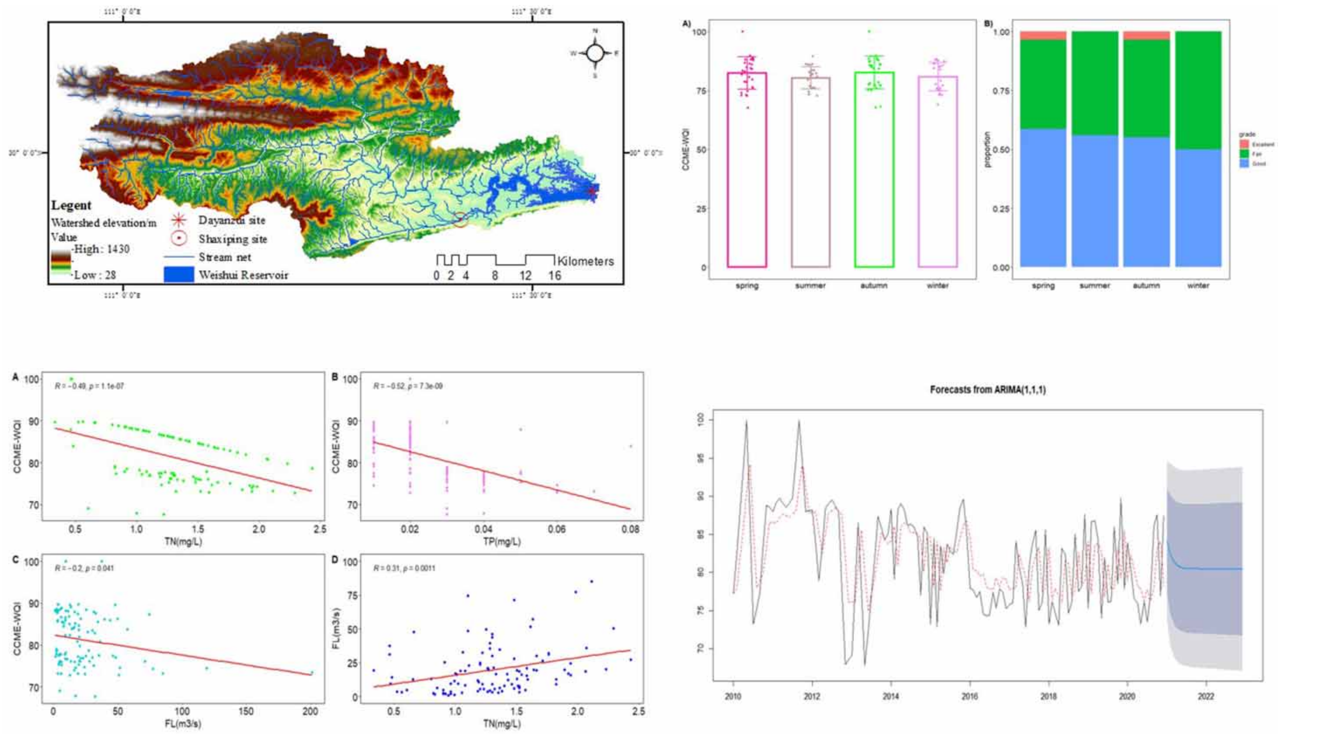
The quality of the drinking water source reservoirs has always been a research hotspot. However, few have studies focused on the water quality of reservoirs over a relatively long period with time series analysis. In this paper, based on water quality and hydrological data from 2010 to 2020, considering 8 water quality parameters, CCME-WQI with time series analysis was used to explore the interannual and seasonal changes in water quality in the Weishui Reservoir. Furthermore, the main factors affecting water quality were discussed through correlation analysis. The ARIMA model is used to predict water quality in the future. The results show that the water quality was seriously polluted from 2012 to 2013. After 2018, the water quality gradually improved and stabilized. In addition, the water quality is affected by inflow, showing the characteristics of poor water quality in summer and winter. The key parameters affecting water quality are TN and TP, which are almost 2 times higher than the grade II standard of water quality standard. Through the ARIMA model, it is predicted that CCME-WQI is maintained at 80.46 indicating that the water quality will be stable in the future.

Key words: ARIMA model, CCME-WQI, time series, water quality, Weishui Reservoir

HIGHLIGHTS

- CCME-WQI with time series analysis was used to explore changes in water quality of the Weishui Reservoir.
- The water quality is mainly affected by inflow.
- The key parameters affecting the water quality are TN and TP.
- The ARIMA model was used to predict the changing trend of the water quality indicating that CCME-WQI is basically maintained at 80.46 and the water quality will be stable in the future.

GRAPHICAL ABSTRACT



1. INTRODUCTION

In the process of social development, reservoirs play an important role in flood control, power generation, water storage, irrigation, and other projects. Even people's daily drinking water cannot be separated from reservoirs (Tian *et al.* 2018; Yan *et al.* 2020). In particular, as a drinking water reservoir, the water quality of the reservoir is related to the health of the local people. Once people drink water with quality problems, it will have a huge impact on people's health and cause a range of diseases (Li & Wu 2019). Therefore, it is necessary to understand the local water quality conditions and its water quality change over time, and the different factors impacting water quality.

Many researchers began to study the theory of water quality evaluation as early as the middle of the 20th century (You *et al.* 2019). There are a large number of methods of water quality evaluation are proposed, e.g. single factor exponent method (Bi *et al.* 2018), hierarchical cluster analysis (El-Hames *et al.* 2013; Ye *et al.* 2017), principal component analysis (Zitko 2006; Praus 2019; Arora & Keshari 2021), fuzzy neural network evaluation (Cheng *et al.* 2021) and water quality index (Cong *et al.* 2020; Zotou *et al.* 2020), etc. Among them, the water quality index (WQI) method is a numerical method (Han *et al.* 2020). It is widely used, which can reflect the water quality condition for different purposes (Wu *et al.* 2017b). WQI model is based on an aggregation function that combines the values of the various water quality parameters as a single value to describe the water quality (Nabizadeh *et al.* 2013).

The first WQI model was proposed by Horton (Horton 1965) and subsequently further developed by many different investigators, such as the NSF index (Deininger 2009), the House index (Uddin *et al.* 2021), the CCME Index (Lumb *et al.* 2006), etc. Among them, CCME-WQI has been widely used to evaluate the water quality of various water bodies, such as rivers, lakes, reservoirs (Gao *et al.* 2016), and groundwater (Venkatramanan *et al.* 2015), etc. Many researchers compared and analyzed the advantages and disadvantages of CCME-WQI and other water quality analysis methods. Dai *et al.* (2019) used CCME-WQI and NPI to evaluate and compare the water quality of the tributaries of the Three Gorges reservoir. It was found that the NPI method overemphasized the most serious pollution factors, while the CCME-WQI method can effectively evaluate the overall water quality. In addition, some studies have compared the Water Framework Directive (WFD) with CCME-WQI on the evaluation of the same water body and found that CCME-WQI evaluation is more reliable (Gikas *et al.* 2020).

In addition, the water quality of drinking water reservoirs has always been a research hotspot (Gu *et al.* 2014; Qin *et al.* 2021). Previous studies mainly focused on the water quality evaluation of reservoir tributaries and reservoir pollution sources (Shen *et al.* 2014; Zhang *et al.* 2016). Hou *et al.* (2016) compared the main pollutants with the water quality of different reservoirs by using WQI. Zhao *et al.* (2020) used the minimum water quality parameter WQI_{min} to study whether the diversion project has an impact on the water quality of Danjiangkou Reservoir. Wang *et al.* (2020) studied the impact of reservoir water level declining on reservoir change and pollution source identification. However, few studies have focused on the water quality changes of reservoirs over a relatively long period of time. In particular, most reservoirs with low flow velocity, which is easily lead to eutrophication for a long time (Wu *et al.* 2017a). Therefore, it is necessary to analyze the change in reservoir water quality over a long time. For long-time water quality analysis, the time series analysis in R is undoubtedly a very useful method (Duan *et al.* 2018). The time series analysis method is mainly used to solve the time series problems with randomness, seasonality, and stationarity (Kim & King 2020). Especially for the water quality in the reservoir, its seasonality is obvious. Through time series analysis, the trend of water quality change can be found easily. Establishing an autoregressive integrated moving average (ARIMA) model can further quantify the water quality of the reservoir in the next few years so that some useful measures can be taken to manage the reservoir and control the water quality in advance.

In this study, the Weishui Reservoir was selected, which is a high-quality water source in Hubei Province. Eight water quality parameters (pH, COD_{Mn}, DO, NH_4^+-N, TP, TN, F^-, BOD_5) were selected to calculate CCME-WQI. The main purposes of this study are (1) to evaluate the water quality changes and differences in Weishui Reservoir from 2010 to 2021 on an interannual scale and seasonal scale, and (2) to evaluate the impact of inflow and water level on the seasonality of reservoir water quality, (3) to determine the key parameters affecting water quality through correlation analysis, and to find out the pollution source causing the water quality change of the reservoir, (4) to understand the water quality change trend in the next few years through the water quality time series data. Based on the above research objectives, it not only evaluates the drinking water safety of the reservoir but also provides a certain basis for the management policy of the reservoir.

2. MATERIALS AND METHODS

2.1. Study area

Weishui Reservoir is in the southwest of Songzi City, Hubei Province, China. It is 14.5 km long from east to west and 6 km wide from north to south with a total surface area of 37 km^2. Weishui is a tributary of Songxi River, the four water systems of Dongting Lake. It is located at the junction of Southwest Hubei Province and Northwest Hunan Province. As a new water intake source for Songzi City, the Weishui reservoir can solve the water supply of Songzi City and 8 towns along with the water transmission network. It is in complex terrain with many islands and is known as the first artificial earth dam in Asia. Its altitude decreases from west to east (Figure 1). With a total reservoir capacity of 512 million m^3, the reservoir plays an important role in irrigation, flood control, power generation, tourism, and water supply. The climate prevailing in the reservoir is hot with rain in summer and cold and dry in winter. The annual average precipitation in the reservoir area is 1,271.3 mm.

2.2. Sampling points and data sources

There are two monitoring points selected to monitor the water quality of the reservoir. One monitoring point is located in Shaxiping (111 °24′13.2″, 29 °54′51.7″), which is located at the junction of the Hubei provinces and the Hunan provinces. It is the inflow control station of the Weishui reservoir and is used to monitor the water quality entering the reservoir. Pollutants such as upstream rainwater can enter the reservoir through the Shaxiping monitoring site. While the other point at Dayanzui (111 °34′55.9″, 29 °57′41.3″), is used to monitor and reflect the water quality in the reservoir (Figure 1). From 2010 to 2013, the water quality data was monitored in the reservoir in January, March, May, July, September, and November, while from 2014 to 2020, the water quality data were monitored in the reservoir every month. To meet the investigation needs, 8 water quality parameters were selected to evaluate the water quality. Those selected parameters are ρ(DO), pH, ρCOD_{Mn}, $\rho(BOD_5)$, ρ(TP), ρ(TN), $\rho(NH_4\text{-N})$, and $\rho(F^-)$.

The water samples were collected at 0.5m below the water surface using a 5 L cleaned plexiglass water collector. Water samples of each site were preserved in polyethylene plastic bottles, which were rinsed at least three times with distilled water and then kept at 4 °C in insulation boxes before analyzing water quality parameters. These parameters, such as pH and DO, were investigated using a multiparametric probe (YSI Incorporated, Yellow Springs, Ohio, USA) in the field, and the sensors of the instrument were calibrated before measurement. In the laboratory, COD_{Mn} was analyzed by the

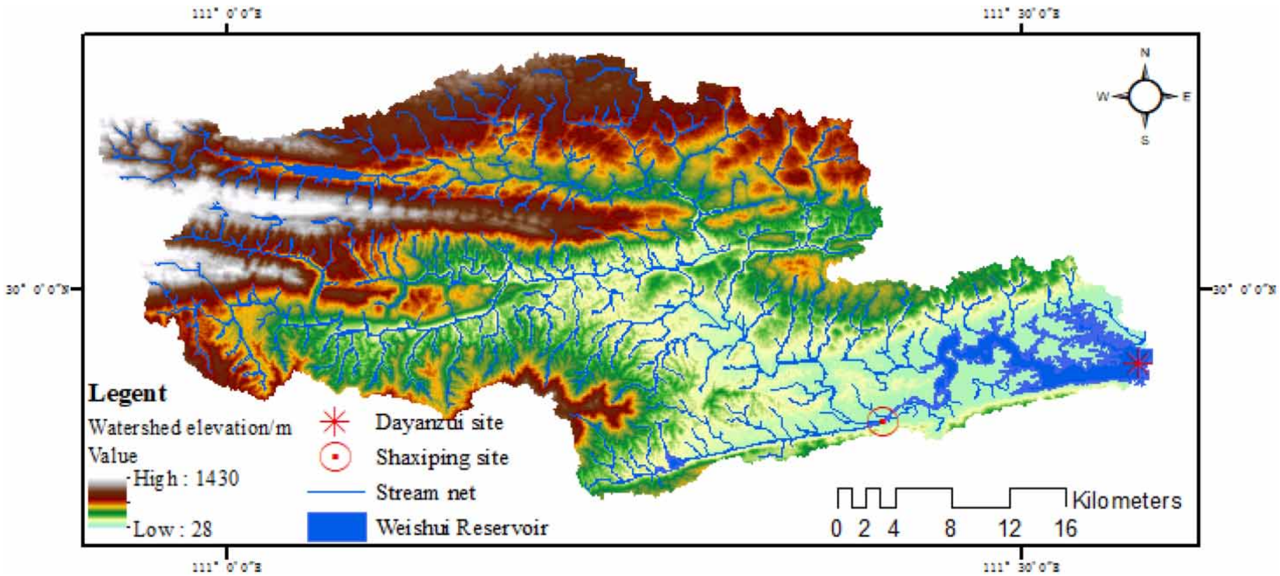


Figure 1 | Geographic information and sampling point map of Weishui Reservoir.

permanganate titration; BOD_5 was measured by a DO monitor and calculated the reduction of DO in the raw water samples after 5 days; TP was determined using the potassium persulfate molybdenum antimony spectrophotometry; TN was analyzed by potassium persulfate oxidation spectrophotometry; NH_4^+-N was measured by the Nessler's reagent spectrophotometry; the concentrations of inorganic anions F^- were gauged using ion chromatography. A detailed description of the water quality analysis methods can be found in the book of national standard methods for examining freshwater and wastewater in China (State Environmental Protection Administration 2002). All water samples were analyzed in the water quality laboratory of Jingzhou hydrology and water resources survey bureau, a (China Metrology Accreditation) CMA laboratory in China.

2.3. Analysis methods

2.3.1. Water quality index method (CCME-WQI)

To evaluate the water quality of the Weishui Reservoir, the CCME-WQI method was used. The CCME-WQI method is based on the following three elements: scope (F_1), frequency (F_2), and amplitude (F_3). F_1, F_2, and F_3 are calculated as follows:

F_1 (Scope)

F_1 is used to represent the percentage of indicators exceeding the standard, which represents the percentage of selected parameters that do not meet their respective parameter standard values at least once during the evaluation period. It can be calculated by Equation (1):

$$F_1 = \frac{\text{Number of failed variables}}{\text{Total number of variables}} \times 100 \tag{1}$$

F_2 (Frequency)

F_2 represents the percentage of monitoring quantity exceeding the standard, which is used to measure how often a water quality objective is not met. It can be calculated by Equation (2):

$$F_2 = \frac{\text{Number of failed test}}{\text{Total number of tests}} \times 100 \tag{2}$$

F_3 (Amplitude)

F_3 is the amplitude, measured by how much the objectives are exceeded, and thus represents the amount by which the failed test values do not meet their objectives.

(Guideline value). The following three steps are required to calculate the F_3.

Step 1: The number of times by which an individual concentration is greater than (or less than, when the objective is a minimum) the objective is called an excursion. When the test value must not exceed the objective, Equation (3) was used to calculate the excursion. While the test value must be no less than the objective, Equation (4) was used.

$$\mathrm{excursion_i} = \left(\frac{\mathrm{Failed\ test\ value_i}}{\mathrm{Objective_i}}\right) - 1 \tag{3}$$

$$\mathrm{excursion_i} = \left(\frac{\mathrm{objjective_i}}{\mathrm{Failed\ test\ value_i}}\right) - 1 \tag{4}$$

Step 2: The total amount by which the individual tests are out of compliance (the normalized sum of excursions) is calculated as the following Equation (5):

$$\mathrm{nse} = \frac{\sum_{i=1}^{n} \mathrm{excursion_i}}{\mathrm{Total\ number\ of\ tests}} \tag{5}$$

The amplitude (F_3) is then calculated by an asymptotic function that scales the normalized sum of the excursions from objectives to yield a value between 0 and 100:

$$F_3 = \frac{\mathrm{nse}}{0.01\mathrm{nse} + 0.01} \tag{6}$$

Finally, the CCME-WQI index is calculated as shown in Equation (7):

$$\mathrm{CCME-WQI} = 100 - \left(\frac{\sqrt{F1^2 + F2^2 + F3^2}}{1.732}\right) \tag{7}$$

According to the above formulas, it can obtain a CCME-WQI value ranging from 0 to 100. Water quality can be divided into five categories based on the CCME-WQI values calculated above, listed in Table 1 below.

To calculate the CCME-WQI value, it is crucial to determine the water quality parameters and objectives. Based on all the monitoring data, all heavy metal index concentrations were within the standard range, so the water quality parameters selected in this study were not included in the heavy metal index. The objectives selected the target concentrations from the Environmental Quality Standards for Surface Water in China (GB3838-2002) published by the Ministry of Environmental Protection in China. As an important drinking water source protection area, the water quality management target of Weishui Reservoir must meet Grade II water quality standards for the Environmental Quality Standards for Surface Water (GB3838-2002). The objectives corresponding to the water quality parameters are listed in Table 2.

2.3.2. Time series analysis

Additive decomposition was performed using RStudio 4.1.2. Time series dates between 2010 and 2020 for the value of the CCME-WQI were analyzed using additive decomposition. In the present study, the time series of CCME-WQI were separated into observed value, seasonal, trend, and random noise components. The observed values show the trend of time series changing with time. Seasonal components express the trend of periodic behavior of time series data. For example, time series data can be monthly or annual. The trend conveys that the data changes over time and may show an additive upward trend, a multiplicative upward trend, or a downward trend. The random noise component explains the rest after removing capture

Table 1 | Classification of water quality status according to the value of the CCME-WQI

CCME-WQI	95–100	80–94	65–79	45–64	0–44
Water quality status	Excellent	Good	Fair	Marginal	Poor

Table 2 | Water quality objectives used in this assessment

Water quality parameter	GB3838-2002 standard value of Grade II
1. pH	6~9
2. COD_{Mn}	4 (mg/L)
3. DO	6 (mg/L)
4. NH_4^+-N	0.5 (mg/L)
5. TP	0.25 (mg/L)
6. TN	0.5 (mg/L)
7. Fluoride	1 (mg/L)
8. BOD_5	3 (mg/L)

trends and seasonal effects. Finally, through the analysis, the ARIMA model is selected to predict the water quality of the reservoir in the future.

For the ARIMA model. Generally, it can be defined by the following Equations (8)–(11):

$$\Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t \tag{8}$$

where

$$\nabla^d = (1 - B)^d \tag{9}$$

$$\Phi(B) = 1 - \phi_1 B - \cdots - \phi_P B^P \tag{10}$$

$$\Theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \tag{11}$$

where ε_t is defined as a white noise process; B is defined as backward shift operator (lag operator); $\Phi(B)$ is defined as the autoregressive polynomial, and $\Theta(B)$ is defined as the moving average polynomial. The expression can be abbreviated as ARIMA (p, d, q). where 'p' denotes the autoregressive lag, 'q' denotes the moving average, and 'd' is the order of differentiation. To predict water quality by the ARIMA model. ARIMA model is usually used for stationary time series, so the stationarity of time series should be tested first. If the time series is unstable, the difference is used to make it stable. To determine whether the stationary sequence is worthy of further analysis, the pure randomness test is carried out for the stationary sequence. The second step is to select appropriate parameters according to the autocorrelation function (ACF) and partial autocorrelation function (PACF) diagrams of stationary data. Finally, Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are used to test the fitting effect and select the optimal prediction model.

Time series analysis through the observation and study of the time series, to find the law of its change and development and predict its future trend. ARIMA is an effective model for forecasting issues, which is widely used in the economy, finance, astronomy, meteorology, oceanics, physics, chemistry, medicine, quality control, and many other fields. It has been especially widely applied in social studies. In the past 2020–2021 years, due to the rapid spread of COVID-19, the time series ARIMA model has been applied to analyze the dynamics of epidemic transmission and predicted the number of epidemic victims in a certain period (Khan & Gupta 2020; Chyon *et al.* 2021). As a time series model, ARIMA describes the data of different random processes and realizes the linear model. It can flexibly construct the optimal model with many time series transformations by using the method of Box-Jenkins. In this paper, the ARIMA model can not only reflect the dynamic changes in water quality in reservoirs in recent years but also predict the water quality status in the next few years, which provides a basis for the management of subsequent reservoirs.

2.3.3. Correlation analysis

SPSS 26.0 was used to analyze the data, calculate the Pearson correlation coefficient between different water quality parameters and CCME-WQI value, and study the linear relationship between them. $P<0.05$ was the significant level and $P<0.01$ was the extremely significant level. Through correlation analysis, the critical factors affecting the water quality of the Weishui Reservoir are studied.

3. RESULTS AND DISCUSSION

3.1. The water quality changes at the interannual scale

To intuitively reflect the change in the Weishui Reservoir water quality, mapping the water quality changes by time series from 2010 to 2020 (Figure 2). Ten years ago, the overall water quality of Weishui Reservoir was good with the average value of CCME-WQI being 84. However, the water quality was severely polluted in 2013, and the mean CCME-WQI values this year were 68.16, and the water quality was considered a 'fair' grade. The water quality got better in 2014, which may be related to the adjustment of the local ban on reservoir fish culture policy. By 2016, the water quality of the reservoir was polluted again. This is consistent with the water quality and eutrophication status of representative reservoirs in Hubei Province 2013 published by the Department of water resources of Hubei Province. The water quality of Weishui Reservoir was classified as class III degree water in 2012 and 2013, and the eutrophication assessment was medium eutrophication (Hubei Provincial Department of Water Resources 2013). In addition, it is reported that at the end of 2013, a large area of water bloom broke out in the Weishui Reservoir, and the water quality deteriorated due to the impact of aquaculture fertilizer and paper mill sewage (Jingchu Net – Chutian Metropolis Daily 2014). During the period from 2013 to 2015, the water quality gradually improved but did not return to the level before 2011. By 2018, the water quality has gradually stabilized.

3.2. Seasonal variation in water quality

Additive decomposition is performed on the time series data CCME-WQI to obtain time series observations, trend factors, seasonal factors, and random factors. This is achieved in this study by the stl function in R. For observations, from 2010 to 2020, the CCME-WQI value of Weishui Reservoir decreased significantly twice, in 2013 and 2016, respectively. From the trend item, the movement of reservoir water quality from the highest point to the lowest can be seen, it is a time series of downtrends. The overall water quality trend is deteriorating, but it tends to be stable. This also indicates the instability of the original water quality data. In this study, the data is processed differentially to make it smooth and determine the value of 'd'. From the seasonal components, water quality has certain seasonal characteristics. random component captures changes in water quality that cannot be explained by trends or seasonal effects (Figure 3).

Overall, the water quality is relatively better in spring and autumn, average CCME-WQI values in spring and autumn were 82.33 and 82.62, respectively. According to the standard of water quality classification, the water quality in spring and autumn was considered a 'good 'grade, while the water quality in the summer and winter is relatively worse and rated a 'Fair' grade (Figure 4(a). As shown in Figure 4(b), the conclusions are the same. Water quality in different seasons was shown by

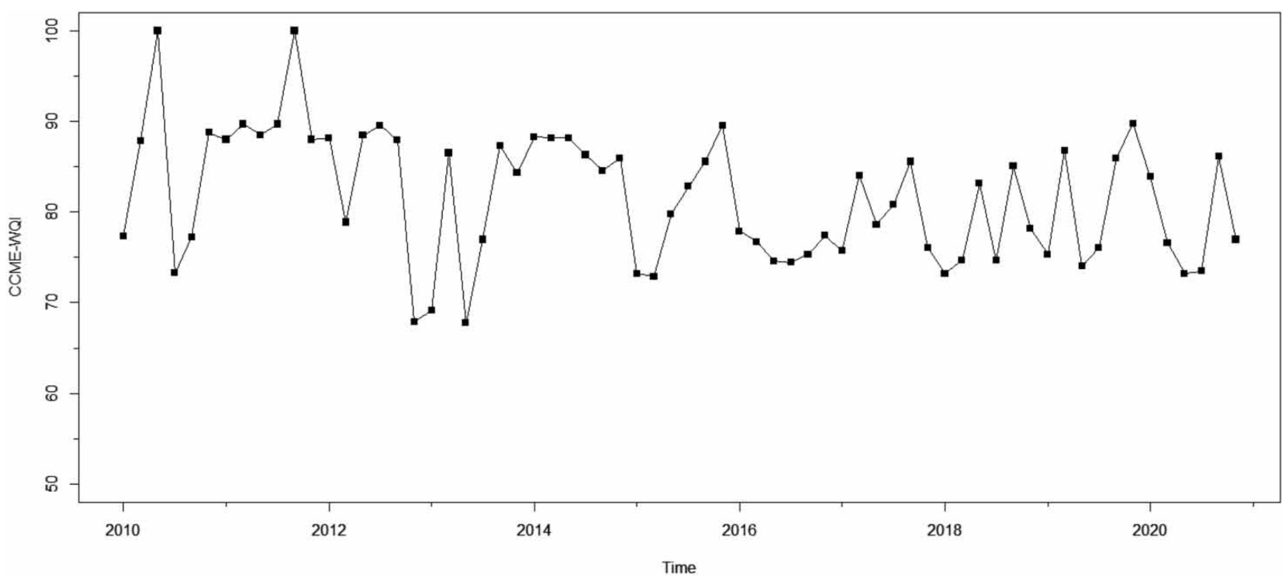


Figure 2 | Time series for the CCME-WQI to Weishui Reservoir from 2010 to 2020.

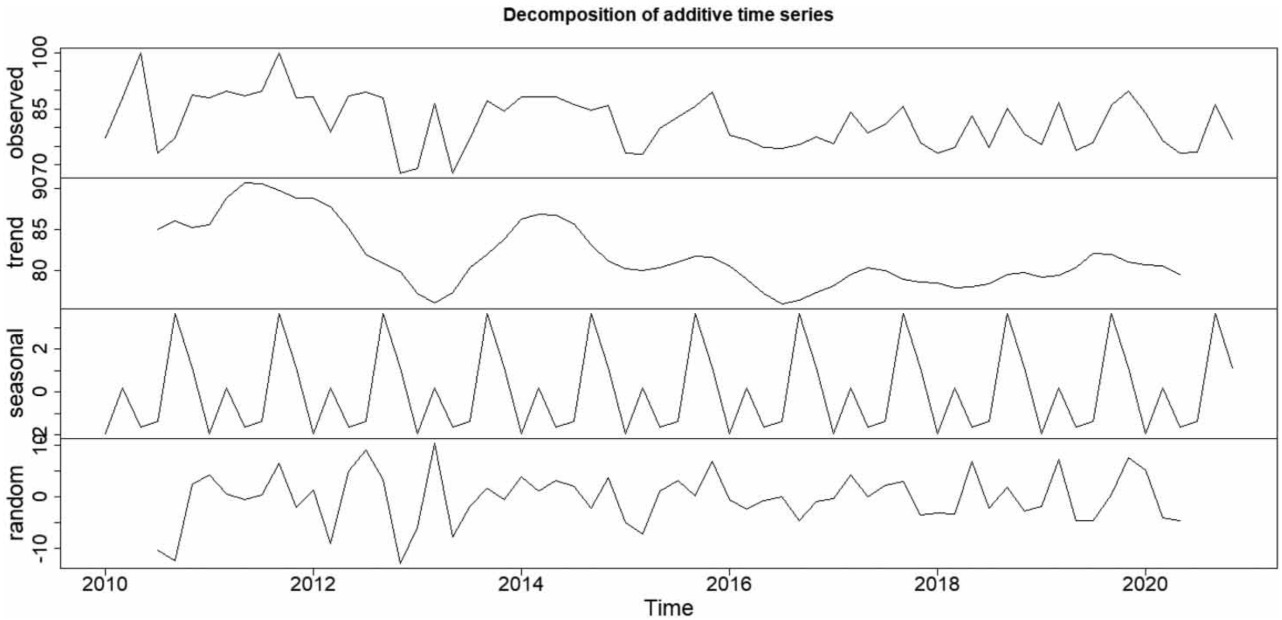


Figure 3 | Decomposition of CCME-WQI data using additive decomposition.

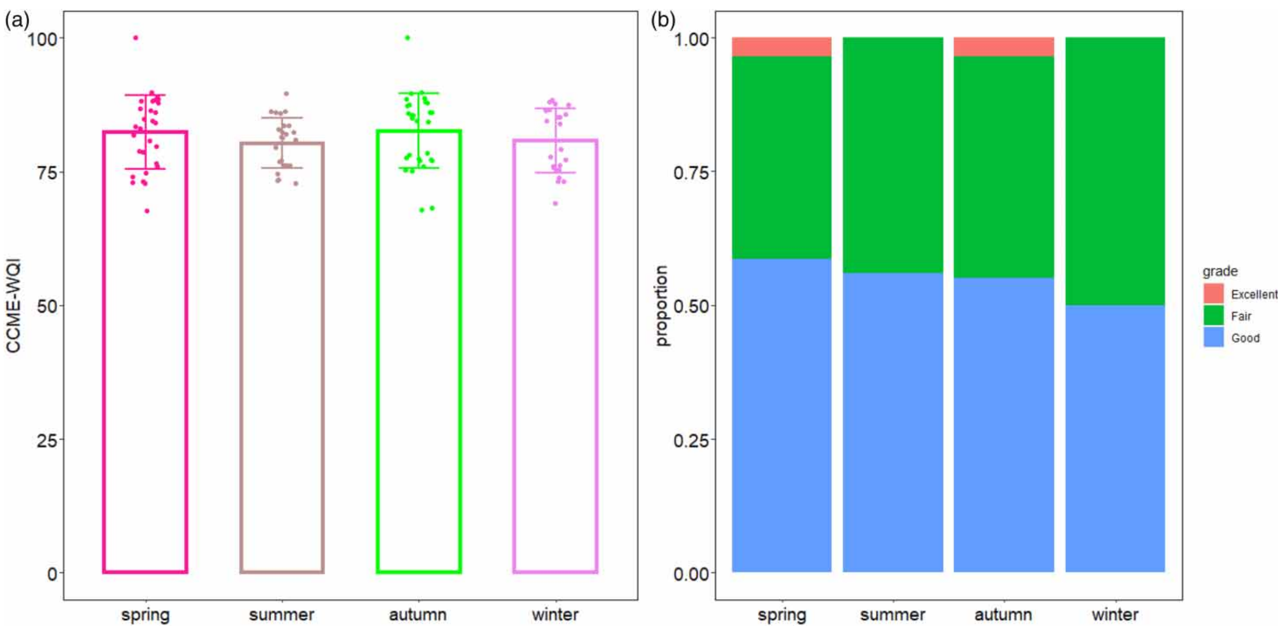


Figure 4 | WQI values for different seasons in the Weishui Reservoir (the season was categorized as spring (March-May), summer (June-August), autumn (September-November), and winter (December-February)).

calculating the proportion of water quality status in four seasons and found that spring and autumn had 'excellent' categories, while not measured in summer and winter.

3.3. Inflow and water level condition

The seasonal variation of water quality is usually related to the inflow of the reservoir. The inflow of the reservoir in different months from 2010 to 2020 is shown in Figure 5. Throughout the inflow changes, the periodic change of inflow is obvious. In

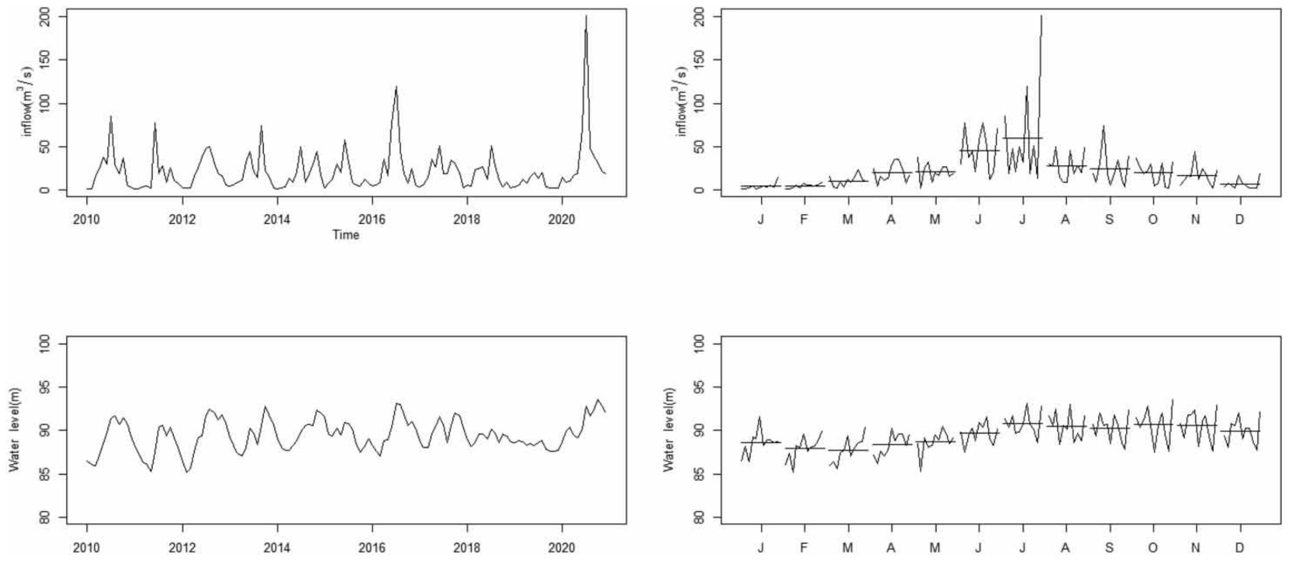


Figure 5 | Reservoir inflow and water level change from 2010 to 2020 in different months.

July 2020, the inflow has a maximum peak, with a monthly average of 201 m^3/s in this year. there is extreme weather of flood and waterlogging, which led to a significant increase in the inflow and water level of the reservoir.

From the monthly change of inflow, the month with the highest inflow is July. Taking July as the boundary, the inflow decreases from both sides. The inflow of Weishui Reservoir in summer was the largest compared to the other seasons, and the lowest inflow was in the winter. From 2010 to 2020, the average inflow of the reservoir is 41.4 m^3/s in summer and 4.56 m^3/s in winter. Similarly, according to the analysis of the water level in Dayanzui, the higher water level still appears in summer. The water level varied between 85 and 95 meters during the study period. It is generally stable at about 90 meters.

According to the water quality analysis, the water quality of the Weishui Reservoir in summer and winter is worse than in the other two seasons. It is not difficult to find that too high or too low an inflow will affect the water quality of the reservoir. Reservoir inflow is affected by rainfall, which is also affected by geography, climate (Wang *et al.* 2018), topography, and other factors. It is worth noting that some studies have reported that rainfall and climate conditions affecting inflow will have an impact on reservoir dynamics and water quality (Roselli *et al.* 2009; Razmkhah *et al.* 2010). In the summer, rain is abundant. Rainwater rushes down to carry a large amount of nitrogen and phosphorus from agricultural non-point source pollution into the reservoir through runoff, which is likely to cause nitrogen and phosphorus in the reservoir to exceed the standard and even cause blooms (Zeng *et al.* 2019). And some of the pollutants in the rainwater can directly contaminate drinking water (John *et al.* 2021), causing the nitrogen and phosphorus in the reservoir to exceed the standard, and even causing a bloom. On the other hand studies by Cooper and Tait reported that flow brings a large amount of sediment transport and settles to the bottom of the reservoir, thus forming the water-worked rough bed (Cooper & Tait 2008). While microbes, such as viruses, bacteria, and protozoa, can attach to sediment, causing microbial contamination and deterioration in water quality (Characklis *et al.* 2005; Krometis *et al.* 2013). Some studies have suggested that non-point source pollution intensifying runoff from cropland during periods of high flow may be the main cause of poor water quality in summer (Shen *et al.* 2008). So, the seasonal variation of water quality is closely related to the reservoir inflow, and part of the explanation for the observed phenomenon was that the reservoir inflow is large in summer, and a large amount of nitrogen and phosphorus in agricultural non-point source pollution enters the reservoir through runoff. However, in winter, once the reservoir is polluted, the low inflow of the reservoir makes the reservoir's self-purification capacity decrease, resulting in serious internal pollution of the reservoir. The inflow and water level of the reservoir affect its self-purification capacity. As a result, the self-purification capacity of the reservoir is low in winter. This is also one of the reasons why the water quality is better in spring and autumn, but not in summer and winter.

3.4. Key water quality parameters to the CCME-WQI

3.4.1. The changes in water quality parameters

The water quality parameters of Shaxiping (MP1, black line in Figure 6) monitoring point before entering the reservoir and Dayanzui (MP2, red line in Figure 6) in the reservoir from 2010 to 2020 were compared and analyzed by time series. In

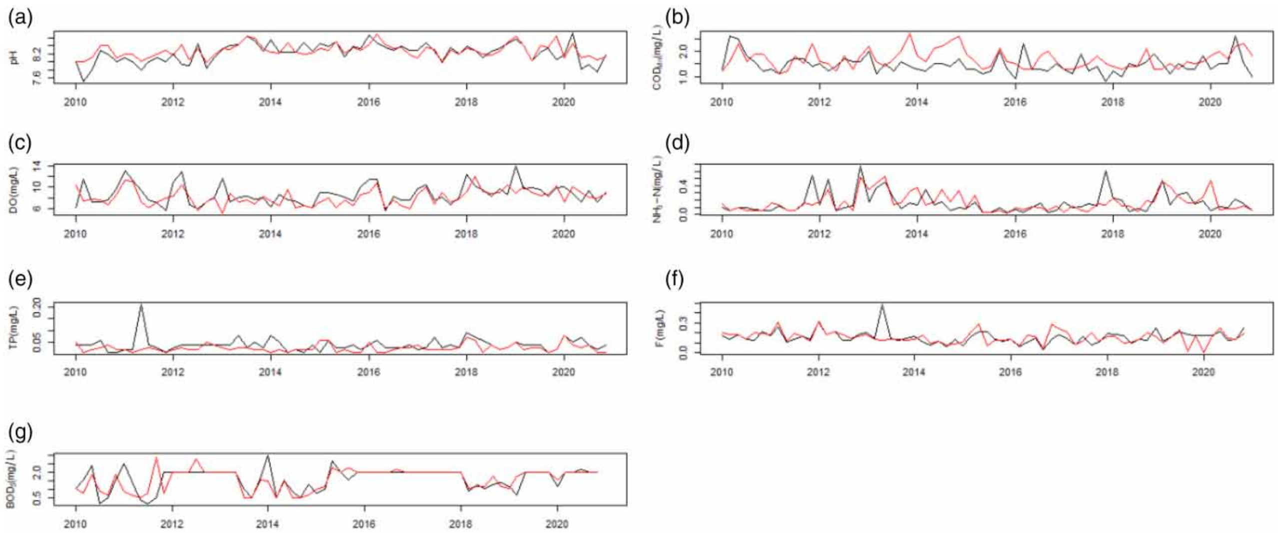


Figure 6 | Time series diagram of each water quality parameters in Shaxiping (MP1, black line) and Dayanzui (MP2, red line) from 2010 to 2020: (a) pH value; (b) Potassium permanganate index (COD_{Mn}); (c) Dissolved oxygen (DO); (d) ammonia nitrogen (NH_4^+-N); (e) Total phosphorus (TP); (f) Fluoride (F); (g) Five-day biochemical oxygen demand (BOD_5).

addition, the statistical description of the water quality parameters of the two stations is shown in Table 3. Among the water quality parameters involved in the water quality evaluation, pH, COD_{Mn}, F^-, and BOD_5 meet the Class II of Surface Water Environmental Quality Standard (*GB3838-2002*). Both BOD_5 and COD_{Mn} indirectly indicate the degree of organic matter contamination in the water based on the dissolved oxygen consumed in the water. While drinking water is one of the largest sources of fluoride intake, excess fluoride can easily lead to poisoning. For 11 years, these water quality parameters in the reservoir have been within the standard limit, indicating that the water quality is relatively safe. DO is lower than the water quality objectives (Table 2) at least once. TP and NH_4^+-N of the two monitoring stations exceeded the Class II water standard of surface water. Although TN is not measured at the Shaxiping monitoring point, the concentration of TN in most months of the reservoir exceeded the standard quality by 2–3 times.

The pH can reflect whether the water quality is suitable for the growth of aquatic organisms, which determines the reproduction of organisms and the water quality status in the water body. Whether its value is too high or too low will directly affect the activity of microorganisms in the water body, resulting in the deterioration of the water body. From the time series plots of each parameter, pH at MP1 and MP2 showed similar trends and were within standard limits during the whole study period (Figure 6(a)), which indicates that the water quality is suitable for the growth of aquatic organisms.

DO is an important indicator to measure the self-purification capacity of water bodies, and the content of dissolved oxygen in water is closely related to water temperature and partial pressure of oxygen in the air. The value of dissolved oxygen was lower than the standard value many times (Figure 6(c)). Minimal dissolved oxygen of MP1 in 2011 was 5.7 mg/L and the average dissolved oxygen 11 years per month was 8.8 mg/L. In January 2013, the minimum dissolved oxygen at the MP2 was

Table 3 | Statistical description of water quality parameters (mg/L exclude pH) of two stations

Sample point		pH	COD_{Mn}	DO	NH_4^+-N	TP	F^-	TN	BOD_5
Shaxiping	Average	8.2	1.47	8.8	0.16	0.04	0.158	–	1.62
	Min	7.5	0.8	5.7	0.03	0.01	0.03	–	0.2
	Max	8.7	2.6	14.0	0.68	0.21	0.49	–	3
	SD	0.061	0.133	3.473	0.021	0.001	0.0042	–	0.40
Dayanzui	Average	8.3	1.7	8.2	0.17	0.026	0.16	1.30	1.62
	Min	8	1.1	5.1	0.01	0.01	0.01	0.33	0.5
	Max	8.7	2.7	12.0	0.53	0.08	0.32	2.43	2.9
	SD	0.030	0.134	2.206	0.017	0.001	0.0038	0.187	0.370

5.1 mg/L. It can be seen that in 2013, the water quality was polluted, and the dissolved oxygen concentration in the reservoir was lower than the surface Class II water standard. At the same time, the COD of the reservoir increased because of the pollution of the water quality of the reservoir in 2013 (Figure 6(b)).

Additionally, NH_4^+-N is the most harmful form of various types of nitrogen. As a nutrient in the water body, it can provide nutrients for algae growth, control ammonia nitrogen to reduce the load of lake reservoir ammonia nitrogen and total nitrogen, and reduce the probability of eutrophication of water bodies. The concentration of NH_4^+-N was high from 2013 to 2014, and the water quality deteriorates at this time. It reached the maximum value of 0.68 mg/L in 2012 at MP1. subsequently, the concentration of NH_4^+-N reached the maximum value in May 2013 at MP2 (Figure 6(d)).

Nitrogen and phosphorus are essential nutrients for biological growth. TN and TP monitoring are crucial for water quality, especially in lakes, reservoirs, bays, and other enclosed waters. Phosphorus enrichment is easy to produce eutrophication, and deterioration of water quality. The TP pollution of the two stations is the most serious. In May 2011, TP reached 0.21 mg/L at MP1, almost 10 times higher than the grade II standard of water quality standard GB3838-2002. The concentration of TP at MP1 is higher than that at MP2 (Figure 6(e)). The annual average concentration of TP at MP1 from 2010 to 2020 varies greatly, varying between 0.033 mg/L and 0.055 mg/L. However, the average total phosphorus concentration fluctuates up and down in the range of 0.05 mg/L, almost twice as much as the Class II water quality standard. In general, the water quality of the reservoir changes due to the changes in the water quality of the inflow monitoring station of shaxiping. Combined with the change in the concentration of each parameter at the two stations, it can be deduced that the water quality of the reservoir is mainly affected by external sources, rather than endogenous pollution.

3.4.2. Correlation analysis

To identify the most important factors affecting CCME-WQI, the relationship between different water quality parameters/inflow (FL) and CCME-WQI in the reservoir was analyzed (Table 4). A significant correlation between the pH, TN, TP, and inflow (FL) and the CCME-WQI is largely found. However, no significant relationship was observed between CCME-WQI and DO or between CCME-WQI and COD_{Mn}, with p-values of 0.849 and 0.120, respectively. While the lowest DO values are correlated with high inflow. The results of a Pearson correlation analysis showed that the CCME-WQI was negatively correlated with the TP ($R=-0.52$, $P<0.01$) (Figure 7(b)). The highest correlation coefficient between TP and CCME-WQI indicates that TP had the greatest effect on water quality. In addition, it was also closely related between TN and CCME-WQI ($R=-0.49$, $P<0.01$) (Figure 7(a)). CCME-WQI is negatively correlated with inflow (Figure 7(c)), while inflow is positively correlated with TN significance (Figure 7(d)), which shows that inflow is an important part of reservoir pollution.

Therefore, TP and TN are the two main key water quality parameters to affect the CCME-WQI. The changing trend of total phosphorus concentration at MP2 before 2014 is opposite to that at MP1, but the changing trend is the same after 2014. Since 2014, reservoir pollution has mainly come from external pollution. This may also indicate that TP in the reservoir is affected by the tributaries upstream of the reservoir. Most studies show that the pollution sources of the reservoir generally come from

Table 4 | Pearson correlation matrix between water quality parameters and the overall CCME-WQI

	pH	COD_{Mn}	DO	NH_4^+-N	TP	TN	F^-	BOD_5	inflow	Water level	CCME-WQI
pH	1	0.0043	0.17	**0.21***	−0.0018	0.15	0.064	0.029	−0.045	**−0.22***	**−0.22***
COD_{Mn}		1	−0.28	0.16	−0.1	−0.2	−0.16	−0.11	0.13	**0.34*****	0.15
DO			1	0.085	0.13	−0.089	0.092	−0.053	**−0.2***	**−0.44*****	−0.019
NH_4^+-N				1	0.07	−0.17	0.15	−0.08	**−0.21***	**−0.23***	−0.035
TP					1	−0.069	−0.13	−0.021	0.0023	0.051	**−0.52*****
TN						1	0.051	0.11	**0.34*****	0.29**	**−0.49*****
F^-							1	0.082	0.0041	−0.12	0.0012
BOD_5								1	0.059	0.15	−0.14
inflow									1	**0.52*****	**−0.2***
Water level										1	−0.19
CCME-WQI											1

The '*' and '***' indicate significant correlation at level of 0.05 and 0.01(bilateral), respectively.

the inflow of tributaries, fish farming (Jia *et al.* 2015), and sediment release (Gao *et al.* 2014), especially the reservoir non-point source pollution (Hsieh *et al.* 2010; Chang & Yu 2020). According to relevant research, Non-point source pollution is the main factor for most reservoirs being polluted (Tong *et al.* 2021).

The elements nitrogen and phosphorus are the main factors affecting reservoir eutrophication. Like most research results, eutrophication is the main reason threatening the reservoir to provide its services (Huang *et al.* 2020). It is very important to control the nitrogen and phosphorus flowing into the reservoir. While TN is affected by the inflow of the reservoir. Inflow was correlated with DO, NH_4^+-N, and TN. The relationship between inflow and other parameters reveals the impact of inflow on the water quality of the Weishui Reservoir. Regulating the inflow plays an important role in improving the water quality of the reservoir. Identifying the impact of reservoir inflow on water quality evaluation results is of great significance to improve the water quality management of Weishui Reservoir.

According to a survey, the livestock and poultry breeding around the reservoir is mainly free range, and the agricultural planting area in the upstream is wide. The reservoir is vulnerable to non-point source pollution, especially domestic non-point source pollution, livestock and poultry breeding pollution, agricultural non-point source pollution, etc.

3.5. Water quality prediction using the ARIMA model

In this paper, the water quality of the Weishui Reservoir is mainly affected by inflow, and non-point source pollution is the main source of water quality deterioration. The application of the time series ARIMA model to the prediction of reservoir water quality can evaluate the water quality dynamics of short-term in the future. Compared with other water quality evaluation methods, it is relatively simple and has high economic benefits. R Studio 4.1.2. is used as a tool to design the ARIMA models. Using the tsdiag function in the stats package in R to test and output three parts of information: (1) residual time series diagram; (2) autocorrelation diagram of residual sequence; (3) white noise test chart of residual sequence. Through the white noise diagram of the residual sequence in the third part, we can judge whether the fitting model is significantly valid. The p value is 0.8177, which indicates that model ARIMA (1,1,1) can better fit the data. The results of the water quality evaluation are shown in Figure 8 below. According to the prediction results, the water quality of the reservoir will be stable in the next two years. CCME-WQI is maintained at about 80.46.

The study of time series data has a wide range of applications in the real world. Using water quality data from the past period to predict water quality in the future is very necessary for regional water quality management. Through the time series model, the time series data can be decomposed, which is conducive to the analysis of the overall trend change of the data and captures the seasonal component of the time series. In addition, seasonal components can be culled from

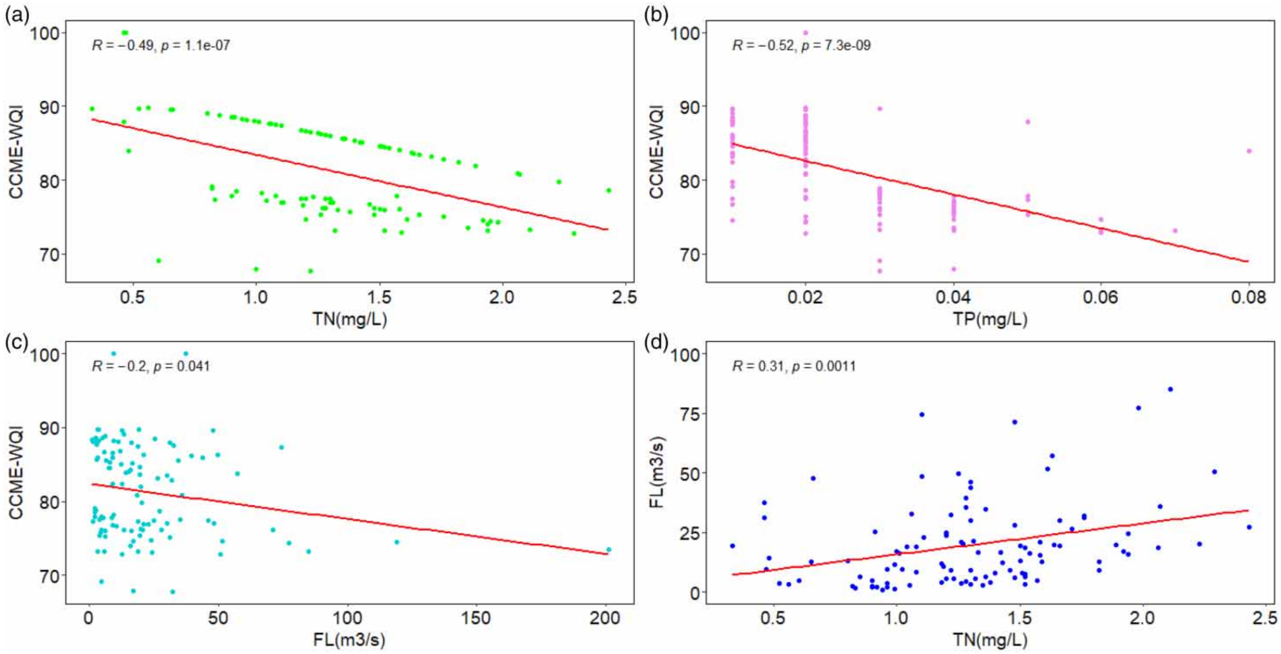


Figure 7 | Correlations between CCME-WQI and parameters TN, TP, inflow (FL); and Correlation between flow and TN.

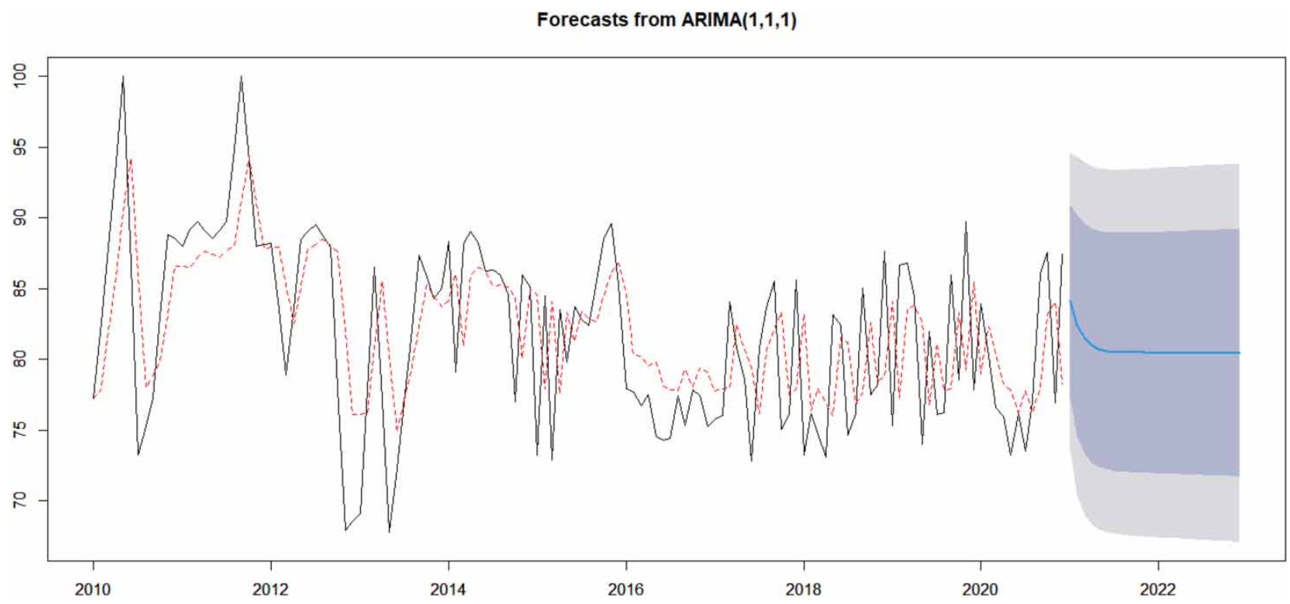


Figure 8 | CCME-WQI sequence fitting and prediction diagram of Weishui Reservoir (In the figure: the solid line is the sequence observation value; the red dotted line and the blue solid line are the model fitting value and prediction value; the dark shadow part is the 80% confidence interval of the prediction value, and the light shadow part is the 95% confidence interval of the prediction value).

time series to achieve seasonal adjustment. Using the ARIMA model to understand the future dynamics of water quality in advance is also conducive to the local government to formulate corresponding policies according to the water quality status.

4. CONCLUSIONS

The water quality of the Weishui Reservoir was severely polluted in 2013, and then gradually recovered in 2018. It was negatively correlated with the inflow of the only major tributary of the reservoir. The key parameters affecting water quality in the reservoir were TN and TP, which were almost 2 times higher than the grade II standard of water quality standard. These indicated that the reservoir is vulnerable to non-point source pollution. Through the ARIMA model, it was predicted that CCME-WQI is maintained at 80.46 indicating that the water quality will be stable in the future. The findings of this study will facilitate the prediction of water quality and better demonstrate the dynamic changes in the water quality of the reservoir. It not only helps to better manage the reservoir but also ensures the safety of drinking reservoirs. In future studies, more models can be explored to improve the accuracy of reservoir water quality predictions and provide technical support for the dynamic monitoring of reservoirs.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Arora, S. & Keshari, A. K. 2021 Pattern recognition of water quality variance in Yamuna River (India) using hierarchical agglomerative cluster and principal component analyses. *Environ. Monit. Assess.* **193** (8), 494. http://dx.doi.org/10.1007/s10661-021-09318-1.

Bi, W., Weng, B., Yuan, Z., Ye, M., Zhang, C., Zhao, Y., Yan, D. & Xu, T. 2018 Evolution characteristics of surface water quality due to climate change and LUCC under scenario simulations: a case study in the Luanhe River Basin. *Int. J. Environ. Res. Public Health* **15** (8). http://dx.doi.org/10.3390/ijerph15081724.

Chang, C. L. & Yu, Z. E. 2020 Application of water quality model to analyze pollution hotspots and the impact on reservoir eutrophication. *Environ. Monit. Assess.* **192** (8), 495. http://dx.doi.org/10.1007/s10661-020-08463-3.

Characklis, G. W., Dilts, M. J., Simmons 3rd, O. D., Likirdopulos, C. A., Krometis, L. A. & Sobsey, M. D. 2005 Microbial partitioning to settleable particles in stormwater. *Water Res.* **39** (9), 1773–1782. http://dx.doi.org/10.1016/j.watres.2005.03.004.

Cheng, L., Tan, X., Yao, D., Xu, W., Wu, H. & Chen, Y. 2021 A fishery water quality monitoring and prediction evaluation system for floating UAV based on time series. *Sensors (Basel)* **21** (13). http://dx.doi.org/10.3390/s21134451.

Chyon, F. A., Suman, M. N. H., Fahim, M. R. I. & Ahmmed, M. S. 2021 Time series analysis and predicting COVID-19 affected patients by ARIMA model using machine learning. *J. Virol. Methods* **301**, 114433. http://dx.doi.org/10.1016/j.jviromet.2021.114433.

Cong, V. H., Lam, N. T., Nui, N. H., Thao, T. P., Giang, N. T. H. & Son, C. T. 2020 Assessment of Cau River water quality assessment using a combination of water quality and pollution indices. *J. Water Supply Res. Technol. AQUA* **69** (2), 160–172. http://dx.doi.org/10.2166/aqua.2020.122.

Cooper, J. R. & Tait, S. J. 2008 The spatial organisation of time-averaged streamwise velocity and its correlation with the surface topography of water-worked gravel beds. *Acta Geophys.* **56** (3), 614–641. http://dx.doi.org/10.2478/s11600-008-0023-0.

Dai, J., Jia, B., Luo, W., Mostafaei, A. & Zhu, S. 2019 Assessing water quality for urban tributaries of the Three Gorges Reservoir, China. *Journal of Water Reuse and Desalination* **9** (1), 105–114. http://dx.doi.org/10.2166/wrd.2018.010.

Deininger, R. A. 2009 A water quality index for rivers. *Water Int.* **5** (3), 16–21. http://dx.doi.org/10.1080/02508068008685872.

Duan, W., He, B., Chen, Y., Zou, S., Wang, Y., Nover, D., Chen, W. & Yang, G. 2018 Identification of long-term trends and seasonality in high-frequency water quality data from the Yangtze River basin, China. *PLoS One* **13** (2), e0188889. http://dx.doi.org/10.1371/journal.pone.0188889.

El-Hames, A. S., Hannachi, A., Al-Ahmadi, M. & Al-Amri, N. 2013 Groundwater quality zonation assessment using GIS, EOFs and hierarchical clustering. *Water Resour. Manage.* **27** (7), 2465–2481. http://dx.doi.org/10.1007/s11269-013-0297-0.

Gao, B., Wei, X., Zhou, H., Lu, J., Hao, H. & Wan, X. 2014 Pollution characteristics and possible sources of seldom monitored trace elements in surface sediments collected from Three Gorges Reservoir, China. *Sci. World J.* **2014**. 170639. http://dx.doi.org/10.1155/2014/170639.

Gao, Q., Li, Y., Cheng, Q., Yu, M., Hu, B., Wang, Z. & Yu, Z. 2016 Analysis and assessment of the nutrients, biochemical indexes and heavy metals in the Three Gorges Reservoir, China, from 2008 to 2013. *Water Res.* **92**, 262–274. http://dx.doi.org/10.1016/j.watres.2015.12.055.

Gikas, G. D., Sylaios, G. K., Tsihrintzis, V. A., Konstantinou, I. K., Albanis, T. & Boskidis, I. 2020 Comparative evaluation of river chemical status based on WFD methodology and CCME water quality index. *Sci. Total Environ.* **745**, 140849. http://dx.doi.org/10.1016/j.scitotenv.2020.140849.

Gu, Q., Deng, J., Wang, K., Lin, Y., Li, J., Gan, M., Ma, L. & Hong, Y. 2014 Identification and assessment of potential water quality impact factors for drinking-water reservoirs. *Int. J. Environ. Res. Public Health* **11** (6), 6069–6084. http://dx.doi.org/10.3390/ijerph110606069.

Han, Q., Tong, R., Sun, W., Zhao, Y., Yu, J., Wang, G., Shrestha, S. & Jin, Y. 2020 Anthropogenic influences on the water quality of the Baiyangdian Lake in North China over the last decade. *Sci. Total Environ.* **701**, 134929. http://dx.doi.org/10.1016/j.scitotenv.2019.134929.

Horton, R. K. 1965 An index-number system for rating water quality. In: *Water Quality Criteria-Stream vs. Effluent Standards, Water Pollut Control Federation*. pp. 292–315. http://doi.org/10.2307/25035201.11.

Hou, W., Sun, S., Wang, M., Li, X., Zhang, N., Xin, X., Sun, L., Li, W. & Jia, R. 2016 Assessing water quality of five typical reservoirs in lower reaches of Yellow River, China: using a water quality index method. *Ecol. Indic.* **61**, 309–316. http://dx.doi.org/10.1016/j.ecolind.2015.09.030.

Hsieh, P.-H., Kuo, J.-T., Wu, E. M.-Y., Ciou, S.-K. & Liu, W.-C. 2010 Optimal best management practice placement strategies for nonpoint source pollution management in the Fei-Tsui reservoir watershed. *Environ. Eng. Sci.* **27** (6), 441–449. http://dx.doi.org/10.1089/ees.2010.0003.

Huang, L., Mo, Y., Wu, Z., Rad, S., Song, X., Zeng, H., Bashir, S., Kang, B. & Chen, Z. 2020 Occurrence, distribution, and health risk assessment of quinolone antibiotics in water, sediment, and fish species of Qingshitan reservoir, South China. *Sci. Rep.* **10** (1), 15777. http://dx.doi.org/10.1038/s41598-020-72324-9.

Hubei Provincial Department of Water Resources 2013 *Hubei Water Resources Bulletin*. Available from: http://slt.hubei.gov.cn/bsfw/cxfw/szygb/201911/t20191129_1549966.shtml.

Jia, B., Tang, Y., Tian, L., Franz, L., Alewell, C. & Huang, J. H. 2015 Impact of fish farming on phosphorus in reservoir sediments. *Sci. Rep.* **5**, 16617. http://dx.doi.org/10.1038/srep16617.

Jingchu Net – Chutian Metropolis Daily Photo: Water bloom erupts in Songziweishui Reservoir. Available from: https://www.163.com/news/article/9ICASB2600014Q4P.html.

John, C. K., Pu, J. H., Moruzzi, R. & Pandey, M. 2021 Health-risk assessment for roof-harvested rainwater via QMRA in Ikorodu area, Lagos, Nigeria. *J. Water Clim. Change* **12** (6), 2479–2494. http://dx.doi.org/10.2166/wcc.2021.025.

Khan, F. M. & Gupta, R. 2020 ARIMA and NAR based prediction model for time series analysis of COVID-19 cases in India. *J. Saf. Sci. Resilience* **1** (1), 12–18. http://dx.doi.org/10.1016/j.jnlssr.2020.06.007.

Kim, T. & King, B. R. 2020 Time series prediction using deep echo state networks. *Neural Comput. Appl.* **32** (23), 17769–17787. http://dx.doi.org/10.1007/s00521-020-04948-x.

Krometis, L. A., Noble, R. T., Characklis, G. W., Denene Blackwood, A. & Sobsey, M. D. 2013 Assessment of E. coli partitioning behavior via both culture-based and qPCR methods. *Water Sci. Technol.* **68** (6), 1359–1369. http://dx.doi.org/10.2166/wst.2013.363.

Li, P. & Wu, J. 2019 Drinking water quality and public health. *Exposure Health* **11** (2), 73–79. http://dx.doi.org/10.1007/s12403-019-00299-8.

Lumb, A., Halliwell, D. & Sharma, T. 2006 Application of CCME water quality index to monitor water quality: a case study of the Mackenzie River Basin, Canada. *Environ. Monit. Assess.* **113** (1–3), 411–429. http://dx.doi.org/10.1007/s10661-005-9092-6.

Nabizadeh, R., Valadi Amin, M., Alimohammadi, M., Naddafi, K., Mahvi, A. H. & Yousefzadeh, S. 2013 Development of innovative computer software to facilitate the setup and computation of water quality index. *J. Environ. Health Sci. Eng.* **11** (1), 1. http://dx.doi.org/10.1186/2052-336X-11-1.

Praus, P. 2019 Principal component weighted index for wastewater quality monitoring. *Water* **11** (11). http://dx.doi.org/10.3390/w11112376.

Qin, G., Liu, J., Xu, S. & Sun, Y. 2021 Pollution source apportionment and water quality risk evaluation of a drinking water reservoir during flood seasons. *Int. J. Environ. Res. Public Health* **18** (4). http://dx.doi.org/10.3390/ijerph18041873.

Razmkhah, H., Abrishamchi, A. & Torkian, A. 2010 Evaluation of spatial and temporal variation in water quality by pattern recognition techniques: a case study on Jajrood River (Tehran, Iran). *J. Environ. Manage.* **91** (4), 852–860. http://dx.doi.org/10.1016/j.jenvman.2009.11.001.

Roselli, L., Fabbrocini, A., Manzo, C. & D'Adamo, R. 2009 Hydrological heterogeneity, nutrient dynamics and water quality of a non-tidal lentic ecosystem (Lesina Lagoon, Italy). *Estuarine Coastal Shelf Sci.* **84** (4), 539–552. http://dx.doi.org/10.1016/j.ecss.2009.07.023.

Shen, Z., Hong, Q., Yu, H. & Liu, R. 2008 Parameter uncertainty analysis of the non-point source pollution in the Daning River watershed of the Three Gorges Reservoir Region, China. *Sci. Total Environ.* **405** (1–3), 195–205. http://dx.doi.org/10.1016/j.scitotenv.2008.06.009.

Shen, Z., Qiu, J., Hong, Q. & Chen, L. 2014 Simulation of spatial and temporal distributions of non-point source pollution load in the Three Gorges Reservoir Region. *Sci. Total Environ.* **493**, 138–146. http://dx.doi.org/10.1016/j.scitotenv.2014.05.109.

State Environmental Protection Administration 2002 *Standard Methods for the Examination of Water and Wastewater(Version 4)*. China Environmental Science Press, Beijing, China.

Tian, L., Li, H., Li, F., Li, X., Du, X. & Ye, X. 2018 Identification of key influence factors and an empirical formula for spring snowmelt-runoff: a case study in mid-temperate zone of northeast China. *Sci. Rep.* **8** (1), 16950. http://dx.doi.org/10.1038/s41598-018-35282-x.

Tong, X., Zhou, Y., Liu, J., Qiu, P. & Shao, Y. 2021 Non-point source pollution loads estimation in Three Gorges Reservoir Area based on improved observation experiment and export coefficient model. *Water Sci. Technol.*. http://dx.doi.org/10.2166/wst.2021.508.

Uddin, M. G., Nash, S. & Olbert, A. I. 2021 A review of water quality index models and their use for assessing surface water quality. *Ecol. Indic.* **122**. http://dx.doi.org/10.1016/j.ecolind.2020.107218.

Venkatramanan, S., Chung, S. Y., Ramkumar, T., Rajesh, R. & Gnanachandrasamy, G. 2015 Assessment of groundwater quality using GIS and CCME WQI techniques: a case study of Thiruthuraipoondi city in Cauvery deltaic region, Tamil Nadu, India. *Desalin. Water Treat.* **57** (26), 12058–12073. http://dx.doi.org/10.1080/19443994.2015.1048740.

Wang, Z., Wang, T., Liu, X., Hu, S., Ma, L. & Sun, X. 2020 Water level decline in a reservoir: implications for water quality variation and pollution source identification. *Int. J. Environ. Res. Public Health* **17** (7). http://dx.doi.org/10.3390/ijerph17072400.

Wang, X., Li, Z. & Li, M. 2018 Impacts of climate change on stream flow and water quality in a drinking water source area, Northern China. *Environmental Earth Sciences* **77** (11). http://dx.doi.org/10.1007/s12665-018-7581-5.

Wu, D., Yan, H., Shang, M., Shan, K. & Wang, G. 2017a Water eutrophication evaluation based on semi-supervised classification: a case study in Three Gorges Reservoir. *Ecol. Indic.* **81**, 362–372. http://dx.doi.org/10.1016/j.ecolind.2017.06.004.

Wu, Z., Zhang, D., Cai, Y., Wang, X., Zhang, L. & Chen, Y. 2017b Water quality assessment based on the water quality index method in Lake Poyang: the largest freshwater lake in China. *Sci. Rep.* **7** (1), 17999. http://dx.doi.org/10.1038/s41598-017-18285-y.

Yan, M., Chen, S., Huang, T., Li, B., Li, N., Liu, K., Zong, R., Miao, Y. & Huang, X. 2020 Community compositions of phytoplankton and eukaryotes during the mixing periods of a drinking water reservoir: dynamics and interactions. *Int. J. Environ. Res. Public Health* **17** (4). http://dx.doi.org/10.3390/ijerph17041128.

Ye, R., Liu, L., Wang, Q., Ye, X., Cao, W., He, Q. & Cai, Y. 2017 Identification of coastal water quality by multivariate statistical techniques in two typical bays of northern Zhejiang Province, East China Sea. *Acta Oceanolog. Sin.* **36** (2), 1–10. http://dx.doi.org/10.1007/s13131-017-0981-7.

You, Q., Fang, N., Liu, L., Yang, W., Zhang, L. & Wang, Y. 2019 Effects of land use, topography, climate and socio-economic factors on geographical variation pattern of inland surface water quality in China. *PLoS One* **14** (6), e0217840. http://dx.doi.org/10.1371/journal.pone.0217840.

Zeng, J., Huang, G., Luo, H., Mai, Y. & Wu, H. 2019 First flush of non-point source pollution and hydrological effects of LID in a Guangzhou community. *Sci. Rep.* **9** (1), 13865. http://dx.doi.org/10.1038/s41598-019-50467-8.

Zhang, T., Ni, J. & Xie, D. 2016 Assessment of the relationship between rural non-point source pollution and economic development in the Three Gorges Reservoir Area. *Environ. Sci. Pollut. Res. Int.* **23** (8), 8125–8132. http://dx.doi.org/10.1007/s11356-016-6344-7.

Zhao, P., Li, Z., Zhang, R., Pan, J. & Liu, Y. 2020 Does water diversion project deteriorate the water quality of reservoir and downstream? A case-study in Danjiangkou reservoir. *Global Ecol. Conserv.* **24**. http://dx.doi.org/10.1016/j.gecco.2020.e01235.

Zitko, V. 2006 Comments on Ouyang, Y., Evaluation of river water quality monitoring stations by principal component analysis. Water Research 39 (2005) 2621-2635. *Water Res.* **40** (16), 3141–3143. http://dx.doi.org/10.1016/j.watres.2006.07.001.

Zotou, I., Tsihrintzis, V. A. & Gikas, G. D. 2020 Water quality evaluation of a lacustrine water body in the Mediterranean based on different water quality index (WQI) methodologies. *J. Environ. Sci. Health. Part A Toxic/Hazard. Subst. Environ. Eng.* **55** (5), 537–548. http://dx.doi.org/10.1080/10934529.2019.1710956.

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