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Effects and prediction of nonpoint source pollution on the structure of aquatic food webs

Chang S. Zhao[1,5] | Xu Pan[1] | Sheng T. Yang[1] | Hua Xiang[2] | Jin Zhao[2] | Xin J. Gan[2] | Su Y. Ding[2] | Qiang Yu[3,4]

[1]College of Water Sciences, Beijing Key Laboratory of Urban Hydrological Cycle and Sponge City Technology, Beijing Normal University, Beijing, China

[2]Jinan Survey Bureau of Hydrology and Water Resources, Jinan, China

[3]State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Yangling, China

[4]School of Life Sciences, University of Technology Sydney, Sydney, New South Wales, Australia

[5]ICube, UdS, CNRS (UMR 7357), Illkirch, France

Correspondence
Sheng Tian Yang, College of Water Sciences, Beijing Key Laboratory of Urban Hydrological Cycle and Sponge City Technology, Beijing Normal University, Beijing 100875, China.
Email: pacorrespondence@126.com

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Abstract

Nonpoint source pollution entering rivers will pollute water quality, degrading the health of aquatic ecosystems. However, owing to the lack of quantitative research on the effects of nonpoint source pollution on the structure of aquatic food webs, there is a lack of quantitative basis for river management. Nonpoint source pollution is not only difficult to control effectively, but also the success rate of water ecological restoration projects is low. With the increasing proportion of nonpoint source pollution in water environmental problems, it is urgent to quantitatively assess and predict the impact of nonpoint source pollution on the structure of food webs. Therefore, this thesis presents a method for quantitatively assessing and predicting the impact of nonpoint source pollution on the structure of food webs through using fuzzy clustering to screen the typical points of the impact of nonpoint source pollution, then using canonical correspondence analysis (CCA) and partial least squares regression analysis to comprehensively filtrate the driving factors affect food web that results in nonpoint source pollution, and then determining the impact of each driving factor on the structure of food webs. Finally, the change trend of food web structure is predicted. The results show that (1) the driving factors that the nonpoint source pollution that affects the food web structure is NH_3-N and chemical oxygen demand (COD). The increase in NH_3-N and COD promotes the growth of phytoplankton, causing the change of the primary productivity of the ecosystem, and ultimately changes the entire food web structure; (2) NH_3-N and COD affect the stability, maturity, connectivity and complexity of the aquatic food web structure. The increase of NH_3-N increases the connectivity and maturity of the food web structure but reduces complexity and stability; the increase of COD increases the connection of the food web structure, while reducing the other three indicators; (3) in some areas with good water quality, aquatic species diversity is high, the relationship of interspecies dietary is complex, food web structure level index is high and the structure of food web is stable. The food web structure in the rainy season will be better than that in the dry season. In some areas with severe water pollution and poor food web structure, the ability of the food web to resist external interference is weak. The food web structure in the rainy season will be worse than that in the dry season owing to rainfall into the river. The methods and conclusions in this treatise can provide a reliable and quantitative scientific basis for river ecosystem management and ecosystem restoration and can improve the success rate of ecological restoration projects.

KEYWORDS

aquatic ecosystem, aquatic food webs, Jinan City, nonpoint source pollution

1 | INTRODUCTION

Nonpoint source pollution has a great impact on river water quality, which changes the water quality of the river, and has a great impact on ecosystems, leading to a great change in the food web structure of river aquatic ecosystems (Coll, Schmidt, Romanuk, & Lotze, 2011; Garay-Narváez, Arim, Fores, & Ramos-jiliberto, 2013; Perkins, Reiss, Yvon-Durocher, & Woodward, 2010), and even seriously affected the ecological value provided by the freshwater ecosystem.

Nonpoint sources and point sources of contaminants constitute most pollution in waters. Point source pollution has been reduced significantly as a result of pollutants source control policies (Zhang, Liu, Zhang, Dahlgren, & Eitzel, 2010). However, in recent years, with rapid socio-economic development, environmental conditions are dramatically changing in many rural regions of developing countries (Kanagawa & Nakata, 2008; Majumder, 2015), and consequently, nonpoint source inorganic pollutants (e.g., nitrogen [N], phosphorus [P], sediments and metals) and organic pollutants (e.g., pesticides and pharmaceutical residues), human pathogens and estrogenic and androgenic compounds, including those from untreated domestic sewage and agricultural sources (i.e., agricultural land, manure, animal feedlots and aquaculture), have polluted rivers, lakes and reservoirs (Adindu, 2019; du Plessis, 2019) and severely deteriorated the food web and its functions. The harm of nonpoint source pollution to the water body is the change of river water quality caused by pollutants entering as the result of rainfall erosion. The main water quality factors include NH_3-N, TN, TP, chemical oxygen demand (COD), biochemical oxygen demand (BOD) and total dissolved solids, of which TP, TN, NH_3-N and COD are important factors affecting the health of aquatic ecosystems (Kuo et al., 2016; Song et al., 2012; Zhou et al., 2019).

In aquatic ecosystems, the food web is a network comprising various organisms and their nutritional relationships, which is formed via the interactions among communities and species (Post, 2002). It describes the complex nutritional interactions of different organisms in biological communities and reveals the material and energy flow of the entire ecosystem. A food web is very sensitive to changes in the biodiversity and the intensity of interactions between organisms in ecosystems (Post & Takimoto, 2007). A food web with a higher level of complexity indicates that it has greater ecosystem resilience to external disturbances (Peralta-Maraver, Lopez-Rodriguez, & de Figueroa, 2017). Research on this topic makes it easier to insight into the flow of material and energy, the composition and structure of the biological communities, and the complex feeding relationship among species (Baird & Ulanowicz, 1989; McIntyre, Jones, Flecker, & Vanni, 2007). It functions as the basis for making ecosystem-based ecological protection and restoration decisions (Harvey, Gounand, Ward, & Altermatt, 2017; McCann, 2007).

According to the First National Survey of Pollution Sources Bulletin of China, rural nonpoint source pollution includes approximately half of the total water pollution, accounting for 57% of the total N and 67% of the total P. Nonpoint source pollution has become the principal source for water pollution in China and severely damaged aquatic ecosystems. It resulted in changes in water quality factors that affect the hierarchy and structure of the ecosystem (Zhao et al., 2018) and the integrity of the food web (Carvalho, Williner, Ciri, Vaccari, & Collins, 2016), deeply influencing ecosystem functions and services (Hemraj, Hossain, Ye, Qin, & Leterme, 2017; Robson et al., 2017). However, there is currently a lack of quantitative research on the impact of nonpoint source pollution on the structure of aquatic food webs. With the increasing proportion of nonpoint source pollution in water environmental problems, it is urgent to quantitatively assess and predict the impact of nonpoint source pollution on the food web structure to restrict and reduce the interference of human activities on the ecosystem, so as to improve the ecosystem functions and services and provide a reliable scientific basis for river ecosystem management and ecosystem restoration (Mor et al., 2018; Sabo, Finlay, Kennedy, & Post, 2010).

So the main objective of this study is to quantitatively analyse and predict the effects of nonpoint source pollution on the structure of aquatic food webs. First of all, the change process of nonpoint source pollution in rivers with rainfall was studied, and then the structural level changes of aquatic food webs in rivers at different periods were analysed. Finally, the changes in the structure level of aquatic food webs due to the effects of nonpoint source pollution were obtained. It concludes that the study will provide scientific and effective basis for river ecosystem restoration and management.

2 | STUDY AREA

In recent years, China proposed the economic development while considering the protection of ecosystems to achieve a natural environment that can sustain economic and social development.

Therefore, China launched a project for ecologically civilized cities used to explore different types of models and experiences for the construction of civilized water ecosystems. In 2016, Jinan City (36.0–37.5°N, 116.2–117.7°E) became a first pilot city in the construction of civilized and freshwater ecological cities of China (Figure 1). The success of urban aquatic ecosystem restoration will determine the fundamental improvement of the living environment of the Chinese people (Zhang, Shao, & Xu, 2010). Hilly areas, piedmont clinoplain and alluvial plains span the city from north to south. The altitude within the area ranges from −30 to 937 m ASL, with highly contrasting relief (Cui, Wang, Tao, & You, 2009; Zhang, Liu, et al., 2010). With rapid industrial development and urbanization in recent decades, the water resources in Jinan have been severely polluted and reduced in quantity because of extraction. Consequently, human health and well-being, aquatic plants and animals, and the food webs they form are becoming increasingly threatened (Hong, Meng, Wang, Wang, & Liu, 2010). In order to explore the effect of pollution discharge on the aquatic ecosystem, 48 stations for the hydrology-water quality-aquatic ecosystem monitoring were set up in the city.

3 | MATERIALS AND METHODS

3.1 | Data

3.1.1 | Water quality factor

In the spring, summer and autumn of 2015 and 2016, seven large-scale field investigations measured 37 hydrological, water quality physical and water quality chemical factors (Table 1) and concurrently sampled the principal communities in a food web inclusive of phytoplankton, zooplankton, zoobenthos and fish.

The physical parameters were measured in situ using portable equipment, and the chemical parameters were obtained by testing

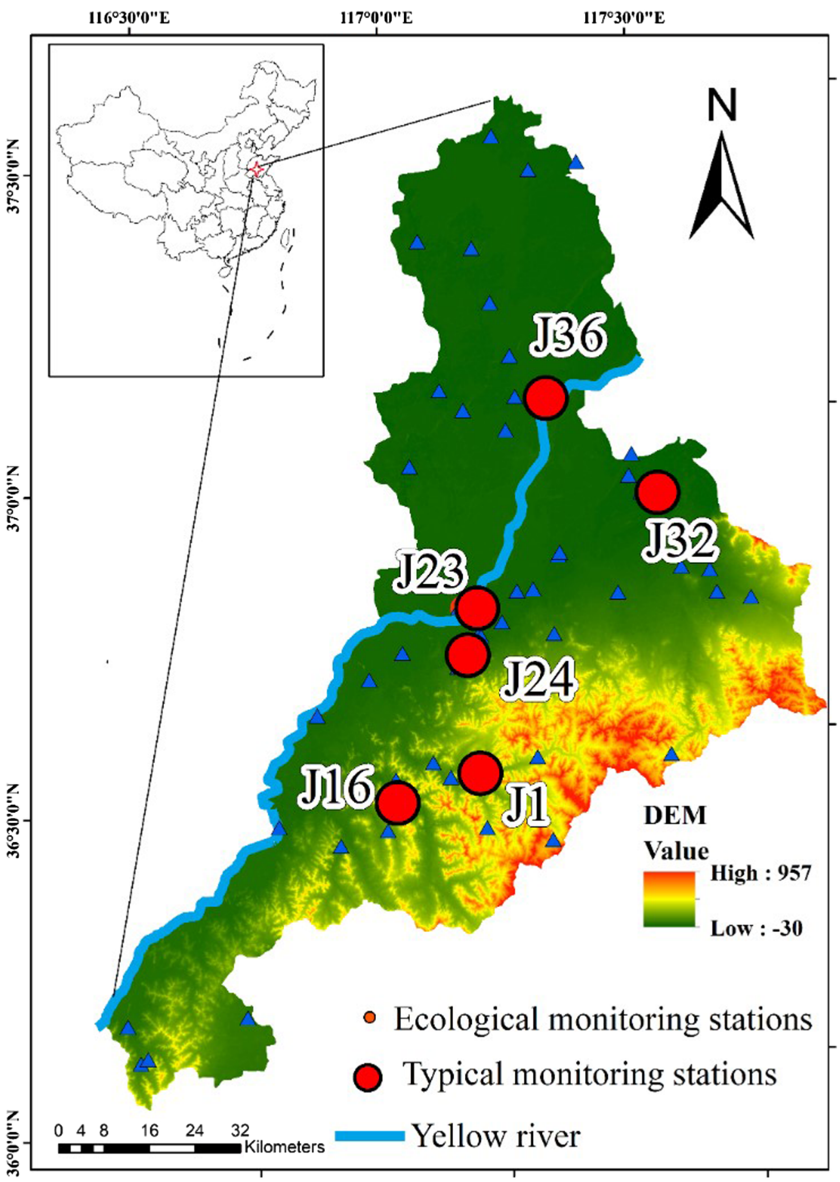

FIGURE 1 Map of the Jinan City ecological monitoring stations and typical stations

water samples in the laboratory within 24 h after they were collected at monitoring sites. A spectrophotometer (DR5000) was used to measure NH_3-N, TP, TN and hexavalent chromium; an atomic absorption spectrophotometer (Thermo M6) was used to measure copper, zinc, cadmium, lead and so forth; and an ion chromatograph (DIONEX-600) was used to measure SO_4, fluoride, chloride and nitrate concentrations (Zhao et al., 2015).

3.1.2 | Hydrological factor

The hydrological data collected are shown in Table 2 based on the flow data obtained from the seven aquatic ecological sampling in Jinan City and the historical data of daily rainfall during the flood season at nine rainfall stations in Jinan City. Among them, the daily scale rainfall data during the flood season are used to predict the nonpoint source pollution and calculate the concentration of nonpoint source pollution into the river based on the measured flow data. The years with missing flow data are interpolated according to historical monitoring data.

Hydrological parameters, such as water depth and flow velocity, were routinely monitored. The flow velocity was measured using a radio flow meter (Stalker II SVR V1.0) and traditional flow meter (LS25-1) to ensure accuracy of results. Water depth and river width were measured using a tape gauge, and flow was calculated from the flow velocity, water depth and cross-sectional area. An unmanned aerial vehicle was used to retrieve river-course cross-sections with high-resolution stereoscopic images (Zhao et al., 2017).

TABLE 2 Hydrological factors

Station			Date
Monitoring stations	J1	Flow	5/2015–11/2016
	J14		
	J23		
	J24		
	J32		
	J36		
Rainfall stations	JY	Rainfall	6/2014–9/2018
	JJY		
	QJZ		
	LCQFB		
	JNDXDXX		
	JNSSZ		
	QD		
	HJT		
	JZ		

3.1.3 | Aquatic data

Sampling of phytoplankton, zooplankton, zoobenthos and fish was carried out simultaneously with water quality and hydrological factors.

For phytoplankton, a 1,000-ml organic glass bottle was used to sample water in the range 0–2 m below water surface. Subsequently, 1.5% concentration Lugol's solution was added to the bottle as quickly as possible. In the laboratory, the sample was first set aside for more

TABLE 1 Water quality chemical factors monitored in the Jinan City monitoring program

Factors	Name	Units	Range (SD)
Ca	Calcium	mg/L	17.63–315.83 (58.39)
Cl	Chlorine		11.85–786.15 (176.39)
SO_4	Sulfate		43.47–932.22 (179.28)
CO_3	Carbonate		0–12.50 (2.83)
HCO_3	Bicarbonate		50.05–845.32 (132.11)
TA	Total alkalinity		51.48–693.35 (107.60)
TH	Total hardness		141.12–989.89 (198.71)
DO	Dissolved oxygen		1.17–9.92 (2.41)
TN	Total nitrogen		0.25–21.84 (4.18)
NH_3-N	Ammonia nitrogen		0.07–9.42 (2.63)
NO_2-N	Nitrite		0–1.41 (0.30)
NO_3-N	Nitrate		0.05–18.85 (2.90)
COD	Chemical oxygen demand		6.32–130.61 (20.84)
COD_Mn	Permanganate index		0.57–16.36 (3.34)
BOD	Biochemical oxygen demand		0–35.80 (7.39)
TP	Total phosphorus		0–3.64 (0.78)
Fluoride	Fluoride		0.18–2.30 (0.49)

Abbreviation: SD, standard deviation.

than 24 h. Then it was concentrated into 30 ml, 0.1 ml of which was extracted and transfused into 0.1-ml plankton counting chamber. Finally, a microscope was used to classify and count phytoplankton (Zhao et al., 2010).

For zooplankton, the sampling methods of protozoon and rotifera are the same as those of phytoplankton. When sampling cladocera and copepods, a 10-L organic glass bottle was used to obtain water. Subsequently, this water sample was filtered and concentrated into 5 ml using a 200-mesh or 125-mesh plankton net. Finally, 4% concentration formaldehyde was added. The number of protozoon and rotifera was determined via the same method as phytoplankton. The method used for cladocera and copepods is different. The 10-L water sample was fully concentrated, and all cladocera and copepods were classified and counted (Zhao et al., 2010).

For zoobenthos, an oyster bucket harvester with a mouth area of 29 × 29 cm was used to dig substrate sludge. Subsequently, the substrate sludge was washed with a 60-mesh filter. Finally, zoobenthos were extracted, and 75% concentration alcoholic solution was added. Owing to the bigger size of zoobenthos, they are usually directly classified and counted with eyes. All aquatic organisms were weighed by using a torque balance or a pharmaceutical scale and classified by using aquatic organism atlas (Zhao et al., 2017).

Concurrently, fish were collected during 30-min periods in three habitat types (i.e., pools, riffles and runs) within 500 m of the river at each sampling site. Specimens caught from the three habitats were combined to represent a site. In wadeable streams, fish were collected by a two-person team (Barbour, Gerritsen, Snyder, & Stribling, 1999). In unwadeable streams, seine nets (mesh sizes of 30 and 40 mm) were used to collect fish from a boat. Furthermore, electrofishing was performed to ensure that a good representation of fish species was collected at each site. All individuals collected were identified in situ according to Chen et al. (1987) and thereafter counted, weighed and recorded in field data sheets. Subsequently, all identified fish were released. A few specimens that could not be identified in the field were preserved in 10% formalin solution and stored in labelled jars for subsequent laboratory identification (Zhao et al., 2017).

3.2 | Method

First of all, based on the water quality factors of nonpoint source pollution, the sampling points are clustered by using fuzzy clustering methods (FCMs) to determine the typical points of nonpoint source pollution. After that, the food web model of typical points is established to obtain the index of food web structure, and then the partial least squares regression (PLSR) analysis method is used to determine the important factors affecting food web structure in nonpoint source pollution. Finally, by coupling canonical correspondence analysis (CCA) and PLSR analysis method, the influence of important factors of nonpoint source pollution on food web structure and the change of the food web structure is determined to predict the changes of food web structure.

3.2.1 | Fuzzy clustering to determine typical points of nonpoint source pollution

In order to analyse the impact of nonpoint source pollution on the structure of aquatic ecological food web, the sampling points are clustered by fuzzy clustering to determine typical points with large differences in spatial of nonpoint source pollution impact. The influence of nonpoint source pollution water quality factors on the structure of food web can be obtained by fuzzy cluster analysis. Then the centre point selection principle is used to select typical points in each cluster. Finally, food web model is established to obtain food web structure index to analyse the effect of nonpoint source pollution factors on food web structure.

Clustering is important for pattern recognition, classification, model reduction and optimization. Clustering analysis can be performed using the traditional hard clustering method or the FCM. The hard clustering method is more suitable for clustering conditions with clear boundaries, whereas for problems with unclear boundaries, an FCM is usually adopted (Pan, 2010; Zhao et al., 2013). In this study, monitoring stations distribute randomly covering the whole study area, and it is hard to find clear boundaries. Therefore, clustering with FCM is the best choice. The advantage of this algorithm is that it can effectively avoid setting thresholds and can solve the difficult problem of multiple branches in threshold segmentation. To facilitate calculation, data in a (n * m) matrix were pre-processed using the model $x'_{ij} = \left\{ \left[\left(x_{ij} - \bar{x_j} \right) \right] / \left[\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(x_{ij} - \bar{x_j} \right)} \right] \right\}$ (I = 1, …, n; j = 1, …, m) with the average value $\bar{x_j} = \sum_{i=1}^{n} \left(x_{ij}/n \right)$. During the establishment of a similar matrix, the widely used Euclidean distance $\left(r_{ij} = 1 - \left\{ \left[\sqrt{\sum_{k=1}^{m} \left(x_{ik - x_{jk}} \right)^2} \right] / \left[\max \left(\sqrt{\sum_{k=1}^{m} \left(x_{ik} - x_{jk} \right)^2} \right) \right] \right\} \right)$ was adopted (Zhao et al., 2013).

3.2.2 | Identification of important factors of nonpoint source pollution

The food web model is established at each typical point to obtain structural index of the food web. Then the PLSR analysis is carried out. According to the different impacts, the important factors of water quality that affect the structural characteristics of food webs are determined. The pollution factors related to nonpoint source pollution are selected for analysis.

The ecopath model provides a quantitative and comprehensive analysis of the structure of the ecosystem, the processes of nutrient flow and the characteristics of nutrient dynamics. First, indices of food web structure were extracted from the established ecopath models. The effects of these indices on the complexity, connectance, stability and maturity of food web structure were thereafter retrieved from the relevant results obtained by scientists worldwide in the last 10 years. The key indices most indicative of food web structure were screened out for later use. As shown in our study, the indices for food web structure mainly include biodiversity (Abonyi et al., 2018; Mor et al., 2018; Thompson et al., 2018), food chain length (Mendonça & Vinagre, 2018; Morillo-Velarde et al., 2018), Shannon's index (Liu, Chen, et al., 2016; Liu, Xiang, et al., 2016), connectance index (Marina et al., 2018), system omnivory index (Wang, Peng, Su, & Cheng, 2017) and total primary production/total respiration (Chen, Xu, & He, 2011; Xu, Chen, Li, & He, 2011).

The PLSR analysis is an extension of multiple regression analysis that evaluates the effects of linear combinations of several predictors on a response variable. This technique can be used to determine the relationship between two sets of variables, the matrix $Xm \times n$, which consists of m variables (columns) and n objects (rows), and a response vector $Yn \times 1$. The PLSR identifies a few linear combinations of the original x values that describe most of the inherent variable (Hu et al., 2018).

Variable importance in the project (VIP) is an indicator obtained during the calculation of PLSR, which can be used to measure the importance of the independent variable to the dependent variable. The VIP of the independent variable is greater than 1, indicating that the independent variable plays a more important role; when the VIP value is between 0.5 and 1, the explanatory effect of the independent variable is not obvious, whereas when VIP is less than 0.5, the independent variable has little explanatory role for the dependent variable (Afanador, Tran, & Buydens, 2013; Hu et al., 2018; Sun et al., 2018). The calculation method is as follows:

$$VIP_j = \sqrt{\left(p \sum_{h=1}^{m} R(Y,T_h) w_{hj}^2 \Big/ \sum_{h=1}^{m} R(Y,T_h)\right.}. \tag{1}$$

Among them, p is the number of independent variables, m is the number of components extracted from the original variables by the partial least squares method, T_h represents the hth component and $R(Y,T_h)$ represents the explanatory power of component T_h to the dependent variable Y, which is equal to the square of the correlation coefficient between the two; w_{hj} is the jth component of the axis w_h, and w_h is the eigenvector of the $X_{h-1}^T Y_{h-1} Y_{h-1}^T X_{h-1}$.

3.2.3 | Analysis of the impact of nonpoint source pollution on food web structure

Based on seven times of water quality monitoring data in 2 years, the water quality data in dry season are taken as the river water quality under the influence of point source pollution, and the water quality monitoring data after rainfall in rainy season are used as the water quality data under the influence of point source pollution and nonpoint source pollution, and the difference between the two values (hereinafter referred to as '△ value') is taken as the impact of nonpoint source pollution on water quality. CCA was performed on the water quality factors at the time of sampling and the corresponding food web structural indicators, and then the nonpoint source pollution factors (NH_3-N and COD) and the changes in food web structural index are analysed by VIP and fitted by curve relationship, and finally, the effect of important factors of nonpoint source pollution on the food web structure is quantitatively analysed. Before CCA, we calculated the unconstrained ordination with detrended correspondence analysis (DCA), which provides a basic overview of the compositional gradients in the species data.

CCA is a multivariate gradient analysis method designed to elucidate relationships between biological assemblages of species and environmental factors and has been widely used to predict interactions between community structure and environmental variables (Biswas et al., 2015). It requires two data matrices that were the food web structure index data matrix and the environmental data matrix in this study (Barrella, Martins, Petrere, & Ramires, 2014). Factors that affect the structure of food webs include hydrological and water quality parameters. The method using single-modal sorting and Monte Carlo displacement test was used to select the main factors ($p < 0.05$) for food web structure differences based on the above two parameters. The numbers for CCA are drawn using Canoco (Zhao et al., 2017).

3.2.4 | Prediction of the impact of nonpoint source pollution on food web

The EcoHAT-NPS nonpoint source pollution model (Equation 2) was used to estimate the nonpoint source pollution load of the subwatershed where typical points are located, to determine the contribution of nonpoint source pollution to river water quality and finally to confirm the impact of nonpoint source pollution on the structure of typical point food webs (Song et al., 2012).

$$C = \left(1 - e^{kRt}\right) * Q * (1 - W) * (1 - U). \tag{2}$$

In the equation, C is the nonpoint source pollution load per unit area, t/km^2; Q is the nonpoint source pollution source intensity per unit area, t/km^2; k is the ground erosion coefficient; R is the standard rain intensity, mm/day; t is the rainfall duration, days; W is the garbage disposal rate; and U is the garbage access rate.

The EcoHAT-NPS model divides the generation and migration of nonpoint source pollution load into dissolved state pollution load and adsorbed state pollution load, respectively. According to the basic characteristics of surface water cycle process and soil erosion, combined with the characteristics of nonpoint source pollution, the dissolved pollution simulation model and the adsorption pollution simulation model are established separately. In the dissolved pollution model, the simulation is performed according to the type of urban run-off (Hao, Yang, Cheng, Li, et al., 2006; Hao, Yang, Cheng, Bu, & Zheng, 2006; Liu, Shen, Ding, Wu, & Liu, 2008). In the adsorption pollution load estimation model, the soil erosion model is first used to estimate the amount of soil erosion in the study area, and then the estimation of the amount of nitrogen and phosphorus adsorbed under the water erosion environment is completed by using the constructed surface soil nitrogen and phosphorus content database. The advantages of the EcoHAT-NPS are that it can calculate the nonpoint source pollution load of each region and each pixel in a distributed manner, identify the key region of nonpoint source and accurately control the nonpoint source pollution (Song et al., 2012).

The concentration of nonpoint source pollution is calculated based on the load and flow of each pollutant simulated by the nonpoint source pollution model and then bring it into the food web structure index prediction model (Table 6) to predict the change of food web structure index.

Changes in the structure of the food web have important impacts on ecosystem functions and ecological value (Hemraj et al., 2017; Robson et al., 2017). In order to further quantitatively analyse the influence of important factors of nonpoint source pollution on the level of food web structure, the overall characteristics of the food web structure are comprehensively evaluated through the food web structure level index model (Zhao et al., 2019).

$$ {}_i = \frac{a_i + 1/b_i + c_i + d_i}{4}. \quad (3) $$

γ_i is the structure level index of the ith food web. a_i, b_i, c_i and d_i represent the Shannon diversity index, total primary production/total respiration, connectance index and system omnivory index of the ith food web, respectively. The structure level index (v) reflects the changes in the structure level of food web in terms of stability, complexity, connectivity and maturity (Zhao et al., 2019). The food web structure level index can be used to evaluate the structural characteristics of aquatic food webs synthetically.

4 | RESULTS

4.1 | Fuzzy clustering to determine typical points of nonpoint source pollution

Nonpoint source pollution will produce a large amount of TP, TN, NH_3-N and COD, which are important factors affecting the health of aquatic ecosystems (Kuo et al., 2016; Song et al., 2012; Zhou et al., 2019), and have a serious impact on the aquatic ecosystem after entering the river. For this purpose, the sampling points (Figure 1) are fuzzy clustered based on the data of TN, TP, COD and NH_3-N, and the results are shown in Figure 2.

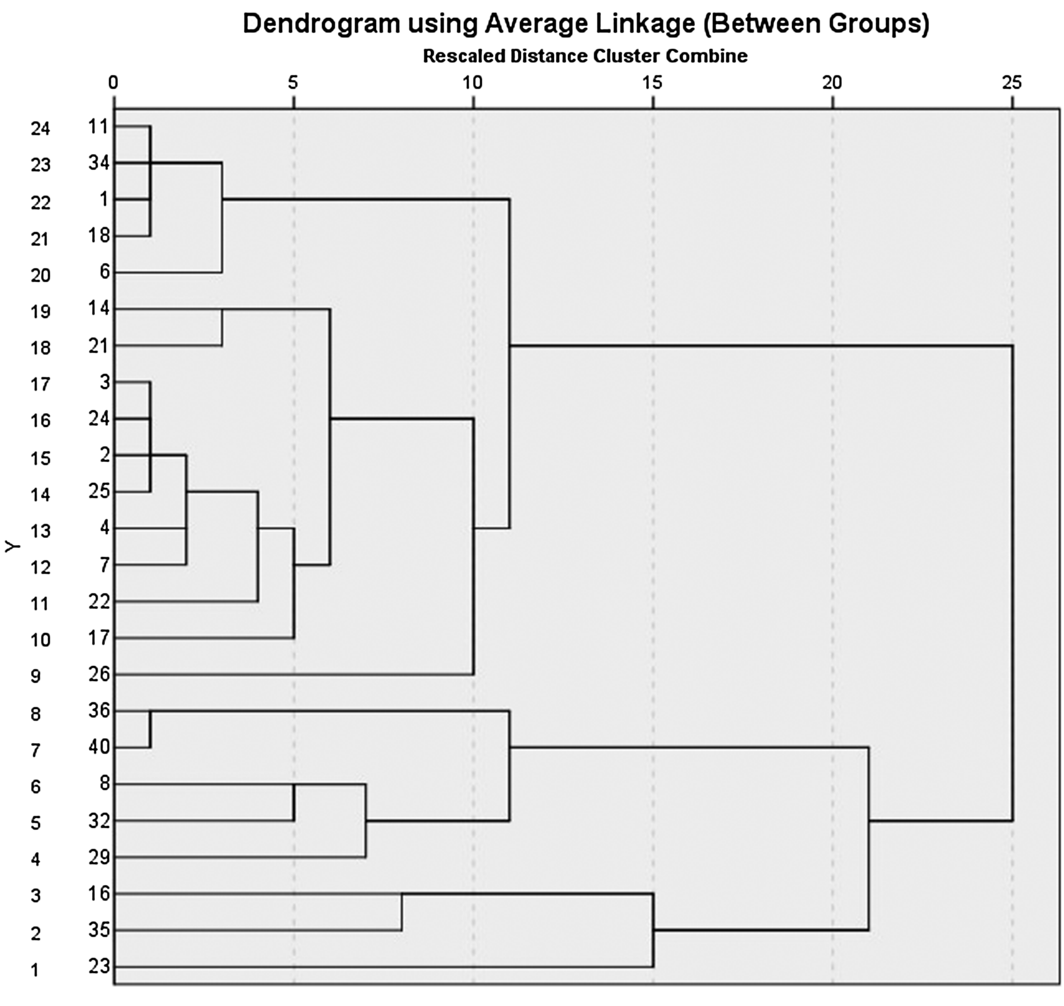

FIGURE 2 Clustering results of sampling points

It can be seen from Figure 2 that the sampling points are clustered according to the concentration of TN, TP, COD and NH_3-N in the nonpoint source pollution. In order to select as many typical points as possible, the selection threshold here is 11 according to the clustering results in Figure 2. The sampling points are divided into six categories. The screening of six points (J1, J24, J36, J32, J16 and J23, which are typical points) analyses the effects of nonpoint source pollution on food web.

4.2 | Identification of important factors of nonpoint source pollution

The ecopath model is established based on aquatic biological data in ecological sampling, including species and biomass of phytoplankton, zooplankton, benthic and fish. Through the establishment of food web model, the food web structure index data (Table 3) of typical points at different times can be obtained, including Shannon's diversity index, total primary production/total respiration, connectance index and system omnivory index. These four indexes reflect the level of food web structure from four aspects: stability, maturity, connectivity and complexity.

PLSR analysis is performed to determine the impact of water quality factors on structural indicators of food webs at typical points J1, J24, J36, J32, J16 and J23. And the VIP (Table 4) is used to screen important factors affecting the structure of the food web from nonpoint source pollution.

From Table 4, it can be seen that among the water quality factors, Na, SO_4, CO_3, NH_3-N, COD and F have a great impact on the structure of the food web (the VIP mean values are 1.10, 1.08, 1.85, 1.03, 1.07 and 1.17). These water quality factors are heavy metals that are toxic to aquatic animals and aquatic plants, or various salt that inhibit the survival and reproduction of aquatic. The excessive concentration of them in rivers can inhibit of the aquatic ecological food web in different levels. Among these important factors, the factors related to the nonpoint source pollution factors (TN, TP, COD and NH_3-N) studied in this thesis are NH_3-N and COD.

4.3 | Effects of nonpoint source pollution on food web structure

First, the CCA method is used to analyse the relationship between water quality factors and food web structure indexes, to determine the driving effect of water quality factors on food web structure. The results are shown in Figure 3. Among them, the effect of NH_3-N and COD in the nonpoint source pollution factors is significantly greater than TN and TP, which is consistent with the VIP results above.

TABLE 3 Structural indicators of typical food webs in spring 2016

Station	SDI	TPR	CI	COI
J1	2.64	0.99	0.07	0.18
J16	2.01	7.16	0.24	0.02
J23	1.91	1.02	0.07	0.06
J24	1.03	0.09	0.08	0.04
J32	2.20	0.49	0.04	0.01
J36	2.27	0.19	0.07	0.09

TABLE 4 Variable importance in the project averages of water quality factors affecting food web structure

	Food web structure				
Water quality factors	SDI	TPR	CI	COI	Mean
Ca	0.52	0.76	0.71	1.21	0.80
K	0.74	0.79	0.50	0.99	0.76
Na	0.58	0.65	2.00	1.16	1.10
CL	0.88	1.36	0.69	0.66	0.90
SO_4	1.05	0.79	1.02	1.44	1.08
CO_3	1.17	2.66	1.56	2.00	1.85
HCO_3	0.32	0.77	0.96	0.56	0.65
TA	0.33	0.82	0.91	0.58	0.66
TH	0.75	0.88	0.59	1.14	0.84
TN	1.29	0.54	0.75	0.82	0.85
NH_3-N	1.67	0.66	0.92	0.85	1.03
COD	0.71	1.34	0.95	1.29	1.07
$KMNO_4$	0.94	1.70	0.56	0.75	0.99
BOD	1.04	0.73	1.03	1.19	1.00
AS	0.51	0.62	0.19	0.52	0.46
TP	1.05	0.69	0.99	0.96	0.92
S	1.16	0.70	1.05	0.77	0.92
F	0.74	1.05	1.27	1.61	1.17
Ais	1.20	0.70	1.06	0.76	0.93

Then the VIP results in the PLSR analysis are used to further determine the influence of important nonpoint source pollution factors (NH_3-N and COD) on the structure index of food web. VIP analysis and curve relationship fitting are performed on nonpoint source pollution factors (NH_3-N and COD) and changes in food web structural indicators (i.e., changes in food web structural indicators with no nonpoint source impact). The results are shown in Tables 5 and 6.

It can be seen from Figure 3 that NH_3-N and COD have important effects on the change of food web structure, and their impact on the structure of food web is greater than TN and TP. Combining Table 5, it can be found that the influence of NH_3-N (VIP mean value of 1.19) on the changes of various structural indicators of the food web is greater than COD (VIP average of 0.76). With the comprehensive analysis of the above results, among the effects of nonpoint source pollution factors on the food web studied in this paper, it was found that the effect of NH_3-N on the structure of the food web is greater than that of COD. Furthermore, according to the results shown in Figure 4, the angle between NH_3-N and CI and TPR is less than 90°, and the angle between NH_3-N and SOI and SDI is greater than 90°. Therefore, NH_3-N has a positive effect on CI and TPR in the food web structure index, whereas it has a negative effect on SOI and

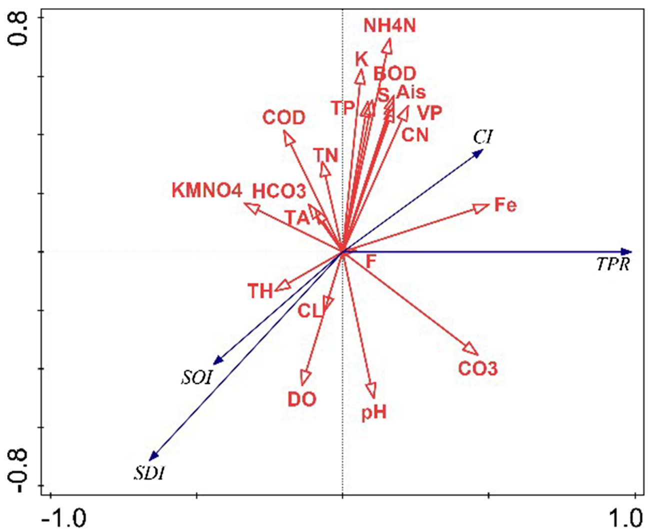

FIGURE 3 Canonical correspondence analysis of water quality factors and food web structure

TABLE 5 Variable importance in the project average of the influence of important factors on changes in food web

	Food web structure				
Factors	△SDI	△TPR	△CI	△COI	Mean
NH_3-N	1.26	1.06	1.26	1.19	1.19
COD	0.65	0.94	0.66	0.76	0.76

SDI. COD only has a positive effect on CI and has a negative effect on other indicators. According to Table 6, it can be obtained that the fitting relationship function between the NH_3-N and COD and the change value of the structure index of the food web are established, and through the *F* test, the change of the structure index of the food web can be predicted by the change of the concentration of NH_3-N and COD. In addition, the changes of SDI, TPR, CI and COI will change with the concentrations of NH_3-N and COD on the basis of a stable value (constant term in the fitting function), which eventually leads to a change in the food web structure index with the concentration changes of COD and NH_3-N.

4.4 | Prediction of nonpoint source pollution on food web structure

Combined with the rainfall data measured by the ground rainfall station, the nonpoint source pollution load of each subwatershed where the typical point is located is estimated through using the EcoHAT-NPS nonpoint source pollution model (Figure 4).

Based on the nonpoint source pollution load combined with the measured rainfall and flow data in the study area, the inflow concentration of nonpoint source pollution is estimated (because J14 and J36 are located in the reservoir area, the reservoir capacity is difficult to determine, and the nonpoint source pollution factor concentration cannot be determined, so the food web cannot be predicted structure index) and then combined with the fitting formula in Table 6 to calculate the food web structure index change value. The food web structure index under the influence of point source pollution is added to obtain the food web structure index under the combined influence of point source and nonpoint source. The results are shown in Table 7. The effect of nonpoint source pollution on the aquatic food web is evaluated according to the variation of the structure index of the food web. According to Figure 5, it can be seen that the nonpoint source pollution in July and August of each year is significantly higher than that of the other months (take J1 as an example, the annual peak months of NH_3-N and COD loads from 2014 to 2018 are July, August, July, July and August). It shows that in the annual flood season, nonpoint source pollution will increase with the increase of rainfall. Comparing the results of other points, it can be seen that the nonpoint source pollution generation at Point J1 is the lowest, mainly because J1 is located in the southern mountainous area of Jinan. The impact of human activities is minimal, and the amount of nonpoint source pollution is minimal. The highest of nonpoint source pollution at Point J23 is mainly because J23 is located in the urban area, with a large population density and a high amount of domestic waste, causing nonpoint sources.

According to Table 7, the average SDI (2.206) of J1 is the highest, the average COI (0.146) is the highest and the average TPR (10.676) is the lowest. It shows that J1 has the best biological species and diversity, the predation relationship among species is complex and the food web structure is the most mature. The main reason is that J1 is located in the southern mountainous area of the study area, with little human activity and the least nonpoint source pollution, which ensures the normal living conditions of aquatic organisms. The SDI mean value

TABLE 6 Fitting relationship between the changes in SDI, TPR, CI and COI of the food web structure index and NH_3-N and COD

Food web structure index	Fitting relation (*x*:NH_3-N, *y*:COD)	R^2	RMSE	*F* test
△SDI	$\triangle SDI = -0.09 - 0.39 * x + 0.08 * x^2 + 0.002 * y$	0.64	0.367	0.028
△TPR	$\triangle TPR = 1.81 + 11.32/x + 12.80 * y$	0.56	14.7	0.045
△CI	$\triangle CI = -0.003 + 0.03 * x - 1.31 * y^3$	0.66	0.038	0.016
△COI	$\triangle COI = -0.005 - 0.02 * x + 0.004 * x^2 - 0.0007 * y$	0.65	0.027	0.008

Abbreviation: RMSE, root mean square error.

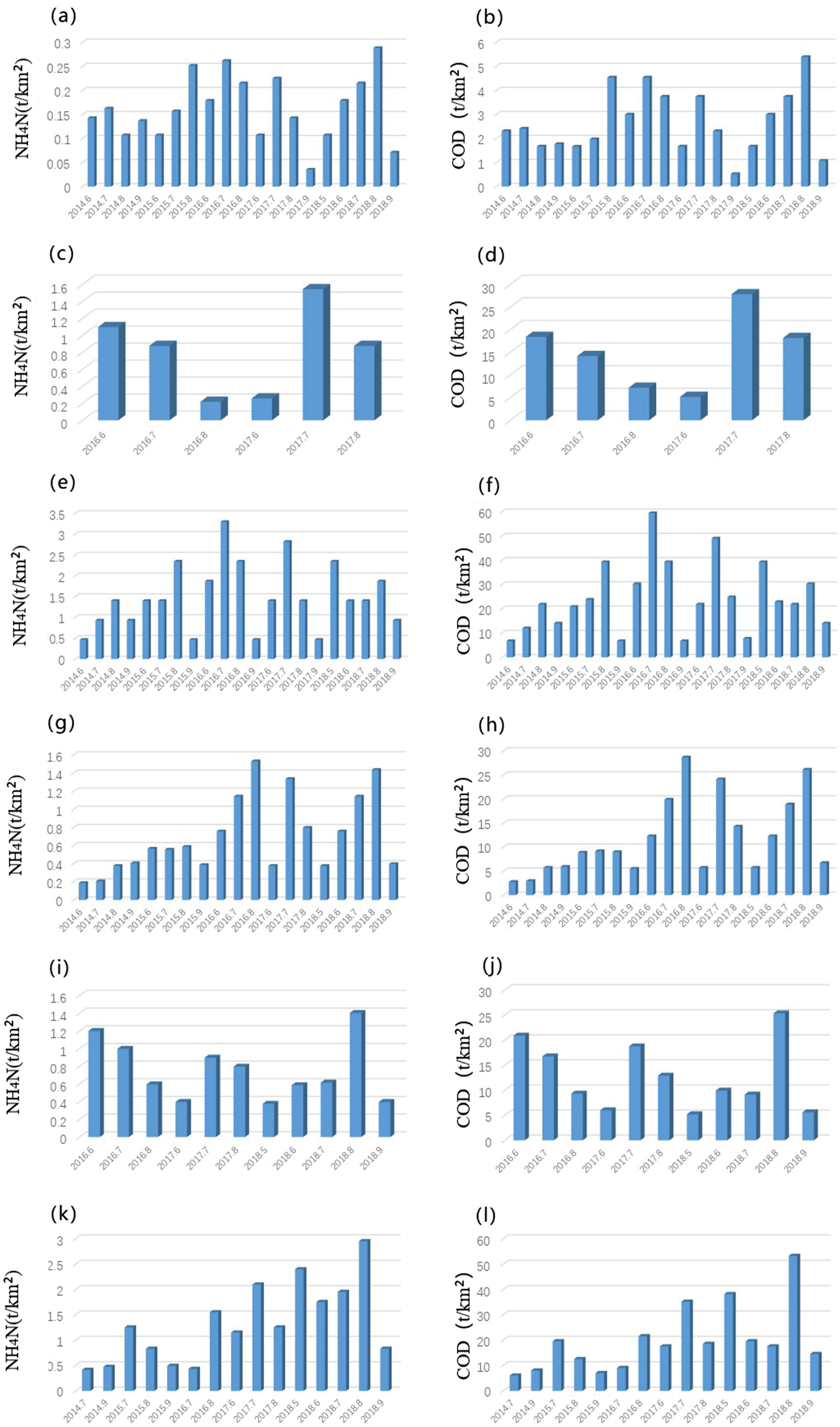

FIGURE 4 Estimation of nonpoint source pollution load in a typical point watershed (a, c, e, g, i and k are the NH_3-N loads of J1, J16, J23, J24, J32 and J36, respectively; and b, d, f, h, j and l are the COD loads of J1, J16, J23, J24, J32 and J36, respectively)

TABLE 7 J1, J23, J24 and J32 food web structure index prediction results

Date	SDI	TPR	CI	COI	SDI	TPR	CI	COI
	J1				J23			
6/2014	2.074	9.529	0.136	0.154	1.665	10.448	0.234	0.044
7/2014	2.072	9.581	0.139	0.153	1.545	15.690	0.174	0.033
8/2014	2.120	10.957	0.117	0.156	1.470	21.273	0.132	0.021
9/2014	2.108	10.956	0.120	0.156	1.549	15.556	0.234	0.032
6/2015	2.121	10.998	0.117	0.156	1.468	21.298	0.162	0.022
7/2015	2.090	10.560	0.126	0.155	1.474	21.230	0.072	0.020
8/2015	2.424	8.511	0.199	0.170	1.419	33.147	0.759	0.005
9/2015	—	—	—	—	1.665	10.448	0.234	0.044
6/2016	2.097	8.862	0.156	0.154	1.426	27.166	0.062	0.012
7/2016	2.424	8.639	0.198	0.170	1.519	45.278	0.304	0.007
8/2016	2.207	8.577	0.177	0.159	1.419	33.147	0.759	0.005
9/2016	—	—	—	—	1.665	10.448	0.234	0.044
6/2017	2.120	10.957	0.117	0.156	1.470	21.273	0.132	0.021
7/2017	2.207	8.705	0.176	0.159	1.450	39.189	0.434	0.002
8/2017	2.074	9.529	0.136	0.154	1.476	21.211	0.042	0.019
9/2017	2.367	25.208	0.083	0.169	1.667	10.233	0.264	0.043
5/2018	2.120	10.957	0.117	0.156	1.419	33.147	0.759	0.005
6/2018	2.097	8.862	0.156	0.154	1.472	21.251	0.102	0.021
7/2018	2.207	8.577	0.177	0.159	1.470	21.273	0.132	0.021
8/2018	2.770	8.583	0.222	0.187	1.426	27.166	0.062	0.012
9/2018	2.222	14.286	0.100	0.162	1.549	15.556	0.234	0.032
	J24				J32			
6/2014	0.873	8.435	0.154	0.025	—	—	—	—
7/2014	0.866	8.410	0.159	0.025	—	—	—	—
8/2014	0.814	8.711	0.228	0.020	—	—	—	—
9/2014	0.804	9.027	0.230	0.019	—	—	—	—
6/2015	0.760	10.427	0.283	0.015	—	—	—	—
7/2015	0.764	10.258	0.295	0.015	—	—	—	—
8/2015	0.755	10.669	0.280	0.014	—	—	—	—
9/2015	0.810	8.912	0.221	0.020	—	—	—	—
6/2016	0.713	12.514	0.307	0.009	1.796	18.200	0.127	0.013
7/2016	0.637	17.081	0.208	0.001	1.831	15.741	0.231	0.018
8/2016	0.586	21.878	0.177	0.010	1.921	11.135	0.250	0.029
9/2016	—	—	—	—	—	—	—	—
6/2017	0.814	8.711	0.228	0.020	1.977	9.260	0.196	0.035
7/2017	0.608	19.460	0.059	0.006	1.859	14.389	0.374	0.018
8/2017	0.706	12.896	0.345	0.007	1.873	13.364	0.267	0.024
9/2017	—	—	—	—	—	—	—	—
5/2018	0.814	8.711	0.228	0.020	1.982	9.297	0.175	0.035
6/2018	0.713	12.514	0.307	0.009	1.926	10.934	0.271	0.029
7/2018	0.635	17.111	0.178	0.001	1.915	11.418	0.237	0.029
8/2018	0.595	20.704	0.060	0.008	1.768	20.710	0.061	0.008
9/2018	0.809	8.669	0.255	0.019	1.976	9.396	0.184	0.035

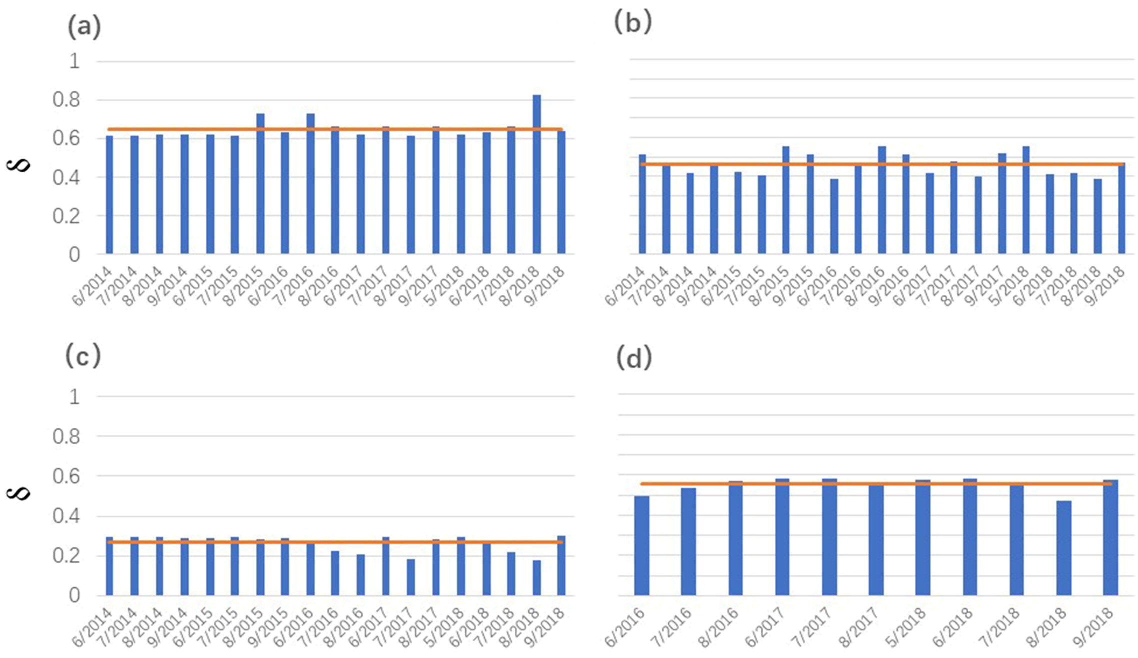

FIGURE 5 Food web structure level index changes of J1, J23, J24 and J32 (a–d represent J1, J23, J24 and J32, respectively, and the time is predicted based on the month of rainfall data collection. The red line in the figure is the mean line)

(0.741) and COI mean value (0.014) of J24 are the lowest. J24 is located in the sewage channel of Jinan City. The river is in eutrophication all year round, and the biological survival status is extremely poor, which leads to the worst biological survival status and the lowest biodiversity index. The food web structure indexes of J23 and J32 are both at a medium level. Taking SDI as an example, the mean values are (1.509, 1.893).

According to the prediction results of the four food web structure indices obtained from Table 7, the formula 3 can be used to calculate the change of the food web structure level index at each point, as shown in Figure 5.

As can be seen from Figure 5, the predicted average value of the food web structure level index (δ) of J1 is the highest (0.65), J24 is the lowest (0.26) and J23 (0.46) and J32 (0.55) belong to the middle level, which is consistent with the results obtained above. The food web structure level index at Points J1, J23 and J32 will go through a process of rising and then decreasing throughout the year. At the beginning of each flood season, the food web structure level index will gradually increase, and with the end of the flood season, the food web structure level index will decrease. It is mainly due to the gradual increase of rainfall in the flood season. With the increase of rainfall, nonpoint source pollutants enter the river with rainfall, resulting in the increase of water concentration in the river, which provides certain nutrients for aquatic organisms and promotes the growth of aquatic organisms. The food web structure level index of J24 showed the lowest value in August (average value of 0.25). The main reason is that the Xiaoqing River, where J24 is located, belongs to the sewage channel of Jinan City. The river pollution is serious, and the concentration of various water quality factors is high all year round, which affects the survival of aquatic organisms at this point, resulting in a low level of food web structure and the weakest ability to resist the interference of external factors (Hu, Liu, & Chen, 2017; Hu, Wei, et al., 2017; Jiao, Ren, Wang, & Liu, 2017; Liu, Cao, Li, Li, & Zhang, 2019). The nonpoint source pollution washed by rainfall in the flood season enters the river. Due to the serious pollution of the river water, the rainwater also brings a certain impact to the already fragile food web, which deteriorates the living environment of aquatic organisms, especially phytoplankton, and further reduces food web structure level.

5 | DISCUSSION

5.1 | Fuzzy clustering to determine typical points

In this paper, the data of water quality factor (TN, TP, COD and NH_3-N) are used for fuzzy clustering for sampling points, and then the central point selection principle is adopted to determine the typical points. In the study of clustering the sampling points, Nguyen et al. (2015) used cluster analysis to divide the 52 groundwater monitoring wells into three clusters of high salinity, low salinity and freshwater in Red River Delta of Vietnam. The characteristics of groundwater in each cluster were analysed, and the reasons for this distribution were analysed (Nguyen et al., 2015), which is consistent with the effect of cluster analysis of sampling points by the concentration of water quality factor in our study. This study is consistent with the method used in our study to reflect changes in water quality factor concentrations through cluster analysis. In the precipitation study at Northeast India, Goyal, Shivam, and Sarma (2019) used fuzzy clustering to cluster the selected sites based on the six parameters of these precipitation indices, namely, latitude, longitude, mean, standard deviation, minimum and maximum (Goyal et al., 2019), and finally divided the sampling points into five categories for analysis, which is consistent with the method of classification analysis of sampling points in our paper. In the study of fuzzy clustering, Mao et al. (2019) used the density centre as the initial cluster centre and finally developed a typical point selection method based on sampling density centre selection, which is consistent with our principles of fuzzy clustering in the study area and the selection of typical points based on the centre points of the clustering results. In summary, in the study of classification of sampling point data, it is feasible to use fuzzy clustering to perform cluster classification and then use the centre point selection principle to determine typical points.

5.2 | Analysis of important factors of nonpoint source pollution in food web structure

In this paper, NH_3-N and COD are the important factors of nonpoint source pollution that affect the food web structure. In the study of the effects of NH_3-N on the structure of aquatic ecosystems, Kuo et al.'s study in the Dajia River watershed at China found that NH_3-N is the main factor that affects the seasonal changes of the epilithic algal biomass in streams, which in turn affects the structural composition of the upper aquatic animal community and eventually leading to changes in the food web structure (Kuo et al., 2016). Shrestha and Dorevitch's (2019) research in Lake Michigan beaches at the United States found that the increase of NH_3-N increased the density and quantity of *Escherichia coli*. Similarly, Zhou et al.'s (2019) research in the Huaihe River Basin in China also found that NH_3-N has an important effect on the composition and change of phytoplankton community structure in rivers during the dry season. In the study of Japan's shallow lake marsh ecosystem, Kanaya et al.'s (2020) research found that NH_3-N promotes parasitic relationships and the growth of flora and fauna. These studies show that NH_3-N has an important impact on the composition of algae and phytoplankton community structures in river aquatic ecosystems. Our research in Jinan also shows that NH_3-N is an important factor affecting the structure index of food web. In the study of the impact of COD on aquatic ecosystems, Ling et al.'s (2015) research in Sanya Bay, China, obtained a significant correlation between COD and the spatial variability of bacterial communities through a large amount of data analysis. Yang et al. (2012) collected a large number of data of aquatic organisms in the Taihu Lake Basin of China and found that COD affected the structure and community of Microcystis in Taihu Lake. The conclusions of these studies are that COD is also an important factor influencing the structure of the biological community of the aquatic ecosystem, which is consistent with our conclusions obtained in the study. It is mainly because changes in NH_3-N and COD concentrations promote the growth of phytoplankton, lead to the changes of the primary productivity of the ecosystem, which in turn affect the growth and reproduction of other aquatic plants and biomass, and ultimately cause changes in the level of the food web structure of the entire ecosystem.

5.3 | Analysis of nonpoint source pollution on food web structure

This study found that NH_3-N and COD have an effect on the stability, maturity, connectivity and complexity of the food web structure. NH_3-N has a positive effect on the degree of connection and maturity of the food web structure but has a negative effect on the complexity and stability. COD only has a positive effect on the connection and has a negative effect on other indexes. In the study of the effect of NH_3-N on the structure of food webs, Kanaya et al. (2019) in the study of the shallow lake marsh ecosystem in Japan found that NH_3-N can promote the parasitic relationship, and parasites are substances, and the potential pathway of energy flow greatly increases the connection of food web, which is consistent with the conclusion that NH_3-N promotes the food web connection obtained in our study. Olatunji et al. conducted a large number of comparative experiments in the study of soil nematode abundance and community composition in China. The results show that NH_3-N can promote the omniverses and enrichment index of nematode (Olatunji et al., 2019). The conclusion is consistent with the NH_3-N obtained, which has a positive effect on the maturity of the food web in our study. Tian et al. research in Nansi Lake in China found that NH_3-N is one of the main environmental factors driving the seasonal changes in phytoplankton communities in lakes. These environmental factors increase the abundance of phytoplankton communities (Tian, Zhang, Zhao, & Huang, 2017). This is consistent with the conclusion that the NH_3-N can promote the maturity of the food web structure in our study. In the study of the impact of COD on the ecosystem, Ling et al. (2015) found that COD promotes bacterial abundance in the study of the spatial variability of bacterial communities and their relationship with water chemistry in South China Sea Sanya Bay. The result is different from the conclusion that in our study, mainly because COD has a positive effect on the abundance of the bacterial community, but our study focuses on the entire food web organization. COD has different effects on other organisms in the food web, which ultimately leads to poor structural stability of the entire food web. Guijun et al. (2012) found in Lake Taihu's zooplankton study that COD was the main water quality factor that caused the changes in the community structure of *Coilia ectenes taihuensis* and *Neosalanx tangkahkeii taihuensis*. The difference in COD that led to the structure of zooplankton community is different in different regions, and the community structure in some areas with lower COD concentration is more complicated, which is consistent with the conclusion in our study. In summary, NH_3-N and COD have a certain effect on the stability, maturity, connectivity and complexity of phytoplankton, zooplankton, parasites and bacterial communities in aquatic ecosystems, which in turn affects the entire aquatic ecosystem. The NH_3-N has a positive effect on the degree of connection and maturity of the food web structure but negatively affects the complexity and stability. COD only has a positive effect on the degree of connection and has a negative effect on other indexes.

5.4 | Prediction of nonpoint source pollution on food web structure

In this paper, the change of food web structure index is predicted by NH_3-N and COD produced by nonpoint source pollution. And then we add the point source pollution to the nonpoint source pollution and get the pollution on food web structure is used to predict the food web structure index. In order to verify the effect of water quality factors on the food web structure index, the measured concentration data of various important chemical factors (Na, SO_4, CO_3, F, NH_3-N and COD) and the food web structure index were curve fitted to obtain the following functional relationship as shown in Table 8.

Comparing the month with the measured food web model and the food web structure index predicted from the same month, the results are shown in Figure 6.

As can be seen from Table 8, there is a good fitting relationship between the food web structure indexes SDI, TPR, CI and COI and the concentrations of chemical factors (Na, SO_4, CO_3, F, NH_3-N and COD) (R^2 all greater than 0.5) and credible by F tests (p values are all less than 0.05), indicating that the food web structure index can be simulated by the concentration of important chemical factors. According to the formula in Table 8, the food web structure indexes SDI, TPR, CI and COI will change as the chemical factor concentration changes. As nonpoint source pollution enters the river, the water quality of the river is changed, leading to changes in the originally stable food web structure. Therefore, it is feasible to predict the food web structure index by analysing the influence of NH_3-N and COD produced by nonpoint source pollution on the change of the food web structure index. It can be obtained from Figure 6 that the

TABLE 8 Fitting relation of food web structure indices SDI, TPR, CI and COI and chemical factors (x_1–x_6 represent the concentration of Na, SO_4, CO_3, F, NH_3-N and COD, respectively, in mg/L)

Food web structure index	Fitting relation	R^2	F test
SDI	$SDI = 2.27 + 0.001x_2 - 0.044x_3 - 0.881x_4 - 0.134x_5 + 0.008x_6$	0.58	0.034
TPR	$TPR = 2.21 - 0.02x_1 - 0.006x_2 + 0.114x_3 + 2.81x_4 - 0.41x_5 + 0.19x_6$	0.65	0.045
CI	$CI = 0.06 - 0.001x_1 + 0.006x_3 + 0.178x_4 - 0.004x_5 + 0.004x_6$	0.65	0.012
COI	$COI = 0.127 - 0.006x_3 - 0.109x_4 + 0.002x_5 - 0.003x_6$	0.56	0.046

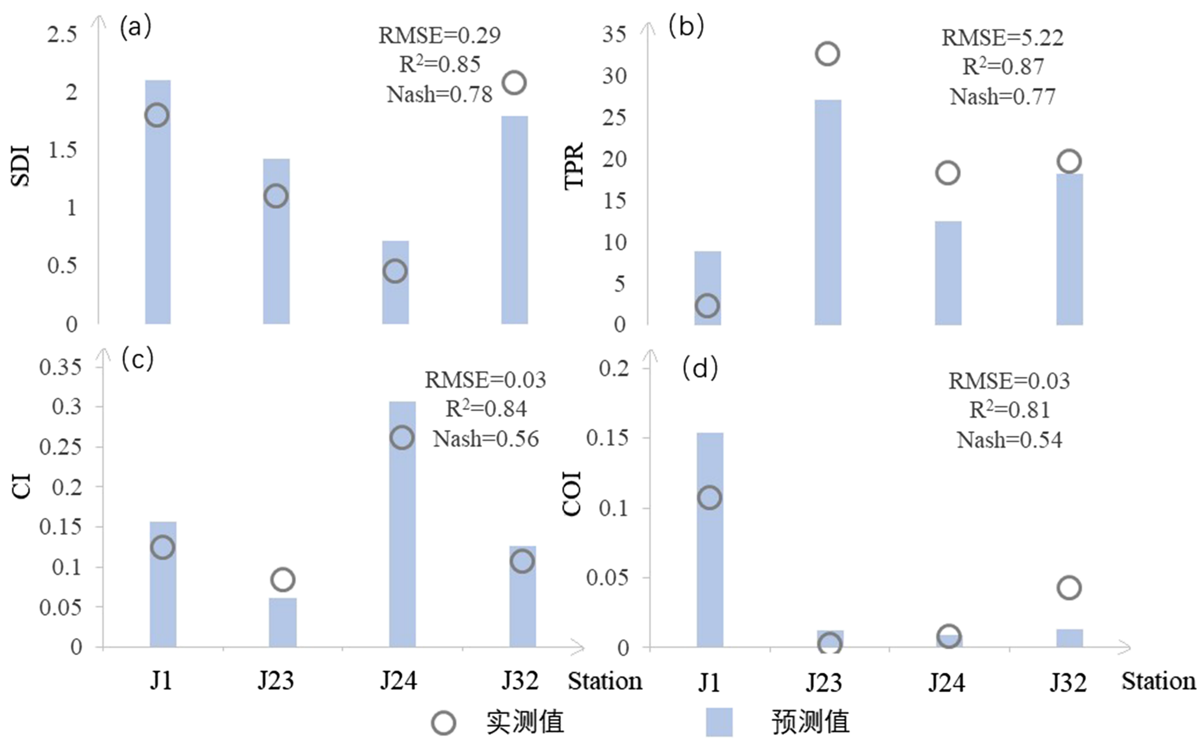

FIGURE 6 Comparison of predicted and measured food web structure index (a–d are SDI, TPR, CI and COI, respectively). RMSE, root mean square error

predicted food web structure index is in good agreement with the measured food web structure index (R^2 is greater than 0.7, and the Nash coefficients are all greater than 0.5), which proves the rationality of the food web structure index prediction.

By predicting the food web structure index and food web structure level index, it is found that in areas with high food web structure index and food web structure level index, the food web structure in the rainy season will be higher than that in the dry season. In areas with severe water pollution and poor food web structure, the food web structure in the rainy season will be worse than that in the dry season. In the study of nonpoint source pollution affecting water ecology and food webs, Shrestha and Dorevitch (2019) found that nonpoint source pollution has seriously affected the density and number of *E. coli* in the study of lake Michigan beaches at the United States. He et al.'s (2018) study found that water nutrients and microbial pathogens are affected by nonpoint source pollution caused by stormwater run-off on Dongshan beach in the Bohai Bay and that nonpoint source pollution affects the original water quality in the aquatic ecosystem and affected the survival of microorganisms, which is consistent with the conclusion that nonpoint source pollution caused by rainfall will affect the structure of the food web in our study. These conclusions indicate that the nonpoint source pollution caused by rainfall will affect the aquatic ecosystem, and the primary productivity of the ecosystem will be changed by the microorganisms and algae that affect the aquatic ecosystem, which will eventually change the structure of the aquatic food web.

6 | CONCLUSIONS

In this study, the typical points of nonpoint source pollution are screened by fuzzy clustering and then use CCA and PLSR analysis to comprehensively screen the driving factors that affect food web in nonpoint source pollution. Finally, the impact of each driving factor on the structure of food web is determined, and the change trend of the food web structure on the monthly scale is predicted. The influence of nonpoint source pollution into the river on the food web structure is analysed. We mainly draw the following conclusions:

1. The important factors affecting the nonpoint source pollution of the food web structure are NH_3-N and COD. The increase of NH_3-N and COD concentrations promotes the growth of phytoplankton, which leads to the change of primary productivity of the ecosystem, and then affects the growth and reproduction of other aquatic animals and aquatic plants. Eventually, the level of the food web structure of the whole ecosystem will change.
2. NH_3-N and COD play an important role in the stability, maturity, connectivity and complexity of phytoplankton, zooplankton, parasites and bacterial communities in the aquatic ecosystem. NH_3-N has a positive effect on the connection and maturity of the food web structure and a negative effect on the complexity and stability. COD only has a positive effect on the connection and a negative effect on other indexes. In addition, because nonpoint source pollution enters rivers and affects water quality, the change of food web structure index can be obtained by fitting function relationship through the change of NH_3-N and COD concentrations, so as to predict the food web structure index.
3. In mountainous areas where human activities have a small impact, the amount of nonpoint source pollution is less. At the same time, in areas with good water quality, the food web structure level index is high, and the food web structure is stable. In areas with serious water pollution and poor food web structure, the food web is weak in resisting external disturbances. Owing to rainfall entering the river, the food web structure in the rainy season is worse than that in the dry season.

In this paper, CCA and PLSR are used to comprehensively determine the impact of nonpoint source pollution on the structure of food webs and then fit the relationship between important factors of nonpoint source pollution, NH_3-N and COD, and changes in food web structure index. Based on the nonpoint source pollution model, the nonpoint source pollution at typical points is simulated, and finally, the food web structure index is predicted based on the nonpoint source pollution. However, due to the shortage of time series of water ecological data, there are some errors in some calculation. In the future, it is necessary to strengthen the research on new methods for obtaining water ecological data of rivers without data to increase the accuracy of nonpoint source pollution simulation and food web structure prediction.

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CONFLICT OF INTEREST

None.

DATA AVAILABILITY STATEMENT

The data used to support the findings of this study are available from the corresponding author upon request.

ORCID

Chang S. Zhao https://orcid.org/0000-0003-1903-1280
Xu Pan https://orcid.org/0000-0003-1589-1638
Hua Xiang https://orcid.org/0000-0002-5028-4596
Xin J. Gan https://orcid.org/0000-0003-2750-3583

REFERENCES

Abonyi, A., Acs, E., Hidas, A., Grigorszky, I., Várbiró, G., Borics, G., & Kis, K. T. (2018). Functional diversity of phytoplankton highlights long-term gradual regime shift in the middle section of the Danube River due to global warming, human impacts and oligotrophication. *Freshwater Biology*, *63*(5), 456–472.

Adindu, T. M. (2019). Impact of Aluminium Extrusion Effluent on Mbaa River in Inyishi Ikeduru Imo State (doctoral dissertation, Federal University of Technology, Owerri).

Afanador, N. L., Tran, T. N., & Buydens, L. M. C. (2013). Use of the bootstrap and permutation methods for a more robust variable importance in the projection metric for partial least squares regression. *Analytica Chimica Acta*, *768*(1), 49–56.

Baird, D., & Ulanowicz, R. E. (1989). The seasonal dynamics of the Chesapeake Bay ecosystem. *Ecological Monographs*, *59*(4), 329–364.

Barbour, M. T., Gerritsen, J., Snyder, B. D., & Stribling, J. B. (1999). *Rapid bioassessment protocols for use in streams and wadeable rivers*. Washington: USEPA.

Barrella, W., Martins, A. G. Jr., Petrere, M., & Ramires, M. (2014). Fishes of the southeastern Brazil Atlantic forest. *Environ. Biol. Fish*, *97*(12), 1367–1376.

Biswas, S., Hussain, K. J., Das, N. P. I., Russell, B., Satpathy, K. K., & Mishra, S. S. (2015). Imprint of monsoonal patterns on the fish assemblage in coastal waters of south-east India: A case study. *Journal of Fish Biology*, *85*(3), 773–799.

Carvalho, D. A., Williner, V., Ciri, F. V., Vaccari, C., & Collins, P. A. (2016). Quantitative food webs and invertebrate assemblages of a large river: A spatiotemporal approach in floodplain shallow lakes. *Marine and Freshwater Research*, *68*(2), 293–307.

Chen, J.X., Xu, T.O. Fang, S., Song, S., Wang, X. (1987). Fishes in Qinling mountain area.

Chen, Z., Xu, S., & He, P. (2011). An ecological model of the artificial ecosystem (northern Hangzhou Bay, China): Analysis of ecosystem structure and fishing impacts. *Helgoland Marine Research*, *65*(2), 217–231.

Coll, M., Schmidt, A., Romanuk, T., & Lotze, H. K. (2011). Food-web structure of seagrass communities across different spatial scales and human impacts. *PLoS ONE*, *6*(7), e22591.

Cui, B., Wang, C., Tao, W., & You, Z. (2009). River channel network design for drought and flood control: A case study of Xiaoqinghe River basin, Jinan City, China. *Journal of Environmental Management*, *90*(11), 3675–3686.

Garay-Narváez, L., Arim, M., Fores, J. D., & Ramos-jiliberto, R. (2013). The more polluted the environment, the more important biodiversity is for food-web stability. *Oikos*, *122*(8), 1247–1253.

Goyal, M. K., Shivam, G., & Sarma, A. K. (2019). Spatial homogeneity of extreme precipitation indices using fuzzy clustering over northeast India. *Natural Hazards*, *98*(2), 559–574.

Guijun, Y., Boqiang, Q., Xiangming, T., Zhijun, G., Chunni, Z., Hua, Z., & Xiaodong, W. (2012). Contrasting zooplankton communities of two bays of the large, shallow, eutrophic Lake Taihu, China: Their relationship to environmental factors. *Journal of Great Lakes Research*, *38*(2), 299–308.

Hao, F., Yang, S., Cheng, H., Bu, Q., & Zheng, F. (2006). Methodology for the calculation of non-point source pollution loads in large scale areas. *Acta Scientiae Circumstantiae*, *26*(3), 375–383.

Hao, F., Yang, S., Cheng, H., Li, Y., Zhu, D., Zhang, J., & Xiong, W. (2006). The significance, difficulty and key technologies of large-scale model app lied in estimation of non-point source pollution. *Acta Scientiae Circumstantiae*, *26*(3), 362–365.

Harvey, E., Gounand, I., Ward, C. L., & Altermatt, F. (2017). Bridging ecology and conservation: From ecological networks to ecosystem function. *Journal of Applied Ecology*, *54*(2), 371–379. https://doi.org/10.1111/1365-2664.12769

He, S., Yin, X. A., Yu, C., Xu, Z., & Yang, Z. (2018). Quantifying parameter uncertainty in reservoir operation associated with environmental flow management. *Journal of Cleaner Production*, *176*, 1271–1282. https://doi.org/10.1016/j.jclepro.2017.11.246

Hemraj, D. A., Hossain, A., Ye, Q., Qin, J. G., & Leterme, S. C. (2017). Anthropogenic shift of planktonic food web structure in a coastal lagoon by freshwater flow regulation. *Scientific Reports*, *7*, 44441.

Hong, Q., Meng, Q., Wang, P., Wang, H., & Liu, R. (2010). Regional aquatic ecological security assessment in Jinan, China. *Aquatic Ecosystem Health & Management*, *13*(3), 319–327.

Hu, Y., Liu, C. Y., & Chen, T. (2017). Ecological improvement and community participation: Lessons from Xiaoqing River Ecological Improvement Project in Jinan, China. *Community Development Journal*, *52*(1), 21–37.

Hu, Y., Wei, X., Hao, M., Fu, W., Zhao, J., & Wang, Z. (2017). Partial least squares regression for determining factors controlling winter wheat yield. *Agronomy Journal*, *110*(1), 281–292.

Hu, Y., Wei, X., Hao, M., Fu, W., Zhao, J., & Wang, Z. (2018). Partial least squares regression for determining factors controlling winter wheat yield. *Agronomy Journal*, *110*(1), 281–292.

Jiao, F., Ren, L., Wang, X., & Liu, W. (2017). Pollution characteristics and potential ecological risk assessment of metals in the sediments of Xiaoqing River, Jinan. *Environmental Science and Pollution Research*, *24*(17), 15001–15011.

Kanagawa, M., & Nakata, T. (2008). Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries. *Energy Policy*, *36*(6), 2016–2029.

Kanaya, G., Solovyev, M. M., Shikano, S., Okano, J. I., Ponomareva, N. M., & Yurlova, N. I. (2019). Application of stable isotopic analyses for fish host–parasite systems: An evaluation tool for parasite-mediated material flow in aquatic ecosystems. *Aquatic Ecology*, *53*(2), 217–232.

Kanaya, Y., Yamaji, K., Miyakawa, T., Taketani, F., Zhu, C., Choi, Y., … Klimont, Z. (2020). Rapid reduction in black carbon emissions from China: Evidence from 2009–2019 observations on Fukue Island, Japan. *Atmospheric Chemistry and Physics*, *20*(11), 6339–6356.

Kuo, M. H., Yu, H. L., Kuan, W. H., Lin, H. J., Kuo, Y. M., & Humbert, J.-F. (2016). Factors controlling changes in epilithic algal biomass in the mountain streams of subtropical Taiwan. *PLoS ONE*, *11*(11), E0166604. https://doi.org/10.1371/journal.pone.0166604

Ling, J., Zhang, Y. Y., Dong, J. D., Wang, Y. S., Feng, J. B., & Zhou, W. H. (2015). Spatial variations of bacterial community and its relationship with water chemistry in Sanya Bay, South China Sea as determined by DGGE fingerprinting and multivariate analysis. *Ecotoxicology*, *24*(7–8), 1486–1497.

Liu, J., Xiang, Z., Xia, J., Wu, S., She, D., & Lei, Z. (2016). Characterizing and explaining spatio-temporal variation of water quality in a highly disturbed river by multi-statistical techniques. *Springerplus*, *5*(1), 1171.

Liu, T., Chen, X., Hu, F., Ran, W., Shen, Q., Li, H., & Whalen, J. K. (2016). Carbon-rich organic fertilizers to increase soil biodiversity: Evidence from a meta-analysis of nematode communities. *Agriculture, Ecosystems and Environment*, *232*, 199–207. https://doi.org/10.1016/j.agee.2016.07.015

Liu, Y., Cao, S., Li, X., Li, F., & Zhang, X. (2019). Combined effect of climate change and human activities on the hydrological processes of an urban river: Case study of the Xiaoqing River, China. *Hydrological Sciences Journal*, *64*(16), 2105–2114.

Liu, R., Shen, Z., Ding, X., Wu, X., & Liu, F. (2008). Application of export coefficient model in simulating pollution load of non-point source in upper reach of Yangtze River Basin. *Journal of Agro-Environment Science*, *27*(2), 677–682.

Post, D. M., & Takimoto, G. (2007). Proximate structural mechanisms for variation in food-chain length. *Oikos*, *116*(5), 775–782.

Majumder, M. (2015). *Impact of urbanization on ưater shortage in face of climatic aberrations*. Andrew Road, Singapore: Springer.

Mao, Y., Liu, Y., Khan, M. A., Wang, J., Mao, D., & Hu, J. (2019). Uncertain interval data EFCM-ID clustering algorithm based on machine learning. *Journal of Robotics and Mechatronics*, *31*(2), 339–347.

Marina, T. I., Salinas, V., Cordone, G., Campana, G., Moreira, E., Deregibus, D., & De Troch, M. (2018). The food-web of Potter Cove (Antarctica): Complexity, structure and function. *Estuarine, Coastal and Shelf Science*, *200*, 141–151.

McCann, K. (2007). Protecting biostructure. *Nature*, *446*(7131), 29.

McIntyre, P. B., Jones, L. E., Flecker, A. S., & Vanni, M. J. (2007). Fish extinctions alter nutrient recycling in tropical freshwaters. *Proc. Natl. Acad. Sci. Unit. States Am.*, *104*(11), 461–4466.

Mendonça, V., & Vinagre, C. (2018). Short food chains, high connectance and a high rate of cannibalism in food-web networks of small intermittent estuaries. *Marine Ecology Progress Series*, *587*, 17–30.

Mor, J. R., Ruhí, A., Tornés, E., Valcárcel, H., Muñoz, I., & Sabater, S. (2018). Dam regulation and riverine food-web structure in a Mediterranean river. *Science of the Total Environment*, *625*, 301–310.

Morillo-Velarde, P. S., Briones-Fourzán, P., Alvarez-Filip, L., Aguíniga-García, S., Sánchez-González, A., & Lozano-Alvarez, E. (2018). Habitat degradation alters trophic pathways but not food chain length on shallow Caribbean coral reefs. *Science Reports*, *8*(1), 4109.

Nguyen, T. T., Kawamura, A., Tong, T. N., Nakagawa, N., Amaguchi, H., & Gilbuena, R. Jr. (2015). Clustering spatio–seasonal hydrogeochemical data using self-organizing maps for groundwater quality assessment in the Red River Delta, Vietnam. *Journal of Hydrology*, *522*, 661–673.

Olatunji, O. A., Gong, S., Tariq, A., Pan, K., Sun, X., Chen, W., … Tan, X. (2019). The effect of phosphorus addition, soil moisture, and plant type on soil nematode abundance and community composition. *Journal of Soils and Sediments*, *19*(3), 1139–1150.

Pan, W. T. (2010). Combining fuzzy sammon mapping and fuzzy clustering approach to perform clustering effect analysis: Take the banking service satisfaction as an example. *Expert Systems with Applications*, *37*(6), 4139–4145.

Peralta-Maraver, I., Lopez-Rodriguez, M. J., & de Figueroa, J. T. (2017). Structure, dynamics and stability of a Mediterranean river food-web. *Marine and Freshwater Research*, *68*(3), 484–495.

Perkins, D. M., Reiss, J., Yvon-Durocher, G., & Woodward, G. (2010). Global change and food webs in running waters. *Ogia*, *657*(1), 181–198.

du Plessis, A. (2019). Primary water quality challenges, contaminants and the world's dirtiest places. In *Water as an inescapable risk* (pp. 79–114). Cham: Springer.

Post, D. M. (2002). The long and short of food-chain length. *Trends in Ecology & Evolution*, *17*(6), 269–277.

Robson, B. J., Lester, R. E., Baldwin, D. S., Bond, N. R., Drouart, R., Rolls, R. J., & Thompson, R. M. (2017). Modelling food-web mediated effects of hydrological nvir124. *Water Research*, *124*, 108–128.

Sabo, J. L., Finlay, J. C., Kennedy, T., & Post, D. M. (2010). The role of discharge variation in scaling of drainage area and food chain length in rivers. *Science*, *330*(6006), 965–967.

Shrestha, A., & Dorevitch, S. (2019). Evaluation of rapid qPCR method for quantification of *E. coli* at non-point source impacted Lake Michigan beaches. *Water Research*, *156*, 395–403.

Song, W., Shengtian, Y., Yang, L., & Weimin, Z. (2012). Large-scale non-point source COD pollution load estimation in the Weihe River Basin. *South-to-North Water Diversion and Water Resources Science and Technology*, 2012, *10*(06), 31–36.

Sun, Q., Zhang, Y., Ma, J., Tian, F., Wang, H., & Liu, D. (2018). Detector location selection based on VIP analysis in near-infrared detection of dural hematoma. *Saudi Journal of Biological Sciences*, *25*(3), 452–456.

Thompson, M. S., Brooks, S. J., Sayer, C. D., Woodward, G., Axmacher, J. C., Perkins, D. M., & Gray, C. (2018). Large woody debris "rewilding" rapidly restores biodiversity in riverine food-webs. *Journal of Applied Ecology*, *55*(2), 895–904.

Tian, W., Zhang, H., Zhao, L., & Huang, H. (2017). Responses of a phytoplankton community to seasonal and environmental changes in Lake Nansihu, China. *Marine and Freshwater Research*, *68*(10), 1877–1886.

Wang, X. X., Peng, L., Su, C. J., & Cheng, G. W. (2017). Impact of hydropower dam development on river ecosystems: Ecopath model application on the red river in China as an example. *Polish Journal of Environmental Studies*, *26*(6).

Xu, S., Chen, Z., Li, S. S., & He, P. (2011). Modeling trophic structure and energy flows in a coastal artificial ecosystem using mass-balance Ecopath model. *Estuaries and Coasts*, *34*(2), 351–363.

Yang, G. J., Qin, B. Q., Tang, X. G., Gong, Z. J., Zhong, C. N., Tang, X. M., … Wang, X. D. (2012). Contrasting zooplankton communities of two bays of the large, shallow, eutrophic Lake Taihu, China: Their relationship to environmental factors. *Journal of Great Lakes Research*, *38*(2), 299–308.

Zhang, X., Liu, X., Zhang, M., Dahlgren, R. A., & Eitzel, M. (2010). A review of vegetated buffers and a meta-analysis of their mitigation efficacy in reducing nonpoint source pollution. *Journal of Environmental Quality*, *39*(1), 76–84.

Zhang, Z., Shao, Y., & Xu, Z. (2010). Prediction of urban water demand on the basis of Engel's coefficient and Hoffmann index: Case studies in Beijing and Jinan, China. *Water Science and Technology*, *62*(2), 410–418.

Zhao, C., Yang, S., Liu, J., Liu, C., Hao, F., Wang, Z., … Lim, R. P. (2018). Linking fish tolerance to water quality criteria for the assessment of environmental flows: A practical method for streamflow regulation and pollution control. *Water Research*, *141*, 96–108.

Zhao, C. S., Liu, C. M., Zhao, J. H., Xia, J., Yu, Q., & Eamus, D. (2013). Zooplankton in highly regulated rivers: Changing with water environment. *Ecological Engineering*, *58*, 323–334.

Zhao, C. S., Shao, N. F., Yang, S. T., Xiang, H., Lou, H. Z., Sun, Y., … Yu, Q. (2017). Identifying the principal driving factors of water ecosystem dependence and the corresponding indicator species in a Pilot City, China. *Journal of Hydrology*, *556*, 488–499.

Zhao, C. S., Sun, C. L., Xia, J., Hao, X. P., Li, G. F., Rebensburg, K., & Liu, C. M. (2010). An impact assessment method of dam/sluice on instream ecosystem and its application to the Bengbu Sluice of China. *Water Resources Management*, *24*, 4551–4565.

Zhao, C. S., Yang, S. T., Xiang, H., Liu, C. M., Zhang, H. T., Yang, Z. L., … Yu, Q. (2015). Hydrologic and water-quality rehabilitation of environments for suitable fish habitat. *Journal of Hydrology*, *530*, 799–814.

Zhao, C. S., Yang, Y., Yang, S. T., Xiang, H., Wang, F., Chen, X., … Yu, Q. (2019). Impact of spatial variations in water quality and hydrological factors on the food-web structure in urban aquatic environments. *Water Research*, *153*, 121–133.

Zhou, L., Zhang, Y. L., De Souza, J. G., Podgorski, D. C., Zhou, Y. Q., Garcia De Souza, J., … Davidson, T. A. (2019). Autochthonous dissolved organic matter potentially fuels methane ebullition from experimental lakes. *Water Research*, *166*. 115048

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