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Impact of spatial variations in water quality and hydrological factors on the food-web structure in urban aquatic environments

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ABSTRACT

Global aquatic ecosystems are essential to human existence and have deteriorated seriously in recent years. Understanding the influence mechanism of habitat variation on the structure of the food-web allows the effective recovery of the health of degraded ecosystems. Whereas most previous studies focused on the selection of driving habitat factors, the impact of habitat variation on the food-web structure was rarely studied, resulting in the low success rate of ecosystem restoration projects globally. This paper presents a framework for exploring the effects of spatial variations in water quality and hydrological habitat factors on the food-web structure in city waters. Indices for the evaluation of the food-web structure are first determined by integrating model-parameter extraction via literature refinement. The key water quality and hydrological factors are then determined by coupling canonical correspondence analysis with partial least squares regression. Their spatial variation is investigated using spatial autocorrelation. Finally, fuzzy clustering is applied to analyze the influence of the spatial variations in water quality and hydrological factors on the food-web structure. The results obtained in Ji'nan, the pilot city of water ecological civilization in China, show that the Shannon diversity index, connectance index, omnivory index, and the ratio of total primary production to the total respiration are important indicators of food-web structural change. They show that the driving factors affecting the aquatic food-web structure in Ji'nan are hydrological factors (e.g., river width, water depth, and stream flow), physical aspects of water quality (e.g., air temperature, water temperature, electrical conductivity, and transparency), and chemical aspects (e.g., potassium, dissolved oxygen, calcium, and total hardness). They also show that the stability of the food-web is more prone to spatial variations in water quality than in hydrological factors. Higher electrical conductivity, potassium, total hardness, and air temperature lead to deteriorated food-web structures, whereas better transparency improves structure and stability. We found that water and air temperature are the most important factors in the spatial variation of the food-web structure in the study area, followed by total hardness. Transparency is the least important factor. Large disparities and varied spatial distributions exist in the driving effects of water quality and hydrological factors across regions attributable to differences in geographical environments, water salinity (fresh vs. sea water), and environmental factors (e.g., water pollution). The above methods and results serve as a theoretical and scientific basis for a high success rate of aquatic ecosystem restoration projects in the study area and other cities worldwide.

1. Introduction

Human activities have a severe impact on hydrological cycles and river water quality (Zou et al., 2018), causing deterioration of

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water quality and the decline in the hydrological state of the water cycle, causing negative effects on the ecosystem. This leads to drastic changes in the food-web structure of rivers (Coll et al., 2011; Garay-Narváez et al., 2013; Perkins et al., 2010). The degradation of river ecosystems is accelerated, seriously affecting the ecological values of freshwater.

Ecosystems can be categorized according to their form and function. The former refers to the community structure, and the latter is the network or trophic levels (Baird and Ulanowicz, 1989; McIntyre et al., 2007) of biological components in the system, organized via the food-web or food chain. The most fundamental link between various elements of an ecosystem is nutrition. Food chain and food-web are important forms of energy transfer in an ecosystem (Post, 2002; Nordström and Bonsdorff, 2017). The food-web is a network comprising various organisms and their nutritional relationships in the ecosystem, 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 an ecosystem (Post and Takimoto, 2007). A food-web with a higher level of complexity indicates greater ecosystem resilience to external disturbances (Peralta-Maraver et al., 2017). Research on this topic readily offers insight into the flow of material and energy, the composition and structure of the biological communities, and the complex feeding relationship among species (Baird and Ulanowicz, 1989; McIntyre et al., 2007). It functions as the basis for making ecosystem-based ecological protection and restoration decisions (Harvey et al., 2017; McCann, 2007).

Presently, the common food-web models are mainly divided into three categories. The first type is the structural model, e.g., random model proposed by Erdos and Renyi (1960) (Xue et al., 2018). The second type is a dynamic model that is primarily used to predict dynamic changes in the structure of the food-web (Chen and Cohen, 2001; Haerter et al., 2016; Grilli et al., 2017). The third type is the energy flow model wherein the ecopath model is commonly used. Ecopath is a nutritionally balanced model of an ecosystem that describes the nutrition flow based on food-web structure of the system and the principle of nutritional dynamics (Natugonza et al., 2016). Its primary function is to quantitatively and comprehensively analyze the structure of the ecosystem, the process of nutrition flow, and the characteristics of nutritional dynamics. This model has been widely used in the study of nutrition structure and energy flow, and the prediction of the future development of aquatic ecosystems. It is recognized by ecologists worldwide as the key instrument in the next-generation research on water ecosystems (Angelini and Agostinho, 2005; Chen, 2010).

Water quality and hydrological habitat factor changes affect the hierarchy and structure of the ecosystem (Zhao et al., 2018a) and the integrity of the food-web (Carvalho et al., 2016), deeply influencing ecosystem functions and services (Hemraj et al., 2017; Robson et al., 2017). Previous studies, however, were mostly conducted on the selection of key driving factors and lack the quantitative investigation of the influence of spatial variations in hydrology and water quality on the food-web structure. Consequently, an assessment of 78 large-scale ecological restoration projects in Europe and the United States shows that only a few have achieved their aims (Palmer et al., 2010). It is therefore pressing to investigate the effects of water quality and hydrological changes on the food-web structure, to quantify the level of human impact on the ecosystem and food-web structure, and to restrain and reduce the influence of human activities on the ecosystem. Doing so will provide solid scientific evidence for the management and restoration of aquatic ecosystems (Mor et al., 2018; Sabo et al., 2010).

This study proposes a framework for analyzing the influence of water quality and hydrological factor variations on the structure of aquatic food-webs and understanding the relationship between the structure of aquatic food-webs in various regions and the spatial changes of water quality and hydrological factors. Ji'nan is the study city for water ecological civilization in China. The Ministry of Water Resources in China proposed a project in 2013 to build "healthy water ecological communities" to promote sustainable development. Jinan City was designated to be the first "pilot" city for this project. The success of ecological restoration in healthy water ecological communities should improve the quality of life for people in China and will be an example for other cities around the world (Zhao et al., 2019). This study will provide a scientific foundation for the effective resolution of problems in the current increasingly grave aquatic ecosystems across the globe.

2. Study area

Ji'nan City (36.0–37.5°N, 116.2–117.7°E) is a pilot in the construction of civilized and freshwater ecological cities in China (Fig. 1). The success of aquatic ecosystem restoration in the city will determine the fundamental improvement of the living environment of the Chinese people (Zhao et al., 2018b). 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 et al., 2009; Zhang et al., 2010). Ji'nan City represents a typical developing city in China, having an area of 8227 km^2 and a population of 5.69M. With rapid industrial development and urbanization in recent decades, the water resources in Ji'nan have been severely polluted and reduced in quantity because of extraction. Consequently, drinking water and human health and well-being, are becoming increasingly threatened (Hong et al., 2010). The same is true for aquatic plants and animals and the food-webs they form. Based on comprehensive analysis of the characteristics of the watershed and administrative regions of Ji'nan City and the consideration of the spatial differentiation of hydrological water quality, 48 stations for the hydrology/water quality/aquatic ecosystem monitoring were set up and distributed evenly in the first-grade freshwater ecoregions of the city.

3. Materials and methods

3.1. Experimental data

In the spring, summer, and autumn of the years 2015 and 2016, six large-scale field investigations measured 37 hydrologic, water quality physical, and water quality chemical factors (Table 1) and concurrently sampled the principle communities in a food-web inclusive of phytoplankton, zooplankton, zoobenthos, and fish (Table 2). Nine stations where the rivers had dried were excluded, and monitored data from the remaining 39 stations were used (Fig. 1).

3.1.1. Water quality and hydrological data

The monitored data includes 27 parameters belonging to three categories, which are four hydrological factors (i.e., flow velocity, water depth, flow, and river width), five physical parameters of water quality (i.e., turbidity, conductivity, water temperature, air temperature, and transparency), and 18 chemical parameters of water quality (i.e., permanganate index, chemical oxygen demand, calcium, sulfate, etc.). The data are listed in Table 1.

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

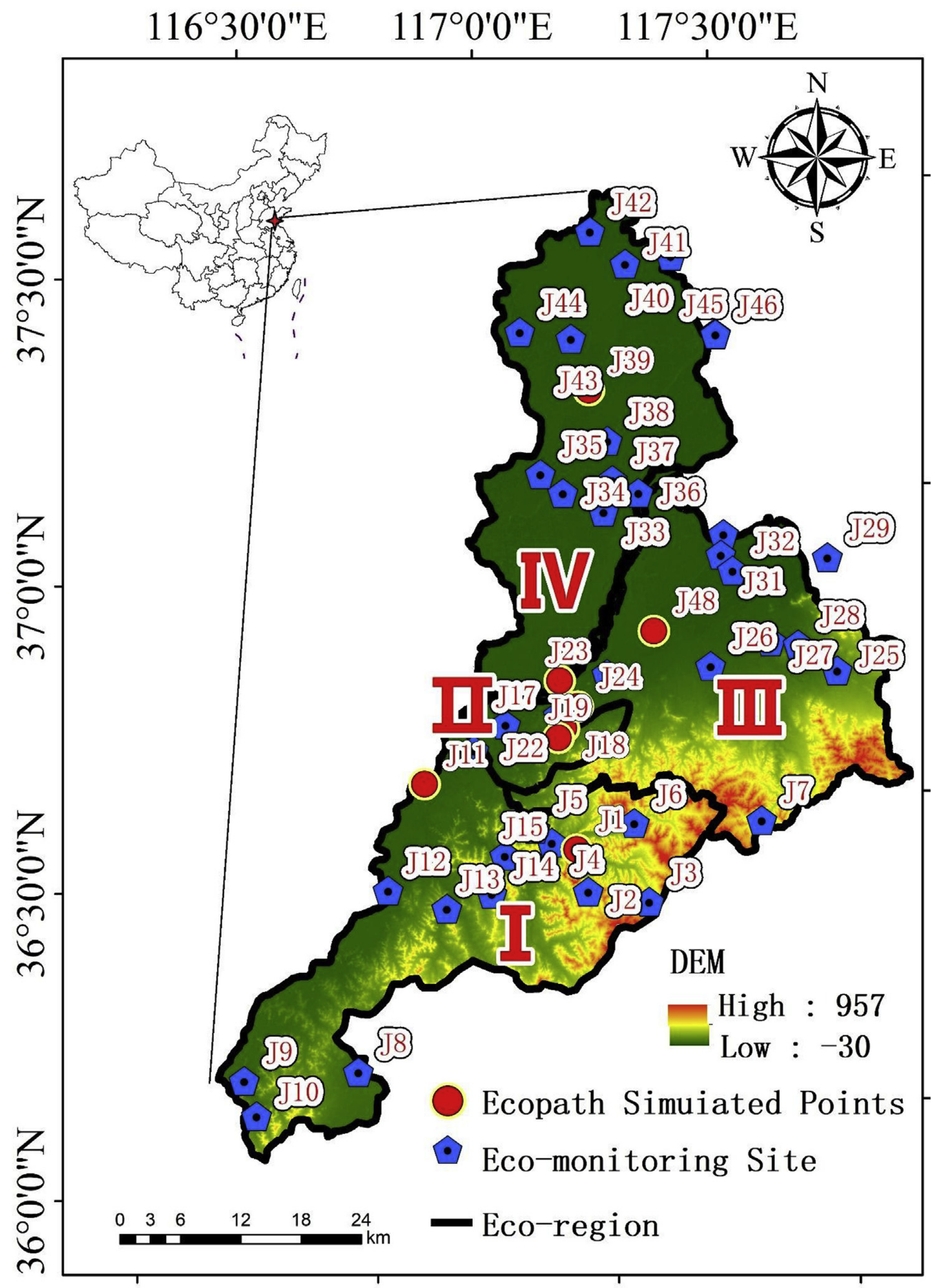

Fig. 1. Hydrology–water quality-freshwater ecosystems monitoring sites and Ecopath simulation points in Ji'nan City (regions I, II, III, and IV are the ecoregions of Ji'nan: I, Yellow River; II, Urban area; III, Xiaoqing River; and IV, Tuhaimajia River, as in Yu et al. (2015)). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(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).

In Table 1, the physical parameters were measured in situ using portable equipment, and the chemical parameters were obtained by testing water samples in the laboratory within 24 h after they were collected at monitoring sites. A spectrophotometer (DR5000) was used to measure ammonia nitrogen, total phosphorus, total nitrogen, and hexavalent chromium; an atomic absorption spectrophotometer (Thermo M6) was used to measure copper, zinc, cadmium, lead, etc.; and an ion chromatograph (DIONEX-600) was used to measure sulfate, fluoride, chloride, and nitrate concentrations (Zhao et al., 2015).

3.1.2. Aquatic biota data

Phytoplankton, zooplankton, zoobenthos, and fish were sampled concurrently with water quality and hydrological factors.

For phytoplankton, a 1000-mL organic glass bottle was used to obtain 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 than 24 h. Subsequently, it was concentrated into

Table 1
Hydrologic, physical, and chemical water quality parameters in the Ji'nan City monitoring program.

Parameter	Abbreviation	Name	Unit	Range (SD)
Hydrologic	FV	Flow velocity	m/s	0–1.69 (0.30)
	RW	River width	m	1.9–320.0 (64.9)
	FL	Stream flow	m^3	0–1110 (148.1)
	WD	Water depth	m	0.01–3.19 (0.73)
Physical	AT	Air temperature	°C	3.0–36.9 (6.83)
	WT	Water temperature	°C	7.0–30.60 (4.83)
	EC	Conductivity	mS/m	290–4130 (717.99)
	Tran	Transparency	cm	0–600 (111.32)
	TB	Turbidity	degree	0.52–924 (139.53)
Chemical[a]	Ca	Calcium	mg/L	17.63–315.83 (49.86)
	Cl	Chlorine		11.85–786.15 (124.12)
	SO_4	Sulfate		38.14–977 (175.83)
	CO_3	Carbonate		0–19.43 (4.33)
	HCO_3	Bicarbonate		50.05–845.32 (92.49)
	TA	Total alkalinity		51.48–693.35 (75.15)
	TH	Total hardness		111.09–1360.22 (205.18)
	DO	Dissolved oxygen		1.17–15 (2.53)
	TN	Total nitrogen		0.25–34.18(5.27)
	NH_4	Ammonia		0.07–27.07 (3.4)
	NO_2	Nitrite		0–1.97 (0.27)
	NO_3	Nitrate		0.05–18.85 (2.64)
	COD	Chemical oxygen demand		0–252.28 (23.06)
	MNO_4	Permanganate index		0.57–64 (5.66)
	BOD	Biochemical oxygen demand		0–35.80 (4.55)
	TP	Total phosphorus		0–3.64 (0.60)
	Fluoride	Fluoride		0.18–2.51 (0.37)
	pH	pH		7.26–9.3 (0.37)

[a] The other 10 heavy metal ions (e.g., copper, zinc and lead) were below detection and are therefore omitted. All units of chemical attributes are in mg/l.

Table 2
Principal types of aquatic life and the number of species in the years 2015 and 2016 (unit: species).

Types of aquatic life (Total number of species)	Classification	Number of species in 2015	2015			Number of species in 2016	2016		
			Spring	**Summer**	**Autumn**		**Spring**	**Summer**	**Autumn**
Phytoplankton	Bacillariophyta	52	43	52	52	43	34	42	43
2015(104)	Chlorophyta	32	32	25	25	29	28	23	24
2016(96)	Cyanophyta	16	11	16	12	14	9	14	11
Zooplankton	Rotifera	22	22	19	17	23	23	21	18
2015(56)	Protozoa	–	–	–	–	12	–	–	–
2016(50)	Cladocera	–	–	–	–	8	–	–	–
Zoobenthos 2015(42) 2016(24)	Gastropoda	14	10	13	14	8	5	6	8
Fish	Cyprinidae	26	17	12	24	19	16	14	19
2015(40)	Cobitidae	3	3	3	3	3	3	3	3
2016(28)	Carangidae	3	2	3	3	2	2	2	2

"–" indicates the lack of corresponding data.

30 mL. Subsequently, 0.1 mL of this concentrated sample 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 cm × 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 et al., 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 labeled jars for subsequent laboratory identification (Zhao et al., 2017).

In total, 440 species of phytoplankton, zooplankton, zoobenthos, and fish were detected in the study area during the six field investigations: 242 in 2015 and 198 in 2016. Further details are presented in Table 2.

3.2. Methods

Food-web models for different sampling sites in different seasons were first set up, followed by the selection of indices for the evaluation of food-web structure from literature. The key driving factors affecting the food-web structure were identified by jointly using canonical correspondence analysis (CCA) and partial least squares. The spatial variation of different types of driving factors were analyzed using the spatial autocorrelation analysis method. Together with fuzzy clustering, they were used to explore the food-web structure and ecosystem stability of Ji'nan under different degrees of water quality and hydrological changes.

3.2.1. Selection of food-web structure indices

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 yrs. 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 and Vinagre, 2018; Morillo-Velarde et al., 2018), Shannon index (Liu et al., 2016a,b), connectance index (Marina et al., 2018), system omnivory index (Wang et al., 2017), and total primary production/total respiration (Chen et al., 2011; Xu et al., 2011).

3.2.2. Identifying the key driving factors affecting food-web structure

CCA analyses were performed on hydrological factors and food-web structure indices, water quality chemical factors and food-web structure indices, and water quality physical factors and food-web structure indices. Partial least squares regression was thereafter used for further quantitative verification to determine the key driving factors affecting the food-web structure.

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: the food-web structure index data matrix and the environmental data matrix in this study (Barrella et al., 2014). Factors affecting the structure of food-webs include water quality and hydrological parameters. A method comprising single-modal sorting and Monte Carlo displacement testing was used to select the main factors ($p < 0.05$) for food-web structure differences based on the above two parameters. CCA was conducted using Canoco software (Zhao et al., 2017).

The partial least squares regression analysis is an extension of multiple regression analysis, which 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 $X_{m \times n}$, comprising m variables (columns) and n objects (rows), and a response vector $Y_{n \times 1}$. Partial least squares regression identifies a few linear combinations of the original x values that describe most of the inherent variable (Hu et al., 2018).

In brief, CCA is a multivariate statistical analysis that uses the correlation between a pair of integrated variables to reflect the overall correlation between the two sets of indices. It is a semi-quantitative analysis of the overall correlation between the two sets of indices. Partial least squares regression is a second-generation regression analysis combining multivariate linear regression, canonical correlation analysis, and principal component analysis. It provides a quantitative description of the correlation between two sets of indicators and indicates the driving factors more clearly. The cross-validation using these two methods ensures the accurate selection of key driving factors.

3.2.3. Spatial variations of the key driving factors

Based on the key driving factors determined above, the spatial autocorrelation analysis method was used to study the spatial distribution of the key driving factors. This method has been commonly used to assess the degree of clustering, randomness, or fragmentation of a spatial pattern. Spatial autocorrelation includes global spatial autocorrelation, which estimates the overall degree of spatial autocorrelation for a dataset, and local spatial autocorrelation, which identifies the location and types of clusters. The two most common spatial autocorrelation measures for continuous data are Moran's I and Geary's C statistics. Moran's I is generally preferred over Geary's C, because the values of the former are more intuitive (i.e., positive values for positive autocorrelation and vice versa). Moran's I was also observed to be generally more robust (Atikaimu et al., 2015).

Spatial autocorrelation analysis in geostatistics is usually used to analyze the spatial variability of certain types of data. The spatial changes of various driving factors are analyzed using ARCGIS and GEODA (Atikaimu et al., 2015). The Moran's I value of the global autocorrelation analysis can be obtained intuitively. The overall degree of spatial autocorrelation of the factors and local autocorrelation analysis can identify the location and type of the cluster.

3.2.4. Impact of key driving factors on food-web structure studied using spatial clustering

After analyzing the spatial heterogeneity of water quality and hydrological factors, further clustering was performed on water quality and hydrological factors and the food-web structure indices to study the impact of spatial-temporal variations of the factors on the 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 fuzzy clustering method (FCM). The hard-clustering method is more suitable for clustering conditions with clear boundaries, whereas, for problems with unclear boundaries, FCM is usually adopted (Pan, 2010; Zhao et al., 2013). In this study, monitoring stations are distributed randomly across the study area, making it difficult to determine 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. There are many algorithms and software for FCM, and detailed algorithms can be found in Li et al. (2007), Pan (2010), and Shafi et al. Here, we use the statistical software called data processing system to perform the fuzzy clustering analysis (Zhao et al., 2013).

Table 3
Food-web structure indices.

NO	Index	NO	Index
1	Sum of all consumption	**8**	Total primary production/total respiration
2	Sum of all exports	**9**	Total primary production/total biomass
3	Sum of all respiratory flows	**10**	Total biomass/total throughput
4	Sum of all flows into detritus	**11**	Connectance index
5	Total system throughput	**12**	System omnivory index
6	Sum of all production	**13**	Shannon's diversity index
7	Calculated total net primary production		

4. Results

4.1. Selection of food-web structure indices

Thirteen indices (Table 3) were obtained from the food-web models constructed. Relevant results obtained by scientists in the international community during the past 10 yrs were thereafter studied to select the six most commonly used and accurate indices (Table 4), which were screened with the indices from the constructed food-web models to obtain the following four evaluation indices: Shannon's diversity index (Iliev et al., 2017; Liu et al., 2016a,b; Wang et al., 2016), total primary production/total respiration (Chen et al., 2011; Wang et al., 2017; Xu et al., 2011), connectance index (Guo et al., 2018; Han et al., 2017; Marina et al., 2018), and system omnivory index (Lira et al., 2018; Wang et al., 2017).

Among these indices, Shannon's diversity index indicates the complexity of food-webs (Liu et al., 2016a,b), connectance index shows its connectivity (Marina et al., 2018), system omnivory index reflects the stability (Wang et al., 2017), and total primary production/total respiration indicates the maturity (Chen et al., 2011; Xu et al., 2011). They are used herein to evaluate the structure of food-webs and the structural and functional integrity of the entire ecosystem.

4.2. Key driving factors affecting food-web structure

The relationship between the three types of monitored data (i.e., hydrologic, physical, and chemical water quality parameters) as shown in Table 1, and the structure indices of food-web (i.e., system omnivory index, Shannon's diversity index, connectance index and total primary production/total respiration) is first analyzed using CCA. Preliminary screening determines the key driving factors (Fig. 2) among the various candidates. The variable importance in projection (VIP) values from partial least squares regression are used to finely select the driving factors affecting food-web structure (Tables 5–7).

For hydrological factors, CCA results (Fig. 2a) show that the flow velocity (FV), stream flow (FL), water depth (WD), and river width (RW) are positively correlated with total primary production/total respiration (TPR), and negatively correlated with Shannon's diversity index (SDI), connectance index (CI), and system omnivory index (SOI). Moreover, VIP values (Table 5) are considered to further screen and analyze the factors that affect TPR, SDI, CI, and SOI specifically. After removing the factors with mean VIP below 1, it is observed that TPR is mainly affected by the environmental factors of river width and flow, SOI by water depth and river width, SDI by river width and water depth, and CI by stream flow and water depth. Combining CCA and VIP results, the river width, water depth, and stream flow are identified as the hydrological factors affecting the food-web structure.

Similarly, the water quality physical factors affecting the food-web structure are observed to be air temperature, water temperature, electrical conductivity, and transparency via CCA analysis (Fig. 2band c) and VIP results (Table 5), whereas the water quality chemical factors with the greatest impact are potassium, dissolved oxygen, calcium, and total hardness.

4.3. Spatial variation of the key driving factors

Autocorrelation was performed on the above key driving water quality and hydrological factors, screened out to study their spatial variations. Global spatial autocorrelation was used to determine the Moran's I index for each factor. A clearly positive Moran's I indicates significant positive correlation; observed values of the factor tend to aggregate in space. Clearly negative Moran's I indicates significant negative spatial correlation, and observed values of the factor tend to be spatially dispersed, which reflects the variation pattern in the value of the factor across spatial sites. Moreover, higher Moran's I signifies greater correlation among the values of a factor in space. Local autocorrelation is thereafter performed on the driving factors showing a strong spatial correlation in their values to yield the detailed spatial change of the factor and its relation with geographical location.

Table 4
Food-web structure indices retrieved from worldwide literature during the past 10 yrs.

Index	Study area	Reference
Biodiversity	Montsant River, Spain	Mor et al. (2018)
	Hungary	Abonyi et al. (2018)
	United Kingdom	Thompson et al. (2018)
Food chain length	Caribbean coast, Mexico	Morillo-Velarde et al. (2018)
	The Atlantic, Mediterranean, Southwest India Ocean and South Pacific Ocean.	Mendonça and Vinagre, 2018
Shannon's diversity index	54 sites globally	Liu et al. (2016a,b)
	Bulgaria	Iliev et al. (2017)
Connectance index	Potter Cove, Antarctica	Marina et al. (2018)
	Red River, China	Wang et al. (2017)
System omnivory index	Red River, China	Wang et al. (2017)
Total primary production/total respiration	Northern Hangzhou Bay, China	Chen et al. (2011)
	Northern Hangzhou Bay, China	Xu et al. (2011)
	Red River, China	Wang et al. (2017)

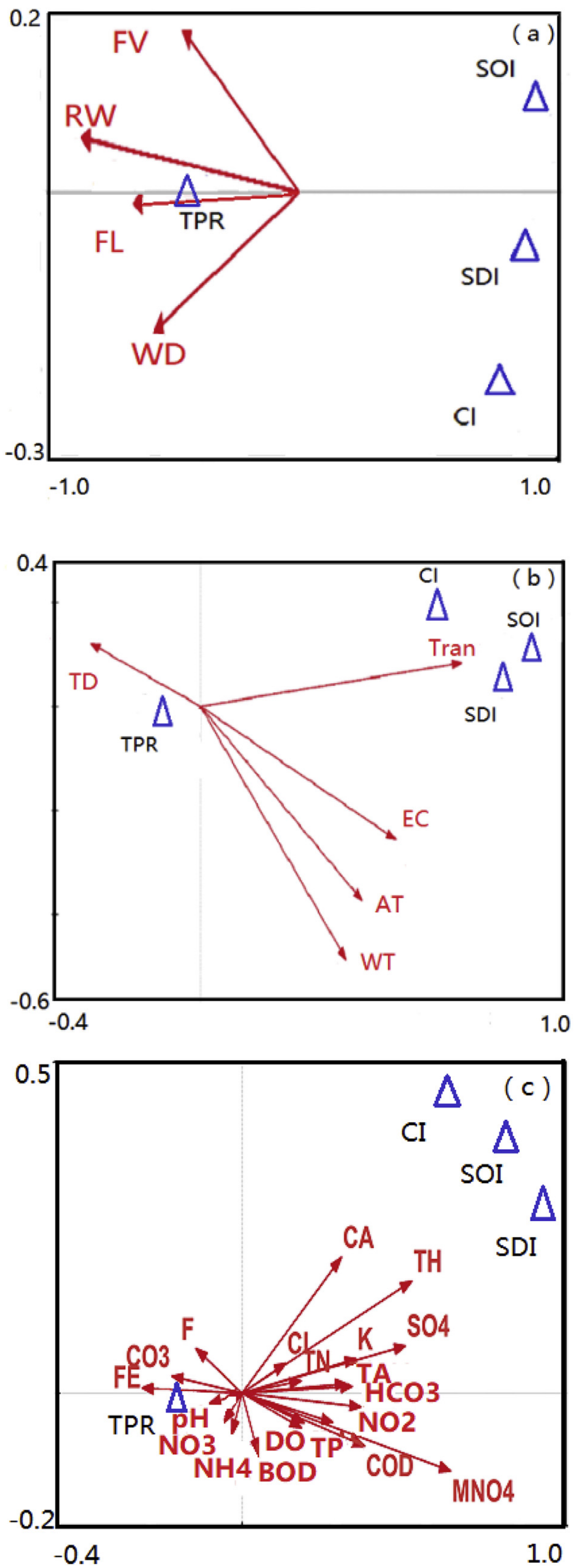

Fig. 2. CCA on (a) Hydrological factors, (b) water quality physical factors, and (c) water quality chemical factors. system omnivory index (SOI), Shannon's diversity index (SDI), connectance index (CI), total primary production/total respiration (TPR), flow velocity (FV), river width (RW), flow (FL), water depth (WD), turbidity (TD), transparency (Tran), electrical conductivity (EC), air temperature (AT), water temperature (WT), calcium (Ca), total hardness (TH), sulfate (SO_4), permanganate index (MNO_4), and biochemical oxygen demand (BOD).

4.3.1. Global spatial autocorrelation

Global autocorrelation analysis of each driving factor using GEODA yields the spatial autocorrelation index (i.e., Moran's I, and its confidence level) (Table 6).

As shown in Table 6, there is almost no correlation in the spatial distributions of hydrological factors (i.e., almost no pattern in the spatial variation) (confidence level<95%). However, a significant correlation is observed among the water quality physical factors (confidence level>95%), which are also positively correlated (Moran's I > 0), indicating substantial spatial aggregation of these factors into distinct high- and low-value zones. Water quality chemical factors show positive spatial correlation (Moran's I > 0), with K and TH being the most significant (confidence level>95%).

4.3.2. Local spatial autocorrelation

As shown in Table 6, water quality physical factors display prominent spatial clustering (autocorrelation), with EC being the most significant, followed by Tran, AT, and WT. Among the chemical factors of water quality, only K and TH exhibit appreciable spatial clustering. These six driving factors with significant spatial clustering are therefore selected for local autocorrelation via ARCGIS to study the relationship between their spatial clustering and geographical location and to further identify the spatial clustering characteristics of driving factors, as shown in Fig. 3.

Fig. 3 confirms the spatial autocorrelation in the driving factors of Ji'nan food-web structure (EC, Tran, AT, WT, K, TH), and the strong regional aggregation in their values. As observed in Fig. 3a, high values of electrical conductivity (EC) are mainly observed in Ecoregion IV and Ecoregion III to the north of metropolitan Ji'nan. The EC values in other regions are low. High-value areas are mostly plains, having higher salt ion levels in water owing to agricultural activities, and thus higher electrical conductivity. The spatial distribution of transparency (Tran) is opposite to that of EC, with higher values concentrated in the southwest and southern hilly region, as shown in Fig. 3b, whereas most of the northern region has low values of transparency. This is because many streams flow in the mountains of Ecoregion I to the south of the city, with Yellow River as the water source. Human activity is also less intense in this area, which ensures good water conditions. In Fig. 3c, high values of air temperature (AT) are mainly observed in the north and center of Ji'nan, whereas low values are present in the southwest and southern mountains. Ji'nan is higher in altitude at the south, where the population is also less dense and the human activity is low, resulting in the low temperatures of Ecoregion I. The trend in WT is opposite to that of AT, with high values located in the southwest of the city. The spatial variations in potassium (K) and total hardness (TH) are similar, as shown in Fig. 3d and f, with high values observed in the Ecoregion IV to the north and some areas in the northern part of Ecoregion III. Ecoregion I to the south and Ecoregion II at the urban center are low-value areas. High-value areas are mostly plains heavily affected by agricultural activities. The levels of potassium and other salt ions in the water body are higher, increasing total hardness. Drinking-grade water is supplied in the urban center, and spring water flows abundantly in the southern hilly region, which is also not significantly influenced by human activity. The level of salt ions and the total hardness are thus lower in the waters of these two zones. Elevated total hardness and electrical conductivity in water affect the food-web structure and the health of ecosystem (Mazzei and Gaiser, 2018; Pekcanhekim et al., 2016).

Table 5
Mean VIP obtained via partial least squares regression.

Food-web structure index		TPR	SOI	SDI	CI
Hydrological factors	**River width**	1.11	1.03	1.29	0.87
	Average water depth	0.66	1.11	1.09	1.36
	Flow	1.31	0.98	0.72	1.15
	Flow velocity	0.84	0.89	0.86	0.58
Water quality physical factors	**Air temperature**	0.58	0.11	1.46	1.4
	Water temperature	1.16	0.68	0.48	0.95
	Transparency	0.97	1.74	1.23	0.3
	Conductivity	1.27	1.03	0.58	0.42
Water quality chemical factors	**Calcium**	1.56	0.81	0.97	1.1
	Potassium	0.86	1.22	1.38	1.08
	Sodium	0.69	0.92	1.26	1.08
	Bicarbonate	0.63	0.85	1.15	1.14
	Total alkalinity	1.01	1.1	0.69	0.87
	Total hardness	0.71	1.19	1.04	0.83
	Dissolved oxygen	1.51	0.87	1.33	1.66
	Total nitrogen	1.43	0.64	0.73	1.14
	Total phosphorus	0.82	0.93	1.52	0.69

Table 6
Moran's I and its confidence level obtained via global spatial autocorrelation of the driving factors.

Factor		Moran's I	Confidence level (%)
Hydrological factor	RW	−0.02	71.3
	WD	0.06	83
	FL	−0.08	63.5
Water quality physical factor	**EC**	0.48	99.9
	Tran	0.26	99.5
	AT	0.17	97.5
	WT	0.11	95.6
Water quality chemical factor	**K**	0.21	98.1
	TH	0.16	98
	Ca	0.09	92
	DO	0.04	79

Table 7
VIP values for the structure level index (∂) of food-web.

Key driving factor	Potential factor						Mean
	1	2	3	4	5	6	
AT	1.541	1.499	1.484	1.472	1.469	1.469	1.49
WT	1.772	1.716	1.694	1.673	1.670	1.670	1.70
Tran	0.451	0.545	0.541	0.645	0.645	0.645	0.58
EC	0.187	0.213	0.431	0.530	0.537	0.537	0.41
K	0.491	0.687	0.713	0.850	0.849	0.849	0.74
TH	0.082	0.111	0.200	0.239	0.267	0.267	0.19

4.4. Impact of key driving factors on food-web structure based on spatial clustering analysis

After the spatial clustering characteristics of key driving factors are determined, the food-web structure indices and the water quality and hydrological factors were analyzed together via FCM clustering. The results are displayed on geospatial maps according to the location of sampling points for visualization of the distribution of clusters (Fig. 4). The spatial clustering results of the food-web structure indices and key driving factors were compared and analyzed to further identify the relationship between the driving factors and the spatial variation in food-web structure.

As shown in Fig. 4a, fuzzy spatial clustering on the food-web structure indices (TPR, SOI, SDI, and CI) reveals the aggregation of low structure index values in the urban center (pentagons in the figure), and the concentration of high values in both the urban center and southern hilly region (circles). The medium values (triangles) tend to be more uniformly distributed in space, and are observed in the south, center, and north of the Ji'nan metropolitan area.

The fuzzy clustering results of hydrological factors (Fig. 4b) show that Ji'nan metropolitan area overall is one of medium to low values (triangles and pentagons), and predominantly low values. The southern hilly region and the eastern region are both areas of low values, whereas the urban center in the middle is an area of medium to high values. Fuzzy clustering on water quality factors (in Fig. 4c, a higher value indicates lower water quality) shows the concentration of high values (circles) in the eastern part of the city. Because this area is under the influence of heavy human activities, the values of EC, Tran, AT, WT, K, and TH are high, and do not benefit the health of the ecosystem. Overall, the values of water quality factors in the southern part of the city are lower than those in the northern part, indicating a healthier aquatic ecosystem in the south. Analyzing the clustering results of water quality and hydrological factors together (Fig. 4b and c), it is observed that Ecoregion IV on the northern plain is moderate in hydrological condition (triangles in Fig. 4b) and water quality (triangles in Fig. 4c), owing to intense agricultural activities. Ecoregion II in the urban center possesses good hydrological condition (circles and triangles in Fig. 4b). The ion, hardness, and water temperature values are low (pentagons and hexagons in Fig. 4c). Streams are observed in the Ecoregion I of the southern hilly region, but the stream flow is small, indicating poor hydrological condition (pentagons in Fig. 4b). The key driving factors of water quality adopt low values, which facilitates ecosystem health (pentagons in Fig. 4c).

Analyzing the clustering results of food-web structure indices (Fig. 4a) and all the key driving factors (Fig. 4b and c) comprehensively, it is observed that both the food-web structure indices and the driving factors assume medium values in the northern plain region (triangles in Fig. 4a, b, and 4c). The food-web structure

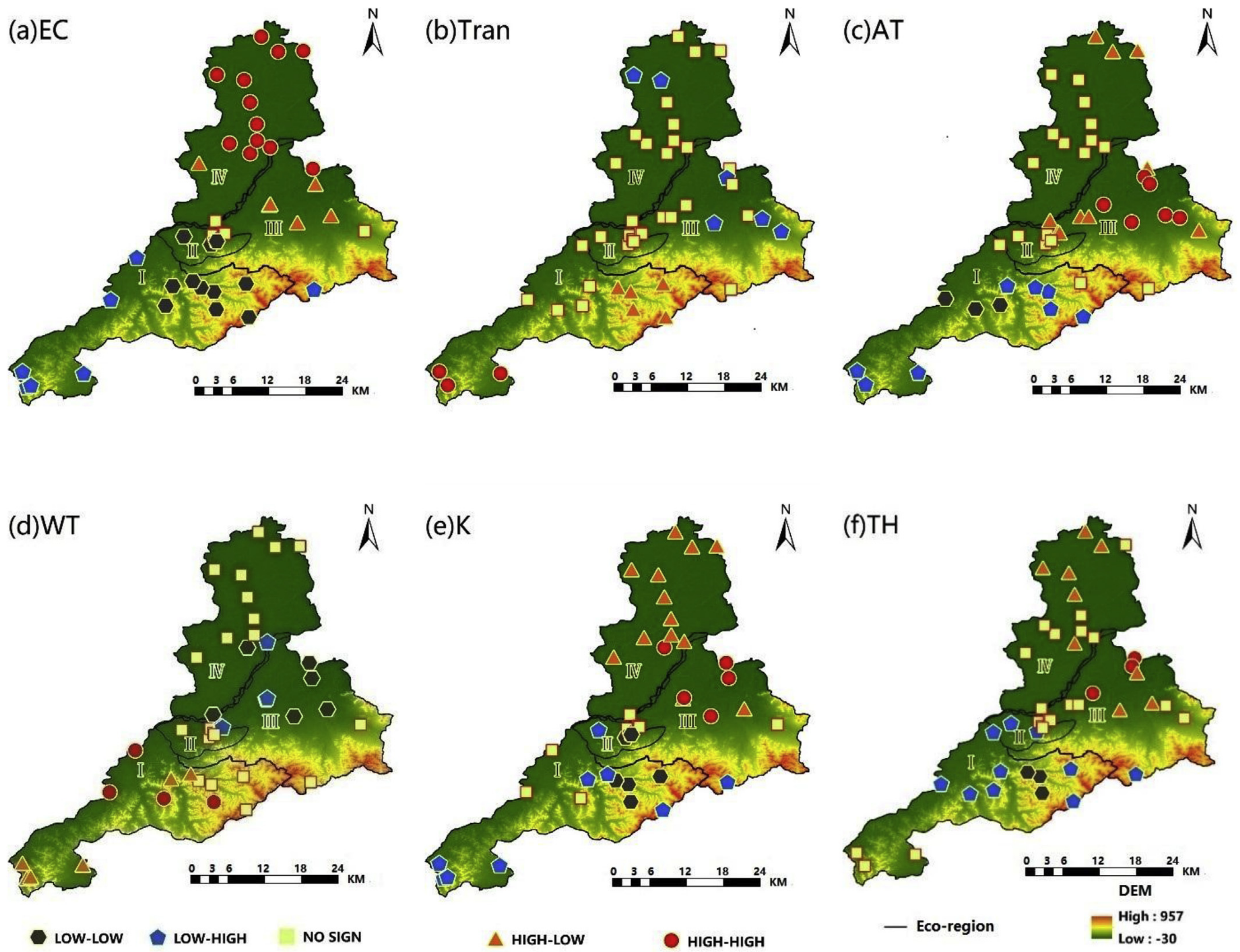

Fig. 3. Local spatial autocorrelation results.

indices and key hydrological driving factors have medium to high values in the central region (circles and triangles in Fig. 4a and b), whereas the key driving factors of water quality have low values (pentagons and hexagons in Fig. 4c). The food-web structure indices have high values in the southern hilly region (circles in Fig. 4a). The hydrological condition is poor (triangles in Fig. 4b), but the water quality is good (pentagons and hexagons in Fig. 4c) owing to the presence of streams. The narrow rivers with small stream flow result in poor hydrological conditions. However, the water quality factors have medium-to-low values, because the level of human activity there is low (Lu et al., 2017). The number of aquatic organisms in this region is abundant, and the food-webs are intact and stable.

The above analyses demonstrate that there is a good spatial correspondence between the key driving factors and the food-web structure. Regions with good hydrological condition and water quality, especially water quality, would have high values of food-web structure indices, and vice versa. Generally, food-web structure indices are negatively correlated with the degree of human activity and are more significantly influenced by water quality than by hydrological factors. As shown by the above results and Fig. 3, the food-web structure of the northern plain is less stable and intact than the southern hilly region, owing to the high levels of electrical conductivity, air temperature, potassium, and total hardness in the former. These water quality factors are inversely related to food-web stability, whereas the opposite is true for transparency.

5. Discussion

5.1. *Key driving factors affecting food-web structure*

Human activities cause changes in water quality and hydrological factors, significantly influencing the food-web structure (Carvalho et al., 2016). Two different methods (i.e., CCA and partial least squares regression (Hu et al., 2018)) are used to select the driving factors. Because these two methods differ in the selection of the driving factors qualitatively and quantitatively, they produce different results. However, CCA, followed by partial least squares regression, would achieve higher precision screening and more reliable results. The main driving factors obtained jointly via these two methods are river width, water depth, flow, air temperature, water temperature, transparency, electrical conductivity, total hardness, potassium, calcium, and dissolved oxygen. Studies conducted on the Montsant River observed changes in the food-web structure of the river caused by the impact of the driving factors,

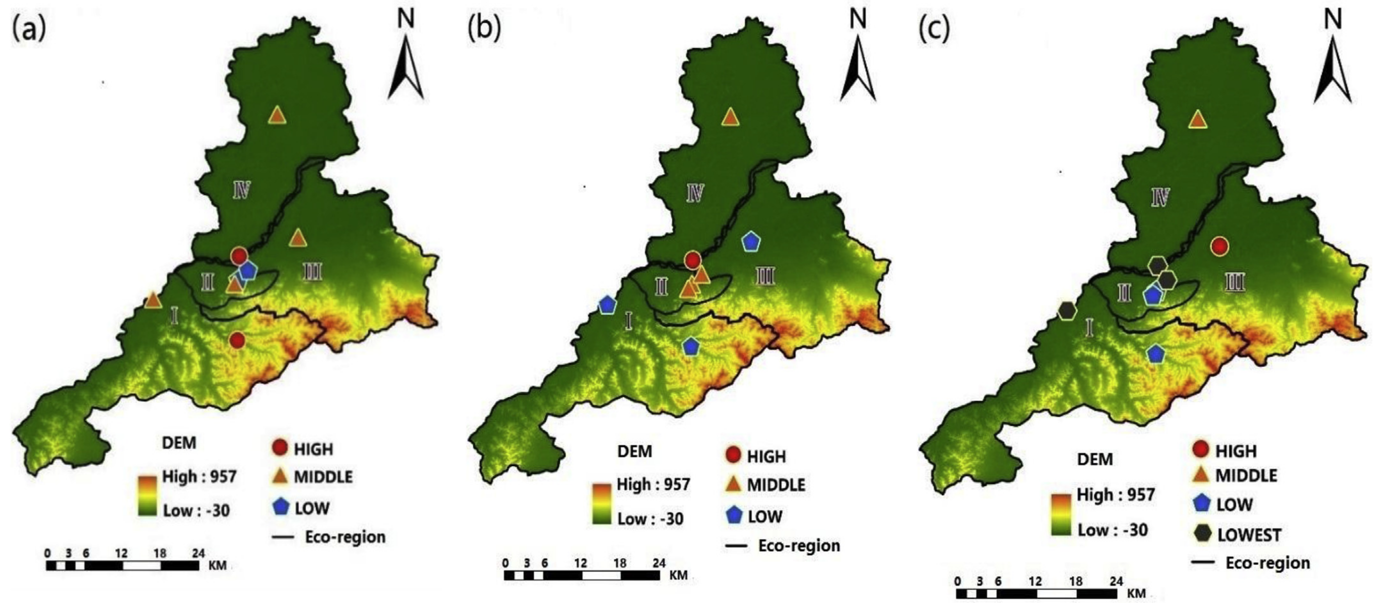

Fig. 4. Spatial clustering analysis. (a) Clustering of the food-web structure indices. Higher value indicates greater stability; (b) clustering of hydrological driving factors; (c) clustering of water quality driving factors. Higher value indicates lower water quality.

including river width, flow, and water depth (Mor et al., 2018). Similarly, research in the Ramsar listed coastal lagoon of India shows the varied influences of habitat environmental factors, such as hydrological condition and water quality, which are under different degrees of human impact, on the food-web, and changes in stream flow and water quality drive the changes in food-web (Hemraj et al., 2017). Sanchez−Carrillo et al. studied 10 lakes around the world and identified temperature and altitude as the important factors leading to the differences in food-web structure (Sánchez−Carrilloet al., 2018). These results are similar to ours and cross-validate our methods of quantitatively studying the effects of water quality and hydrological factors on food-web structure.

5.2. Analyses of the spatial-temporal variation in key driving factors

This study reveals the apparent variation in the autocorrelation properties of driving factors. However, owing to topography, spatial autocorrelation is not observed in hydrological factors. Water quality physical factors show good positive autocorrelation, as do the potassium and total hardness among water quality chemical factors. Water quality and hydrological changes were also studied on the Lancang River Basin in China. It was observed that the degree of changes along the river diameter increased downstream, and the changes in hydrological factors became more intense. However, the changes were less stable (i.e., there is no definite autocorrelation) (Li juan et al., 2002). Similarly, the spatial-temporal changes of surface water quality were studied on the Yinghe River Basin of China. The spatial autocorrelation among the variables was quantified using Moran's I. The spatial autocorrelation of water quality showed that the water quality factors changed in a complex way with season and geographical location (Liu et al., 2016a,b). This is consistent with the spatial variation patterns obtained for the key driving factors of hydrological condition and water quality in our study. Hamidi et al. (2018) studied the chemistry of coastal aquifers of Rmel−Oulad Ogbane in Morocco and observed no autocorrelation in the water chemical factors. Armt et al. (2017) obtained the highest spatial autocorrelation with sodium ions while investigating the water quality and spatial variability of groundwater in Sylhet district, Bangladesh. Gorgij et al. (2017) observed the most significant autocorrelation in bicarbonate during their evaluation of the water quality of 21 groundwater samples from the Azarshahr Plain of Iran. These results differ from ours, because ionic content varies with environmental factors, such as geographical condition, water salinity, and water pollution, leading to the differences in spatial distribution of water quality chemical factors across study areas.

5.3. Impact of key driving factors on ecosystem health

Low values of food-web structure indices are observed primarily in the urban center, whereas medium values are observed in all four regions, with high values in the southern hilly region and the Yellow River Basin. Streams flow in the southern hills, and the region is not significantly affected by human activity (Lu et al., 2017). The Yellow River receives external sources of stream flow and has a relatively integral and stable food-web structure. Moreover, the spatial distribution shown in the clustering results is consistent with the ecological zoning of Ji'nan metropolitan area (Yu et al., 2015), because variations in geographical location and intensity of human activity, such as the different distributions of water sources, population, and industrial and agricultural productions among places could lead to differences in hydrological condition and water quality (Carvalho et al., 2016). Similarly, Mazzei and Gaiser (2018) also observed changes in the diatom assemblage by even small variations in the electrical conductivity at the bottom wetland during their study conducted in southern Florida wetlands. Quiroga et al. (2017) identified total hardness and electrical conductivity as the most important factors affecting the structure of bacterial assemblage while studying the bacterioplankton of five peatland pools. Tunney et al. (2018) surveyed 35 Canadian lakes and observed water transparency to be an important factor affecting the predation relationship of food-web. These results indicate the temporal-spatial variations in water quality and hydrological factors have great influences on food-web structure.

Our research reveals a negative correlation between the stability of food-web and human activity level, and greater influence of water quality than hydrological factors. Higher electrical conductivity, air temperature, potassium, and total hardness lead to less stable food-web, and vice versa, indicating that these factors are inversely related to food-web stability. The opposite is true for transparency. Pekcanhekim et al. (2016) studied several sub-basins of the Baltic Sea, concluding that salt concentration is the most important factor driving the changes in offshore biota composition of Bothnian Bay. Temperature, on the contrary, was not deemed as important, possibly owing to changes in the environment. In our study, the conductivity, potassium, and total hardness were also affected by salt concentration. Kautza and Sullivan (2016) observed a positive correlation between river width and food chain length in 12 river reaches along an ~185-km-long section of the Scioto River system (Ohio, USA). The study by Sullivan (2013) in the mountain drainages of northern Idaho showed the effect of stream geomorphology on food-web structure. Whereas the above results indicate hydrological factors as an important factor influencing food-web, such a driving effect is not apparent in the hydrological factors studied in our study. This may be caused by the graver water pollution in our study area as compared with the two studied in the United States. This could overshadow the influence of hydrological factors on food-web structure. Comprehensive analyses show that conductivity, air temperature, water temperature, total hardness, transparency, and potassium ions affect food-web structures to a certain extent.

Changes in food-web structure will have important impact on ecosystem functions and ecological values (Hemraj et al., 2017; Robson et al., 2017). To further quantify the effects of the above key driving factors on the structure level of food-web, a structure level index ($\partial_i = \frac{a_i+\frac{1}{b_i}+c_i+d_i}{4}$) is established by assigning equal weight to the four food-web structure indices identified before. This formula is used to evaluate the overall structural characteristics of the food-web. ∂_i is the structure level index of the ith food-web. a_i, b_i, c_i, and d_i are the Shannon's diversity index, total primary production/total respiration, connectance index, and system omnivory index of the ith food-web, respectively. The structure level index (∂) reflects the changes in the structure level of food-web in terms of stability, complexity, connectivity, and maturity.

The VIP values of the key driving factors on the structure level index of food-web (∂) are calculated via partial least squares regression (Table 7), from which the influence of each factor on the index of the food network (Table 7) could be used to analyze the influence of each key driving factor on the potential factors in the regression analysis. The mean VIP of each key driving factor is obtained to indicate the effect of that factor on the structure level index of food-web. The impact levels of the factors on ∂, ranging in descending order are as follows: water temperature (WT), air temperature (AT), potassium ion (K), transparency (Tran), electrical conductivity (EC), and total hardness (TH) (the left 2 columns of Table 8). WT and AT could be observed to have the greatest influence (VIP>1.0).

The mean VIP of each key driver factor on the four food-web structure indices could be similarly obtained (Table 8). It can be observed that four factors out of five (AT, TH, K, WT and EC) have strong influence on SDI (VIP>1.0), two factors (WT and AT) have great influence on TPR, four factors (WT, EC, AT and TH) have strong impact on CI, and four factors (EC, Tran, K and TH) have great impact on SOI.

Overall, the six key driving factors selected affect the different aspects of the food-web. Water temperature and air temperature influence ∂, SDI, TPR, and CI more. Conductivity has greater influence on CI and SOI. Potassium ion influences SDI and SOI more. Total hardness has a significant influence on SDI, CI, and SOI. Transparency only influences SOI to a significant degree. Generally, the most important factors that drive the spatial variation of food-web structure are water temperature and air temperature, followed by total hardness, with transparency being the least influential.

6. Conclusions

Study on the influence of water quality and hydrological factor variations on the structure of aquatic food-webs shows that, (1) complexity, connectivity, stability, and maturity are important features in the structural stability of the food-web, and are well-reflected by the Shannon's index, connectance index, system omnivory index, and total primary production/total respiration; (2) in our study area, the three types of driving factors affecting the food-web structure are the hydrological driving factors (river width, water depth, and flow), water quality physical factors (air temperature, water temperature, electrical conductivity, and transparency), water quality chemical factors (potassium, dissolved oxygen, calcium, and total hardness); (3) hydrological factors do not show spatial correlation, whereas the above four water quality physical factors and two water quality chemical factors (potassium and total hardness) display good positive correlation; (4) food-web stability is more susceptible to the influence of spatial variations in water quality than hydrological condition. High electrical conductivity, potassium, total hardness, and temperature lead to the decline in food-web stability, whereas transparency improves the stability; (5) water-quality factors tend to be more dominant than hydrological factors in regions of drastic environmental changes, such as serious water pollution.

In this study, the driving factors affecting food-web structure are selected based on the structural characteristics of aquatic food-webs and the respective water quality and hydrological states. The results can guide the successful recovery of aquatic ecosystem in the study area. They can also provide scientific evidence for the restoration of similar aquatic ecosystems in other cities worldwide.

Owing to the complexity of aquatic ecosystems, some of the results obtained here are preliminary and qualitative and further investigation is required in this respect to achieve more

Table 8
Mean VIP for the food-web evaluation indices (ranked in descending order of the influence exerted by the factors on food-web evaluation indices). Underscore indicates significant influence.

Evaluation index of food-web									
∂		SDI		TPR		CI		SOI	
WT	<u>1.70</u>	AT	<u>1.37</u>	WT	<u>1.70</u>	WT	<u>1.43</u>	EC	<u>1.72</u>
AT	<u>1.49</u>	TH	<u>1.16</u>	AT	<u>1.43</u>	EC	<u>1.26</u>	Tran	<u>1.43</u>
K	0.74	K	<u>1.11</u>	K	0.69	AT	<u>1.25</u>	K	<u>1.23</u>
Tran	0.58	WT	<u>1.05</u>	Tran	0.67	TH	<u>1.24</u>	TH	<u>1.06</u>
EC	0.41	EC	<u>1.03</u>	EC	0.53	K	0.94	WT	0.46
TH	0.19	Tran	0.57	TH	0.30	Tran	0.81	AT	0.42

comprehensive protection and promotion of water ecosystems health. Moreover, long-term monitoring and routine data collection should be performed on aquatic ecosystems to obtain rigorous quantitative results and more definite conclusions.

Conflicts of interest

There is no conflict of interest among authors.

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