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Effects of spatial variation in water quality and hydrological factors on environmental flows

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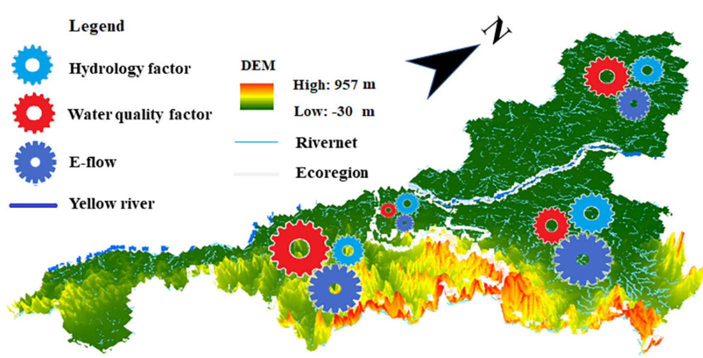
HIGHLIGHTS

- We studied impact of hydrological and water quality factors variation on e-flow.
- The four methods are used to calculate the e-flows for the typical stations.
- A geostatistical method is used to analyze the spatial variation of hydrological and water quality factors.

GRAPHICAL ABSTRACT



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ABSTRACT

Environmental flow is the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems. Environmental flows (e-flows) are crucial parameters for ecosystem restoration. Understanding the effects of spatial variation in the hydrological and water quality factors on e-flows aids the determination of recovery prior areas and helps to improve the success rate of ecosystem restoration projects. However, few studies have investigated the effects, which severely hinder the restoration of aquatic ecosystems and the sustainable use of water resources in inland waters. This paper therefore presents a framework for studying such effects. Spatial autocorrelation, a geostatistical method, is used to analyze the spatial variation in the hydrological and water quality factors and to further analyze the effects of various factors on the spatial heterogeneity of e-flows. Four different methods including the Tennant method, wetted perimeter method, AEHRA, and integrated water quality method are integrated to comprehensively evaluate e-flows. The former three methods consider the demands of biota on the streamflow, whereas the latter considers the demands on both the streamflow and the water quality. The results show that the Tennant and wetted perimeter methods, which focus on the statistics of only streamflow, result in similar spatial distribution of e-flows; the AEHRA and integrated water quality method, which consider the effects of water quality and other hydrological factors such as flow velocity and water depth on fish, also result in a similar spatial variation. Consideration of both demands on the hydrological factors and the water quality

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environmental factors makes the integrated water quality method more practical, particularly in developing regions with excessive pollutant discharge into rivers. In addition, spatial variation in the hydrological and water quality factors influenced the presence of principal fish species and consequently affected the e-flows. Of the 37 water quality factors identified, water transparency had a negative impact on e-flow because the increase in transparency could reduce the number of principal fish species. Of the four hydrological factors, flow velocity and river width had positive impacts on fish because the increase in flow velocity can provide breeding sites and habitats for more fish, respectively, both of which result in increases in the numbers of principal fish species. We found that spatial variation in the hydrology and water quality factors had a profound impact on the living environments of aquatic organisms; negative changes in these factors lowered the survival probability of principal species, which changed the hierarchy and structure of the ecosystems and thus led to variation in e-flows. The results can provide priori knowledge for e-flow methods selection and a reference for ecosystem restoration helping improve the success rate of project elsewhere in the world.

1. Introduction

Global increase in human pressures on freshwater environments have led to severe water pollution and water resource shortages, which have resulted in river blanking, river drying, soil loss, environmental deterioration, and biodiversity loss (Tazioli, 2009; Joniak and Kuczyńska-Kippen, 2010; Tazioli et al., 2012; Wilbers et al., 2014; Aquilanti et al., 2016; Wang et al., 2019a, 2019b). However, the deterioration of freshwater ecosystems and the uncontrolled use of water resources have resulted in river flows that are insufficient for supporting the aquatic biota.

Projected hydroclimatic changes and human activities affect the hydrological cycle and increase the pressure on water allocation (Li et al., 2018). Environmental flows (e-flows) methodologies are practical methods of environmental and ecosystem management for river basins. These methods focus on the inherent relationship between the ecological environment and water resources (Almazán-Gómez et al., 2018); emphasize the coordination of water resources, ecosystems, and society (Rolls et al., 2018); and change traditional river basin management concepts centered on human activity. E-flows provide an important index for evaluating whether water resources are reasonably exploited and utilized and are critical for maintaining a balanced ecosystem (Yang et al., 2013), particularly in river systems.

Numerous methods are used for calculating e-flows and can be roughly divided into areas of hydrology (Armentrout and Wilson, 1987; Li et al., 2011, 2012), hydraulics (Wang et al., 2009; Peng et al., 2012; Yu et al., 2015; Poff et al., 2010), and habitat (Wu et al., 2014; Pan et al., 2015; Mackie et al., 2013); comprehensive measurement (Shokoohi and Hong, 2011; Gopal, 2016); and other types (Chen et al., 2011; Li, 2012). These methods have various data requirements and can be applied to rivers with different datasets.

Among the methods used for calculating e-flows, the Tennant method is representative of the hydrological method (Tharme, 2003). Tennant (1976) used 11 different rivers in Montana, 58 cross-sectional areas, 33 different flows, and hundreds of observations in addition to data from 21 other countries. The flow percentages were determined on the basis of these observations. This method is simple and convenient to use, and the results are easily combined with water resources planning measures. The most commonly used method in hydraulics, the wetted perimeter method, has relatively fewer requirements for data than those needed for hydrological methods, and it considers biological habitat. This method includes a direct relationship between the wetted perimeter and the habitat conditions of the river in riffle habitats. The adapted ecological hydraulic radius approach (AEHRA; Liu et al., 2011) is a method employed for estimating the e-flows of rivers by using information of aquatic biology and river channels. It fully considers the hydraulic characteristics required for aquatic habitats in river channels and considers the suitable flow velocity and water level required for the survival and reproduction of aquatic organisms. Thus, AEHRA is particularly suitable for rivers lacking hydrological and ecological data. The integrated water quality method considers the effects of water quality factors on e-flows, which closely links the tolerance of aquatic biota with water quality standards. This method has relatively low data demands and is easily used in developing regions. In addition, it plays an important role in the management of polluted rivers (Zhao et al., 2018). Therefore, all four were used in the present study to comprehensively evaluate e-flows.

Changes in hydrology and water quality have important impacts on the living conditions of the organisms and the structure of the ecosystem (Bae et al., 2018), thereby influencing the hierarchy and structure of ecosystems (Zhao et al., 2018), resulting in changes in e-flows. However, very few studies conducted thus far have investigated how the spatial variation in the hydrological and water quality factors affect the outcomes of different e-flow methodologies. This consequently hinders the restoration of aquatic ecosystems and the sustainable use of water resources. Therefore, the effects of these variations on e-flows are essential for providing scientific references for basinal aquatic ecosystem restoration and sustainable water resource management. Accordingly, these effects on e-flows are evaluated and clarified in the present study. This research addresses the lack of existing relevant research, and the conclusion of this study provides scientific guidance for ecological restoration, particularly in areas with poor hydrological and water quality conditions.

The objective of this paper is to study the influences of spatial variation in the hydrological and water quality factors on e-flows in rivers. The four methods discussed above are used to calculate e-flows for typical stations, and a geostatistical method is used to analyze this spatial variation to study the effects of various factors on the spatial heterogeneity of the e-flows. These results can help to identify the principal environmental factors and to prioritize regions for maintaining ecosystems and the sustainability of water resource management in developing regions worldwide.

2. Study area

Jinan City (36.0–37.5°N, 116.2–117.7°E), also referred to as "Spring City," is a pilot city for the construction of a civilized and ecological city in China. It is bordered by Mount Tai to the south and the Yellow River to the north and west, and the topography is steeper in the south than in the north (Fig. 1). Hilly areas, piedmont clinoplains, and alluvial plains span the city from north to south. The elevation within the area ranges from −30 to +937 m above sea level with highly contrasting relief. The semi-humid continental monsoon climate in the city area is characterized by cold, dry winters and hot, wet summers. The average annual precipitation is 636 mm, with 75% falling during the high-flow periods, and the average annual temperature is 14 °C. The average monthly temperature is highest in July and lowest in January, ranging from 26.8 °C to 27.4 °C and from 3.2 °C to 1.4 °C, respectively (Cui et al., 2009; Zhi-guo et al., 2010).

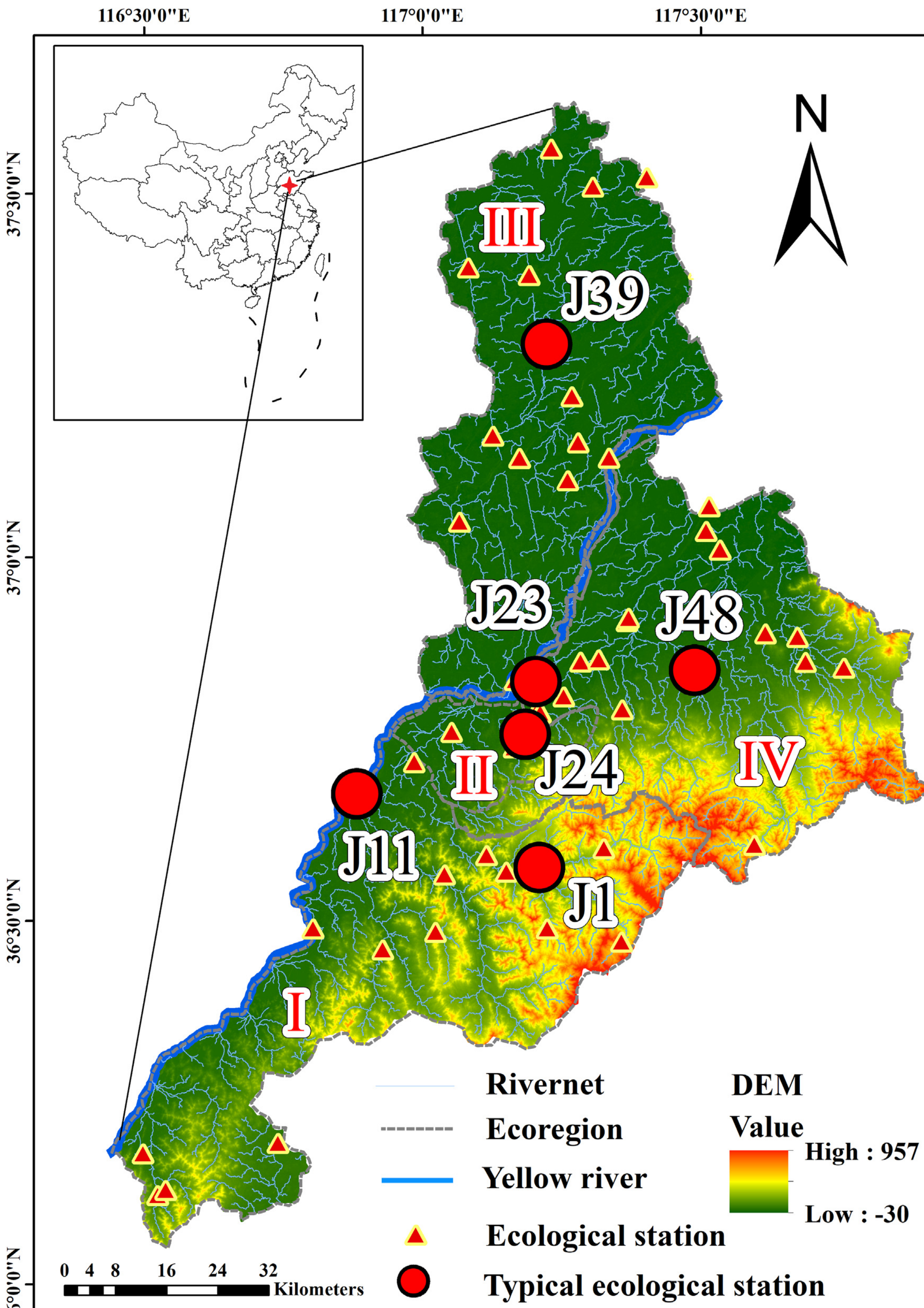

Fig. 1. Map of the Jinan City ecological monitoring stations and typical stations. Regions I, II, III, and IV are the ecoregions of Ji'nan, Yellow River, urban area, Xiaoqing River, and Tuhaimajia River, respectively (following Yu et al., 2015).

With an area of 8227 km^2 and a population of 5.69 million, Jinan City represents a typical developing city in China. Owing to the rapid industrial development and urbanization in recent decades, the water resources in Jinan are severely polluted and are reduced in quantity through extraction. As a result, the spatial heterogeneity of the water quality and quantity poses a great threat to ecosystems, drinking water, and human health and well-being (Hong et al., 2010). These serious ecological problems urgently need to be resolved. Therefore, it is increasingly necessary to explore the effects of spatial variation in the water quality and hydrological parameters to effectively evaluate the e-flows for sustainable management of water resources and to ensure successful restoration of the water ecology throughout the city area.

For this research, we selected typical monitoring stations as representative sites to analyze the effects of hydrological and water quality factors on e-flows in 54 ecological monitoring stations based on the differences in hydrology, water quality factors, and geographical location.

3. Materials and methods

3.1. Data

During the spring, summer, and fall of 2014 (dry year), 2015 (normal year), and 2016 (wet year), we measured 37 hydrologic factors and water quality physical and chemical factors during 9 large-scale field investigations (Table 1). The three representative years were used to reflect the changes of the ecosystem under different climatic conditions.

The water depth and flow velocity were monitored at the aforementioned monitoring stations. The flow velocity was measured by using a radio flow meter (Stalker II SVR V1.0) and a traditional flow meter (LS25-1) to ensure the accuracy of the results. The water depth and river width were measured with a tape measure, and the streamflow was calculated from the flow velocity, water depth, and cross-sectional area. An unmanned aerial vehicle (UAV) was used to retrieve river-course cross-sections with high-resolution stereoscopic images (Zhao et al., 2017a, 2017b).

During the 9 field investigations, 480 water samples were collected. The physical parameters of the water quality (Table 1) were measured in situ with portable equipment, and water samples obtained from the monitoring sites were tested in the laboratory within 24 h. A spectrophotometer (DR5000) was used to measure the amounts of ammonia nitrogen, total phosphorus, total nitrogen, and hexavalent chromium, and an atomic absorption spectrophotometer (Thermo M6) was used to measure the concentrations of copper, zinc, cadmium, and lead. An ion chromatograph (DIONEX-600) was used to measure the sulfate, fluoride, chloride, and nitrate concentrations (Zhao et al., 2015).

Table 1
Hydrologic and physical and chemical water quality parameters in the Jinan City monitoring program.

Parameter	Abbreviation	Name	Unit	Range (SD)
Hydrologic	FV	Flow velocity	m/s	0–1.69 (0.31)
	RW	River width	m	2.1–320 (60.2)
	FL	Streamflow	m^3	0–1110 (166)
	WD	Water depth	m	0.01–4 (0.83)
Physical	AT	Air temperature	°C	3.0–33.1 (8.35)
	WT	Water temperature	°C	5.6–33.40 (5.6)
	pH	pH		6.9–9.20 (0.39)
	EC	Conductivity	mS/m	287–5775 (863)
	Tran	Transparency	cm	0–650 (94.14)
	Turb	Turbidity	degree	0.52–924 (118.6)
Chemical	Ca	Calcium	mg/L	17.63–486 (59.08)
	Cl	Chlorine		11.62–1156 (170.9)
	SO_4	Sulfate		43.47–1045.7 (185.8)
	CO_3	Carbonate		0–38.50 (4.69)
	HCO_3	Bicarbonate		50.05–2247 (158)
	TA	Total alkalinity		44.68–1057 (88.75)
	TH	Total hardness		119–1400 (240.7)
	DO	Dissolved oxygen		1.1–15 (2.296)
	TN	Total nitrogen		0.25–80.03 (6.286)
	NH_4	Ammonia		0.07–75.8 (4.7)
	NO_2	Nitrite		0–1.97 (0.272)
	NO_3	Nitrate		0–22 (3.51)
	COD	Chemical oxygen demand		6.32–275 (21.42)
	KMnO4	Permanganate index		0.57–71.5 (4.83)
	BOD	Biochemical oxygen demand		0–57.5 (4.89)
	TP	Total phosphorus		0–8.06 (0.71)
	F	Fluoride		0.18–2.30 (0.33)

Concurrently, fish were collected during 30 min periods in three habitat types (i.e., pools, riffles, and runs) along a 500 m length of river at each sampling site. Individuals caught from the three habitats were combined to represent a site. In wadeable streams, fish collection was performed by a two-person team (Barbour et al., 1999); in unwadeable streams, seine nets with mesh sizes of 30 mm and 40 mm were used to collect fish from a boat. In addition, electrofishing was conducted to ensure that a representative sample of fish species was collected at each site. All individuals collected were identified in situ at the species level according to Chen et al. (1987) and were then counted, weighed, and recorded in field data sheets before being released. Specimens that could not be identified in the field were preserved in a 10% formalin solution and stored in labeled jars for subsequent laboratory identification (Zhao et al., 2015).

3.2. Methods

Spatial autocorrelation analysis was conducted to study the spatial variation in the hydrological and water quality factors to obtain their spatial agglomeration, whereby the high and low values of the spatial distribution of each factor were determined to select the typical stations in the study area. Four widely used e-flow calculation methods including the Tennant method, wetted perimeter method, AEHRA, and the integrated water quality method were then applied to comprehensively identify the e-flows at each typical station. The results from the four e-flow methods were ultimately used to analyze the effects of spatial variation in the hydrological and water quality factors on e-flows and to provide references for ecological restoration of the entire area in Jinan City.

3.2.1. Spatial variation analysis of hydrological and water quality factors

The spatial autocorrelation analysis method is commonly used to assess the degree of clustering, randomness, or fragmentation of a spatial pattern. It includes global spatial autocorrelation, which estimates the overall degree of spatial autocorrelation for hydrological and water quality datasets, and local spatial autocorrelation, which identifies the location and types of hydrological and water quality factors (Atikaimu et al., 2015; Zhao et al., 2019). The spatial data of hydrological and water quality factors are often analyzed by using ARCGIS (https://www.arcgis.com) and GEODA (https://geoda.com) software (Atikaimu et al., 2015), in which the Moran's I value of the global autocorrelation analysis can be obtained intuitively. The spatial aggregation characteristics of the hydrological and water quality factors can be obtained by using Moran's I index to obtain the spatial positive/negative correlation of each factor. This method is used to study the spatial aggregation characteristics of each factor.

Global autocorrelation of the hydrological and water quality physical and chemical factors obtained by field sampling was analyzed by using GEODA software, as shown in Supplementary Table 1. According to the decline rate of the Moran I index of each factor, which is the proportion of difference between the Moran I index of a factor and the sum of the indices, the representative factors were selected from the three types of factors for local spatial autocorrelation analysis. Supplementary Table 1 shows that the spatial agglomeration of hydrological factors was very poor and did not show a spatial cluster distribution. EC and Tran as well as Cl, Na, SO_4, and F (Supplementary Table 1) were selected as representative water quality physical and chemical factors, respectively, according to the index decline rate with 99% confidence ($\alpha < 0.01$). The Moran I indices of these factors were relatively high, at 0.26–0.64. The spatial agglomerations were the highest, and a significant regional distribution of the high and low values was noted. These factors can be used to analyze the impact of water quality on the variability in e-flows. Wang et al. (2019a, 2019b), Brown et al. (2016), and Yang et al. (2016) suggested that hydrological factors are of great significance for e-flow assessment. Zhao et al. (2018) reported that river width (RW), water depth (WD), and streamflow (FL) are important factors affecting the structure of aquatic ecological food webs. A reasonable food web is the foundation for the survival of principal ecosystem species and therefore affects the amount of e-flows. Therefore, we selected RW, WD, FL to analyze the spatial agglomeration of the hydrological factors.

3.2.2. Tennant method

The Tennant method, the most widely used method for evaluating e-flows (Tharme, 2003; D'Ambrosio et al., 2018), calculates the e-flows based on the measured data and considers the effects of years of average streamflows on the e-flows. Karakoyun et al. (2016) reported that streamflow was divided into two different streamflow groups from optimum rate (annual average rate 60–100%) to weak and very low (annual average streamflow 10% or zero streamflow). In the Tennant method, the year is divided into two parts, that is 6 months. According to Arthington (2012), when Tennant and its derivatives are examined around the world, it was seen that these time intervals reflected considering seasonal changes. On the other hand, while creating the Tennant flow model, it was stated that overflow and maximum (200% of the annual average streamflow) values also have positive effects on the sustainability of the habitat quality. In determining percentages, 10% of the annual average streamflow defines the shortest momentary streamflow amount for sustaining short-term water life, and 30% or more of the annual average streamflow is thought to be the necessary for providing the biological integrity of the river and its sustainability (Tharme, 2003).

3.2.3. Wetted perimeter method

The most commonly used method in the hydraulic approach is the wetted perimeter method, which requires river channel information and streamflow data and considers the influence of the river shape on e-flows. The cross-section, water level of the river channel, and streamflow are used in this method. By plotting the wetted perimeter and streamflow relationship and deriving the point of greatest curvature in the curve as the index point, the minimum environmental flow can be determined. In this method, the discharge equivalent to the maximum curvature of the function is computed and applied as the minimum e-flow (Gippel and Stewardson, 1998; Shang and Shang, 2018).

3.2.4. Adapted ecological hydraulic radius method

The AEHRA analyses the changes in principal fish species at various stations to obtain the ecological flow velocity and to further evaluate e-flows. The core of the AEHRA is the determination of the ecological flow velocity $v_{ecology}$ and the ecological water depth at stations, from which the e-flow Q_E can be estimated (Liu et al., 2011) as

$$Q_E = \frac{1}{n} R_{ecology}^{\frac{2}{3}} A j^{\frac{1}{2}}, \tag{1}$$

where Q_E is the e-flow in $m^3 \cdot s^{-1}$; $R_{ecology}$ refers to the watercourse hydraulic radius; A is the flow area for e-flows in m^2; n is the roughness or Manning's n-value; and j is the hydraulic slope in %. To evaluate e-flows by using AEHRA, the principal fish species and the corresponding ecological flow velocity/water depth must be determined beforehand.

3.2.4.1. Principal fish species screening. The principal fish species determine the behavior of the entire fish community. Abundance and biomass are fundamental indices for evaluation of the contribution of a species to the entire community. The two indices often rank differently, which makes it difficult to objectively assess the dominance or importance of a species in a community (Liu et al., 2011). To address this, Zhao et al. (2014) combined these into one index using Eq. (2):

$$I_{impor\ tance} = \omega_1 PCT_{abundance} + \omega_2 PCT_{biomass}, \tag{2}$$

where $I_{importance}$ represents the dominance of a species; $PCT_{abundance}$ and $PCT_{biomass}$ represent the biomass and density of the species relative to the entire community, respectively; and ω_1 and ω_2 are the weights of $PCT_{abundance}$ and $PCT_{biomass}$, respectively, which are determined by the weighting determination method of the center-of-mass-system (CMS; Zhao et al., 2015): $\omega_1 + \omega_2 = 1.0$. By determining the dominance of various fish species calculated using Eq. (2) the principal fish species at a station can be screened by using the curvature method (Eq. (3)).

The curvature (k, Eq. (3)) is the rate at which a curve turns. The maximum curvature suggests the location in which where the breakpoint of the curve appears (Zhao et al., 2015).

$$k = \frac{\frac{d^2y}{dx^2}}{\left[1 + \left(\frac{dy}{dx}\right)^2\right]^{\frac{3}{2}}} \tag{3}$$

For the cumulative dominance curve, the dominance increment after the breakpoint, i.e., the maximum curvature point, is rather small compared with that before the breakpoint. That is, the species showing dominance before the breakpoint contribute more to the whole communities compared with those showing dominance after the breakpoint. Therefore, the maximum curvature is used to identify the breakpoint, thus facilitating the selection of the dominant species within the fish communities in the study area.

3.2.4.2. Determination of the ecological flow velocity and ecological water depth. To make the calculated e-flows reflect the requirements for the survival of principal fish species, we calculated the integrated ecological flow velocity and ecological water depth required for principal fish using the Habitat Suitability Index (HSI) model based on the sampling data collected from the entire Jinan city area (Zhao et al., 2015).

In general, the appropriate range of factors affecting a species can be identified by using the HSI model (Yi et al., 2017), as

$$Hi = \frac{hi}{m}, m = \sum_{i=1}^{n} hi, \tag{4}$$

where Hi represents the habitat suitability index of a species, hi is the number of species in the i-th gradient range of the habitat index (such as flow velocity), m is the total number of this species, and n is the number of gradient intervals of the habitat index. This model can determine the optimal range of the habitat index (e.g., flow velocity) for a certain species.

Based on the above calculation, the ecological flow velocity $v_{ecology}$ and ecological water depth for each station at different periods can be obtained on the basis of the principal fish species present at the station.

3.2.4.3. Calculation of e-flows. AEHRA can then be used to calculate e-flows. By using the previously determined ecological flow velocity $v_{ecology}$ and ecological water depth as well as the channel roughness n and the channel hydraulic gradient j, the ecological hydraulic radius of the river cross-section $R_{ecology} = n^{\frac{3}{2}} * v_{ecology}^{\frac{-3}{2}} * j^{\frac{-3}{4}}$ (Liu and Men, 2007) can be calculated. Then, the ecological hydraulic radius $R_{ecology}$ is used to estimate the cross-sectional area A of the river. The relationship between the cross-section and the hydraulic radius is discussed in Liu and Men (2007). Finally, Eq. (1) is used to calculate e-flows Q_E based on n, A, j, and $R_{ecology}$.

3.2.5. Integrated water quality method

The integrated water quality method combines both the requirements of the ecosystem and pollution control into e-flow assessment and closely couples the water quantity and quality requirements of aquatic ecosystems (Zhao et al., 2018). This method comprehensively considers the tolerance of fish to water quality factors and the water quality standards for pollution control to obtain suitable e-flows. This is accomplished by modifying the water quality criteria with fish according to the pollutant tolerance. Traditional water quality criteria for pollutants are usually determined on the basis based of the water use type, such as that used for industry, agriculture, or drinking. The tolerance of fish to pollutant concentrations is integrated into the determination of water-quality criteria with which the water environmental capacity (WEC) of a river-section can be calculated considering both human and ecosystem requirements. The advantages of this method include the ease of operation and the relatively lower data requirements as well as the recommended streamflow regulation and pollution control coefficients. These attributes give the method great potential to be widely used in developing countries/regions that may lack long-term datasets on hydrology water quality, or ecology. The calculation process is given in Zhao et al. (2018).

3.2.6. Effects of hydrological and water quality factors on e-flows

The principal hydrological and water quality factors were initially selected by partial least squares regression (PLSR) analysis, which is an extension of multiple regression analysis used to evaluate 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 $X_{m\times n}$, which consists of m variables (columns) and n objects (rows), and a response vector $Y_{n\times 1}$. The PLSR identifies a few linear combinations of the original x values that describe most of the inherent variables (Hu et al., 2018).

Variable Importance in the Project (VIP) is an indicator obtained during the calculation of PLSR that can be used to measure the importance of the independent variable to the dependent variable. A VIP of the independent variable >1 indicates that the independent variable has a more important role; when the VIP value is between 0.5 and 1, the explanatory role of the independent variable is not obvious. A VIP <0.5 indicates that the independent variable has no explanatory role for the dependent variable (Hu et al., 2018). The calculation method is as follows:

$$VIP_j = \sqrt{(p\sum_{h=1}^{m} R(Y,T_h)w_{hj}^2 / \sum_{h=1}^{m} R(Y,T_h)}, \quad (5)$$

where p is the number of independent variables; m is the number of components extracted from the original variables by the PLSR method; Th represents the h-th component; $R(Y,Th)$ represents the explanatory power of component Th to the dependent variable Y, which is equal to the square of the correlation coefficient between the two; and whj is the j-th component of the axis wh, which i the eigenvector.

Afterward, the relationships between the principal factors and the e-flows are determined by using the correlation analysis module in SPSS software (https://www.ibm.com). The effect of each principal factor on the e-flows was determined on the basis of the correlation coefficient, from which the principal factors of the e-flows can be evaluated. The spatial distribution characteristics of the hydrologic and water quality principal factors were obtained on the basis of the spatial autocorrelation analysis. The spatial distribution of the e-flows at each station was compared with that of the hydrologic and water quality principal factors, and the spatial correspondence between them was summarized.

4. Results

4.1. Selection of typical stations

The local autocorrelation analysis module in ArcGIS was used to analyze the spatial agglomeration for the nine factors selected from the hydrological and water quality physical and chemical factors, including RW, WD, FL, EC, Tran, Cl, Na, SO_4, and F. The results are shown in Fig. 2.

As shown in Fig. 2a, b, and c, the high values of Cl, Na, and EC occurred mainly in the northern part of Jinan City, whereas the low values were distributed in the south. No significant variation was noted in other areas. As shown in Fig. 2d, regions with high water transparency were located mostly in the central and southern parts of the city, and the transparency was low in the north. Because the Moran I index and the confidence level of the hydrological factor were relatively low, no spatial agglomeration was exhibited. Fig. 2e and f show that the F and SO_4 concentrations were low in the south and high in the north. Moreover, Fig. 2i shows that FL had a high value in the south, where the Yellow River flows through; no spatial agglomeration was noted in other regions. Fig. 2g and h show that RW and WD were more affected by the shape of the river channel; no spatial agglomeration was noted.

Based on the characteristics of spatial agglomeration of the above factors, we selected six typical stations in the study area of Jinan City (Fig. 2). Two stations, J39 and J1, were selected on the basis of the high and low concentrations of Cl, Na, EC, F, and SO_4 in the north and the south. Two other stations in ecoregion II, J23 and J24, were selected from the central area of the city, where the population is concentrated, to represent the different surface water characteristics including significant hydrological (FL) and water quality (Cl, Na, EC) differences. J23 is located in the Yellow River, where the streamflow is higher than that at J24. The water quality factor of J24 was generally lower than that of J23, which indicates that the water quality of the former was better. Considering these factors, Station J11 was selected at the passage of the Yellow River near the city center. Finally, Station J48 was selected in the eastern region near the city center. The hydrological and water quality conditions of this station were at medium levels. These selection principals ensured the representativeness and scientific rationality for the subsequent analysis.

4.2. E-flows calculated by Tennant method

The e-flows at each station were calculated by applying the Tennant method, as shown in Table 2.

The Table 2 shows that the e-flow of Station J23 was the highest, and that of other stations was relatively low. This station was located near the Yellow River in ecoregion II, which has sufficient streamflow. The e-flow of Station J24 was medium, whereas that of J48 was lowest. This occurred mainly because stations J39 J48 were located in the plain areas at ecoregions IV and III, whereas Station J1 was located in the southern mountainous region of the study area at ecoregion I, where the streamflow was relatively low. Stations J39 and J48 were located in agricultural areas, and the higher water demand has led to a low streamflow in spring. J1 was located in the mountainous area, with lower streamflow caused by the small river width. In addition, the e-flow from April to September was significantly higher than that from October to March based on the e-flow values of each station at different times. From the e-flows values of the typical stations, it is concluded that the e-flow of the downtown area (J23) was relatively high, and those in the southern mountainous (J1) and northern areas (J48) were relatively low.

4.3. E-flows calculated by wetted perimeter method

According to the cross-section data at each station and the measured streamflow from the ecological monitoring of Jinan city, the

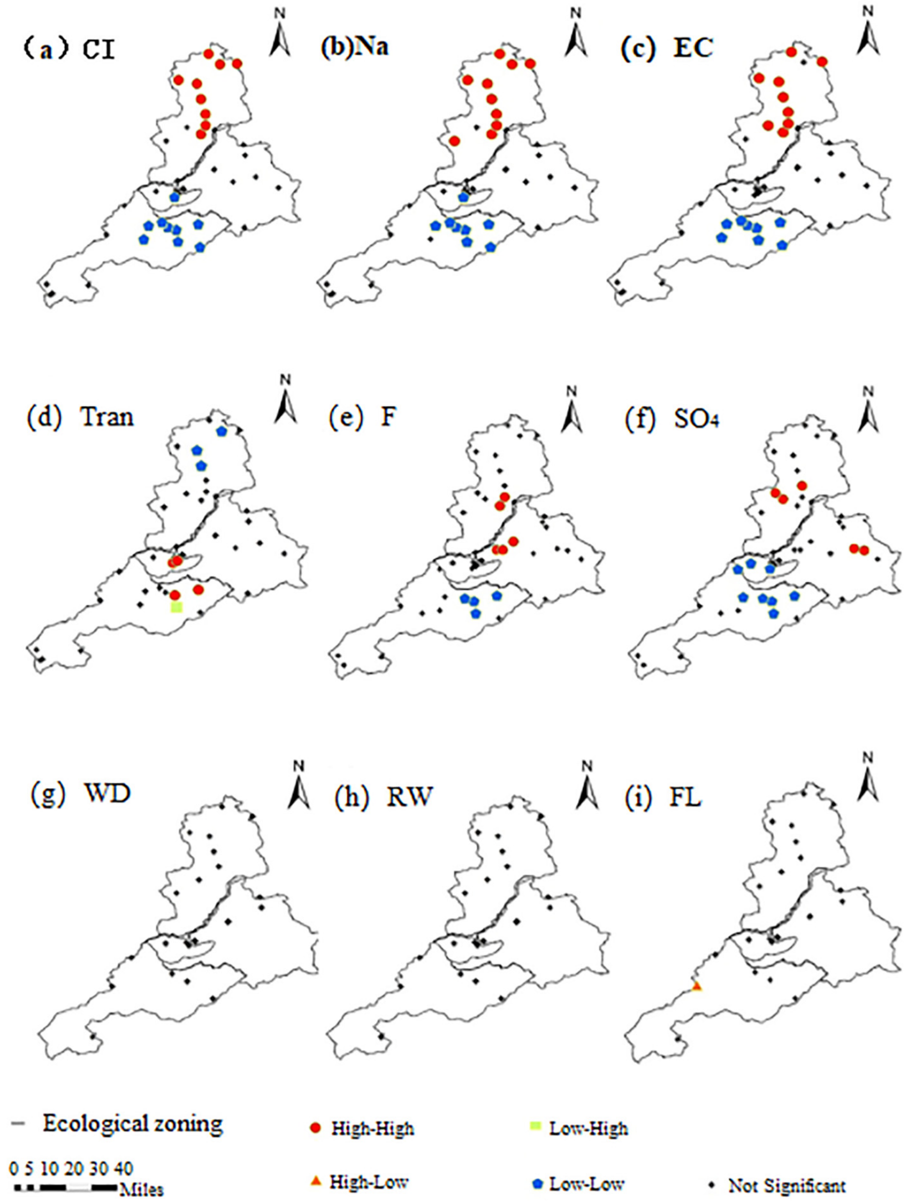

Fig. 2. Results of local autocorrelation of each factor (The values of each factor gradually decrease from 'high-high' to 'low-low').

streamflow (FL) and wetted perimeter (P) curve of each station were fitted (Fig. 3).

The breakpoint of each curve is shown in Fig. 3, whereby the e-flows values can be obtained. The shape of the lower HTQ channel is rectangular, and an abnormal point is shown on the curve. This indicates that the wetted perimeter method is not applicable for this channel shape. By using the breakpoints, the e-flows of the other stations were determined to be 10 m^3/s for BDK, 298 m^3/s for BDSH, 21 m^3/s for JYH, 39 m^3/s for ZGNL, and 317 m^3/s for LK. The e-flows in the downtown area of Jinan city at Station J23 (Fig. 1) were the highest, followed by those at J39 in the northern plain area; those at J1 in the southern mountainous area were the lowest.

4.4. E-flows calculated by AEHRA

The principal fish species were initially determined by using the dominance model (Eq. (2)), as shown in Supplementary Fig. 1.

Supplementary Fig. 1 shows that the principal fish species *Misgurnus anguillicaudatus*, *Carassius auratus*, *Abbottina rivularis*, and *Hemiculter leucisculus* have larger weights. Among the six stations, J1 had the most fish species (17 ind) and the highest density, whereas J24 had fewer fish species (5 ind); the biomass of *Carassius auratus* was dominant at these two stations. The overall number of fish species from 10 samples of Station J23 was lower (8 ind). Fewer fish species were recorded at J39 (8 ind), and the weights of *Carassius auratus*, *Hemiculter leucisculus*, and *Pseudorasbora parva* were high. The principal number of fish species at J48 was at a medium level (12 ind), with *Carassius auratus* and *Misgurnus anguillicaudatus* dominating the principal species at 48% and 26%, respectively.

On the basis of the selected principal fish species, the HSI model (Eq. (4)) was used to obtain the ecological flow velocity and ecological water depth of each station. To protect fish and their eggs during spawning periods, the flow velocity and water depth requirements during such periods were also considered in updating the determined ecological flow velocity and ecological water depth (Supplementary Table 2).

The ecological water depth and ecological flow velocity were then and combined with the river cross-section data, from which the e-flows at each station were calculated by using AEHRA (Eq. (1)), as show in Table 3.

Table 2
E-flows calculated by applying the Tennant method.

Station	J1		J11		J23		J24		J39		J48	
Streamflow status	Oct.–Mar.	April–Sep.	Oct.–Mar.	April–Sep.	Oct.–Mar.	April–Sep.	Oct.–Mar.	April–Sep.	Oct.–Mar.	April–Sep.	Oct.–Mar.	April–Sep.
Flushing or maximum	1.75	1.75	0.93	0.93	966.57	966.57	16.93	16.93	2.73	2.73	0.688	0.688
Optimum range	0.52–0.87	0.52–0.87	0.28–0.465	0.28–0.465	289.97–483.29	289.97–483.29	5.08–8.465	5.08–8.465	0.82–1.37	0.82–1.37	0.21–0.344	0.21–0.344
Outstanding	0.35	0.52	0.19	0.28	193.31	289.97	3.39	5.08	0.55	0.82	0.14	0.21
Excellent	0.26	0.44	0.14	0.23	144.99	241.64	2.54	4.23	0.41	0.68	0.1	0.17
Good	0.17	0.35	0.09	0.19	96.66	193.31	1.69	3.39	0.27	0.55	0.07	0.14
Fair or degrading	0.09	0.26	0.05	0.14	48.33	144.99	0.84	2.54	0.14	0.41	0.03	0.1
Poor or minimum	0.09	0.09	0.05	0.05	48.33	48.33	0.84	0.84	0.14	0.14	0.03	0.03
Severe degradation	0–0.09	0–0.09	0–0.05	0–0.05	0–48.33	0–48.33	0–0.84	0–0.84	0–0.14	0–0.14	0–0.03	0–0.03

Table 3 shows that the e-flows at most of the stations in May and June were high because with the increase of principal species in the summer, the ecological flow velocity and ecological water depth reached the highest levels. Stations J1, J23, J24, J11, J48, and J39 had highest to lowest e-flows. Station J1 had the highest e-flows because it is located in the southern mountainous region of the study area, where it is less affected by human activities, resulting in aquatic organism enrichment and large biomass. Stations J23 and J24, located in the downtown area with a high human population density, had the second highest e-flows. Better management measures and governance effects in the urban area resulted in well-maintained principal fish species were, which in turn resulted in abundant principal species and higher e-flows.

The area with the lowest e-flows was located in the north plains area dominated by croplands. Excessive water withdrawal and sewage discharge in this area resulted in severe degeneration of the water ecosystems and a reduction in principal fish species, causing low e-flows. In general, the e-flows of Jinan city decreased spatially from south to north.

4.5. E-flows calculated by the integrated water quality method

By using the integrated water quality method, the principal water quality factors affecting fish survival in the study area, ammonia nitrogen and chemical oxygen demand (COD; Zhao et al., 2017a, 2017b) were used as the water quality factors to analyze and calculate the WEC, water regulation coefficient α, and water quality adjustment coefficient β to integrally determine e-flows that meet the water quantity and quality demands for fish and socio-economic development (Supplementary Fig. 2).

Supplementary Fig. 2 shows that the WEC at J23 and J24 was significantly higher than that at the other four stations, of which J23 had the highest value at 528 m^3/s. Stations J23 and J24 were located in the downtown area near the Yellow River, where the hydrological conditions such as streamflow and flow velocity were better than those at the other stations. Moreover, these stations provide water resources for populated urban places; thus, the pollutant load entering the river is restricted to low levels, which results in higher WEC. Spatially, the highest WEC was distributed in the downtown area; the next highest was in the southern mountainous area; and the northern plain area had the lowest value. Temporally, the WEC of each station was higher in the summer and fall than in other seasons.

Supplementary Fig. 3 shows that the pollution control coefficient (β) of Station J1 was <1 for each month. This indicates that the two water quality factors of ammonia nitrogen and COD calculated at this station did not exceed the water quality standard and did not affect the fish survival. Therefore, β required no adjustment. The streamflow adjustment coefficient α ($\alpha = \frac{QE}{Q}$) was then calculated (Supplementary Fig. 4).

Supplementary Fig. 4 shows that the values of α were mostly >1, which indicates that the calculated e-flows exceeded the actual streamflow. Therefore, it was necessary to adjust α to reduce the e-flow value and thus to reduce the requirement on flow velocity. Moreover, this ensured that the new flow velocity would still maintain α and β values <1. The calculated e-flows are listed in Table 4. For some stations at specific times (e.g., J11 in May 2016), a lack of streamflow and flow velocity observations hindered the e-flow calculation.

4.6. Impact of hydrological and water quality factors on e-flows

The results obtained by the four e-flow calculation methods showed that the e-flows were highest in the downtown area and varied in the southern mountainous and northern plain regions. The e-flows from the four different methods are listed and compared in Fig. 4. The Tennant method determined 10% of the average streamflow, show poor or minimum results (D'Ambrosio et al., 2018).

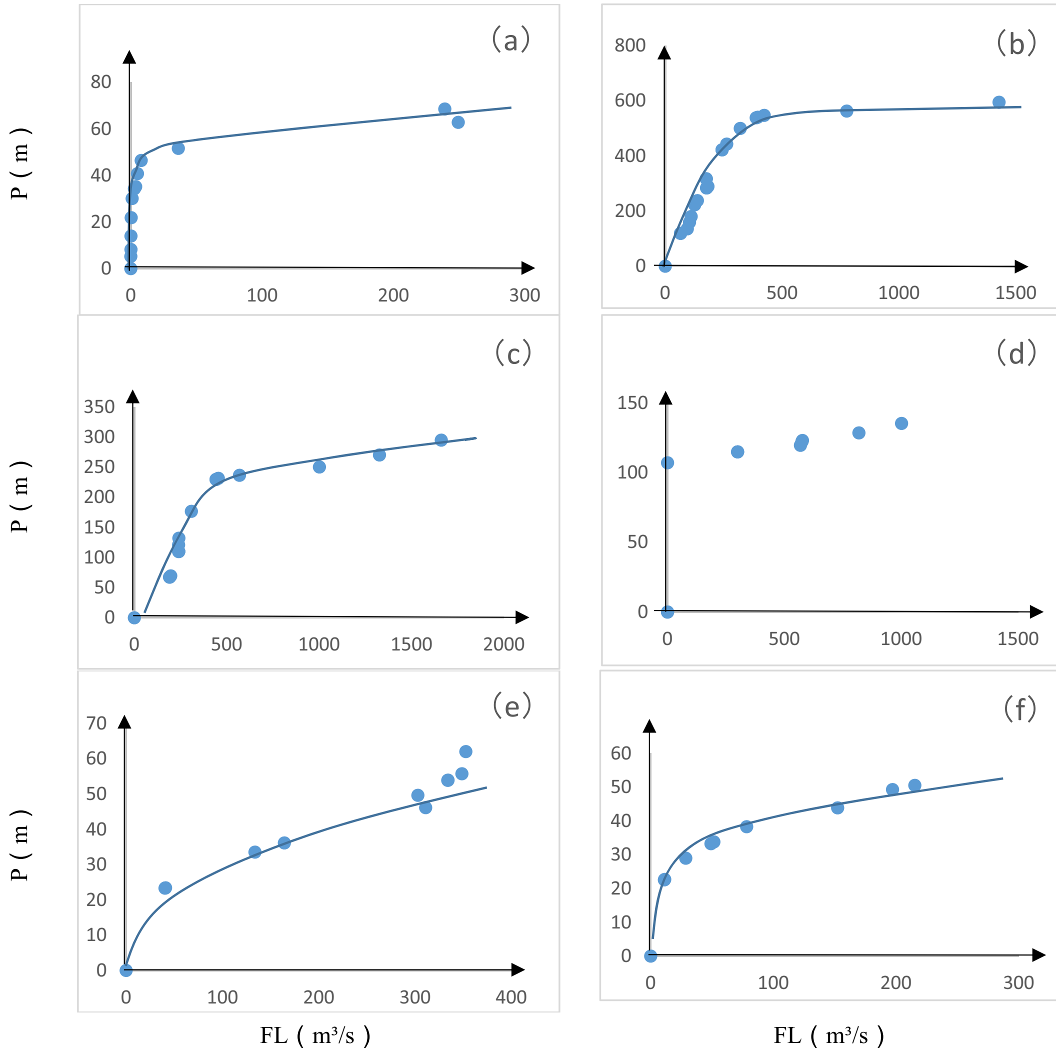

Fig. 3. FL (streamflow)-P (wetted perimeter) curves determined for each station: (a) J1 BDK, (b) J11 BDSH, (c) J23 LK, (d) J24 HTQ, (e) J39 ZGNL, (f) J48 JYH. The J24 HTQ is a rectangular channel and does not apply to the wetted perimeter method; therefore no curve fitting was performed.

The e-flows calculated by the wetted perimeter method were relatively high, whereas those calculated by the AEHRA and the integrated water quality method were relatively low. To take full advantage of the multiple methods and to effectively reduce the uncertainty introduced by a single method, we selected the mean value calculated by the four methods to analyze the effects of the hydrological and water quality factors on the e-flows. The mean e-flows values (annual) of each station were determined to be 3.05 m^3/s for J1, 74.79 m^3/s for J11, 91.68 m^3/s for J23, 0.67 m^3/s for J24, 9.84 m^3/s for J39, and 5.41 m^3/s for J48.

To quantitatively analyze the effects of the spatial variation in the hydrological and water quality factors on the e-flows, further research was conducted to include the nine selected factors (RW, WD, FL, EC, Tran, Cl, Na, SO_4, and F). Among the three hydrological factors (RW, WD, FL), FL is the basis for calculating the Tennant and wetted perimeter methods, and the correlation between FL and WD was relatively high, at

Table 3
E-flow results calculated by applying AEHRA. Q_E_min is given in m^3/s; Z_E_min is given in m.

Station	J1	J11	J23	J24	J39	J48
Date	Q_E_min	Q_E_min	Q_E_min	Q_E_min	Q_E_min	Q_E_min
5/2014	1.35	0.84	0.66	0.59	0.18	–
8/2014	6.18	–	0.66	0.59	–	–
11/2014	0.66	0.38	0.66	0.59	0.09	–
5/2015	1.35	0.84	0.66	0.59	0.18	0.49
9/2015	0.66	0.38	1.39	–	0.09	0.24
1/2015	0.66	0.38	0.66	0.59	0.09	0.24
5/2016	1.35	0.84	0.66	–	0.18	0.49
6/2016	0.66	0.84	–	–	0.09	–
9/2016	0.66	0.38	0.66	–	0.09	0.24
11/2016	0.66	0.38	–	–	–	0.24

Table 4
E-flows calculated by applying the integrated water quality method. Q_E_min is given in m^3/s.

Station	J1	J11	J23	J24	J39	J48
Date	Q_E_min	Q_E_min	Q_E_min	Q_E_min	Q_E_min	Q_E_min
5/2014	0.68	–	–	0.59	0.18	–
8/2014	1.26	–	0.66	0.59	–	–
11/2014	0.66	0.38	0.66	0.59	0.09	–
5/2015	0.58	–	–	–	0.18	0.49
9/2015	0.66	–	–	–	0.09	0.24
1/2015	0.66	–	–	0.59	0.09	0.24
5/2016	–	–	–	–	0.18	–
6/2016	0.48	0.84	–	–	0.09	–
9/2016	0.66	0.38	–	–	0.09	0.24
11/2016	0.66	–	–	–	–	0.24

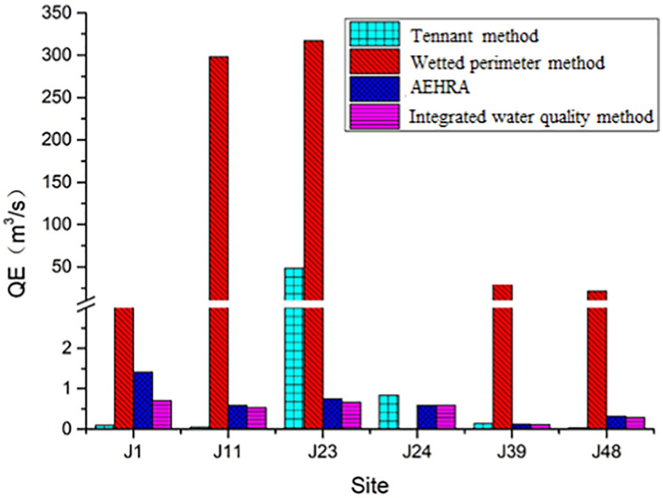

Fig. 4. Comparison of multiple methods used for calculating e-flows.

$R = 0.7$. Therefore, FL and RW were selected as principal hydrological factors. Among the six water quality factors (EC, Tran, Cl, Na, SO_4, F), the spatial agglomeration of Cl, Na, Tran, EC, SO_4, and F was significant, yet the correlation between Cl, SO_4, F, and EC was relatively high, at $R = 0.94$, 0.86, and -0.7. Therefore, EC, Na, and Tran were selected as principal water quality factors. Afterward, the effects of FL, RW, EC, Na, and Tran on the e-flows were analyzed by using VIP, as shown in Table 5. The positive and negative correlations between each factor and the mean value of the e-flows were obtained through correlation analysis (Fig. 5).

It can be concluded from Table 5 that among the five factors, RW, FL, and Tran were principal factors affecting the change in e-flow because the mean values of VIP were all >1. The effects these factors were large for FL, medium for RW, and small for Tran.

Fig. 5 shows that the principal factors RW and FL were positively correlated with the e-flows and that Tran was negatively correlated. This is because the increase in RW and FL improved the species number and density of principal fish, which caused the positive correlation of FL with the e-flows. The increase in Tran could lower the number of principal fish species in the water (Lajus et al., 2015) to result in the lower e-flow value.

Fig. 6 represents the mean value of the calculated e-flows at each station. Those in the downtown area were relatively high, whereas those in the north and south were lower. Owing to the large streamflow in the downtown area, the e-flows values calculated by the Tennant and the wetted perimeter methods were larger than those calculated by the AEHRA and integrated water quality methods. This result combined with the spatial high and low value clustering of each factor in Fig. 2, indicates that the Station J23 e-flow value in the downtown area was the highest, mainly because the station is located in the Yellow River, and the streamflow and river width are large. At Station J24, the e-flow value was the lowest, and the transparency was high, which is the same as the effect obtained by the above correlation between the factor and the e-flow mean value. The e-flow values were lower at J1 mainly because the that station is located in the mountainous area, where the river width and streamflow rate are small.

Table 5
Results of variable importance in the projection analysis.

Variables	Latent factors			
	1	2	3	Mean
RW	1.111	1.230	1.302	1.214
Na	0.383	0.559	0.538	0.493
EC	0.663	0.592	0.647	0.634
FL	1.418	1.236	1.290	1.315
Tran	1.082	1.159	1.161	1.134

5. Discussion

5.1. Spatial distribution of hydrological and water quality factors

In this paper, we used cluster analysis to obtain the spatial distribution of the high and low values of each factor. This method has been applied all over the world (Gonçalves and Alpuim, 2011; El-Hames et al., 2013; Nguyen et al., 2015; Trancoso et al., 2016; Zhao et al., 2017a, 2017b). Hydrological factors did not have a regular pattern of spatial distribution as per the spatial autocorrelation analysis, while water quality factors (Cl, Na, EC, and Tran) showed good spatial autocorrelations and significant spatial distribution in our study. Li juan et al. (2002) investigated the changes in hydrological and water quality factors considering the Lancang River Basin of China as the study area, and found an increment in streamflow from upstream to downstream. Changes in the hydrological factors increased, whereas stability decreased, indicating the absence of autocorrelation of hydrological factors. Similarly, the temporal and spatial changes in surface water quality were also studied in the Ying River Basin of China. Liu et al. (2016) analyzed the spatial autocorrelation and Morian's I index of the water quality; complex changes in water quality factors with the changes in season and geography were observed. Armt et al. (2017) concluded that the spatial autocorrelation of groundwater quality was highest for Na in the Sylhet region of Bangladesh. These results are generally consistent with analysis of the spatial distribution of hydrological and water quality factors in our study. The hydrological factors are not characterized by spatial agglomeration, and the spatial autocorrelation of water quality factors is complicated. However, some water quality factors, especially Na, have good spatial agglomeration. Hamidi et al. (2018) investigated the spatial distribution of water quality chemical factors in the coastal aquifer of Rmel-Oulad Ogbane, Morocco, and reported no autocorrelations for these parameters. The study by Omo-Irabor et al. (2008) in the western Niger Delta region found that the water quality chemical factors had a random spatial distribution. These conclusions are different from those indicated by our research. As a consequence of the fragmentation of land use in these areas, the area of industrial, agricultural and residential land is small and interspersed, resulting in the randomization of the distribution of water quality chemical factors; these do not exhibit good spatial agglomeration. However, the land use in our study area is clearly different. The northern plain is an agricultural area, the city center is a human settlement, and the southern region is a mountainous area. Therefore, the distribution of water quality chemical factors shows obvious spatial agglomeration. High conductivity values occur mainly in northern Jinan. EC values are lower in other regions. Most of the high-value areas are plains, which have higher salt ion content in water due to agricultural activities and therefore have higher electrical conductivity. The spatial distribution of transparency is the opposite of the electrical conductivity, with higher values concentrated in the southwest and southern hilly areas, while most northern areas have lower transparency. This is because in the mountains in the south of the city where the Yellow River is the source of water. In summary, the spatial distribution of hydrological and water quality factors are closely related to land use patterns and distribution characteristics. Later, differences in hydrological and water quality conditions led to differences in environmental flow results.

5.2. Comparison of e-flow calculation methods

Among the four e-flow methods used in the study, the Tennant method requires accurate long-term hydrological data (Poff et al., 2010), which are not yet available for several rivers (Sanderson et al., 2012). In practice, it is more appropriate for natural rivers and is best

Fig. 5. Correlation between e-flows and hydrological and water quality factors.

used as an estimative verification of other approaches (Liu and Men, 2007; Zhao et al., 2017a, 2017b). This method does not consider the geometric variation of the river, which is the effect of sediment erosion; this is particularly pronounced in areas with high anthropogenic activities. It has limited the use of the Tennant method in areas with extensive human activity (Guo et al., 2009). The study area in our research is intensely populated and affected by human activity. Due to a short time series of the measured streamflow data, some unavoidable uncertainties in the obtained results were observed.

The wetted perimeter method of e-flows requires the establishment of a relationship between the wet perimeter and the streamflow (Men et al., 2012); hence, it has higher data demands on the previous streamflow and cross-section. When calculating the e-flows by the wetted perimeter method, the channel shape of the HTQ station in our study area was rectangular, and the obtained streamflow-wetted perimeter scatter plot was obviously abnormal. The wet perimeter existed when the flow velocity was zero, and the point in the FL-P curve was not the inflection point needed to determine the e-flows (Xiao et al., 2010), indicating that the wetted perimeter method is not applicable for the calculation of e-flows in rectangular rivers.

The AEHRA not only considers the survival and reproduction of the principal organisms in the river but also refines the e-flows based on the months. It can provide more detailed data to relevant departments for ecological restoration and protection of the rivers (Liu et al., 2011). Compared with the surrounding areas, the central area of Jinan City (J23) has better hydrological and water quality conditions, where the e-flows value and its satisfaction ratio are high (Zhao et al., 2017a, 2017b), resulting in a healthy aquatic ecosystem with a robust food-web (Zhao et al., 2019). In the eastern region of Jinan City (J48), hydrological conditions and water quality are poor, and the e-flows value and its satisfaction ratio are also very poor (Zhao et al., 2017a, 2017b), resulting in a poor food-web structure (Zhao et al., 2019). In the southern region of Jinan City (J11), the hydrological condition is poor yet the water quality is good, and the satisfaction ratio of e-flows fluctuates over time between good and poor (Zhao et al., 2017a, 2017b), resulting in a medium food-web structure (Zhao et al., 2019). In the northern region of Jinan City (J39), the hydrological condition is relatively good yet the water quality is poor; here also, the satisfaction ratio of e-flows fluctuates but the situation is better than that in the southern region (Zhao et al., 2017a, 2017b), also resulting in a medium food-web structure (Zhao et al., 2019).

In brief, good hydrological and water quality conditions lead to a robust food-web structure and consequently high e-flows, and vice versa. Moreover, the variation in hydrological and water quality factors resulted in differing e-flow patterns in the study area. Consideration of the effects of the variation in hydrological and water quality factors on the determination of e-flows is an urgent necessity, which justifies the last method in this study. In other words, consideration of the demands of water ecosystem species on both hydrological and water quality factors makes the last method feasible and practical, especially in regions in which excessive quantities of pollutants are discharged into rivers. Since hydrological and water quality factors have important impacts on aquatic community and e-flows, only the e-flows method that comprehensively considers the influence of both these factors in those regions is reliable. In this study, the Tennant method, wetted perimeter method, and AEHRA were found to have their own advantages and disadvantages, but none of them directly included the water quality factors. Zhao et al. (2018) added the water quality factors control module, based on the AEHRA, and proposed the integrated water quality method. This method compares the water environment capacity with the actual pollution to obtain the water organism bearing capacity after the sewage is reduced, and this further improves the living environment quality of the aquatic organisms.

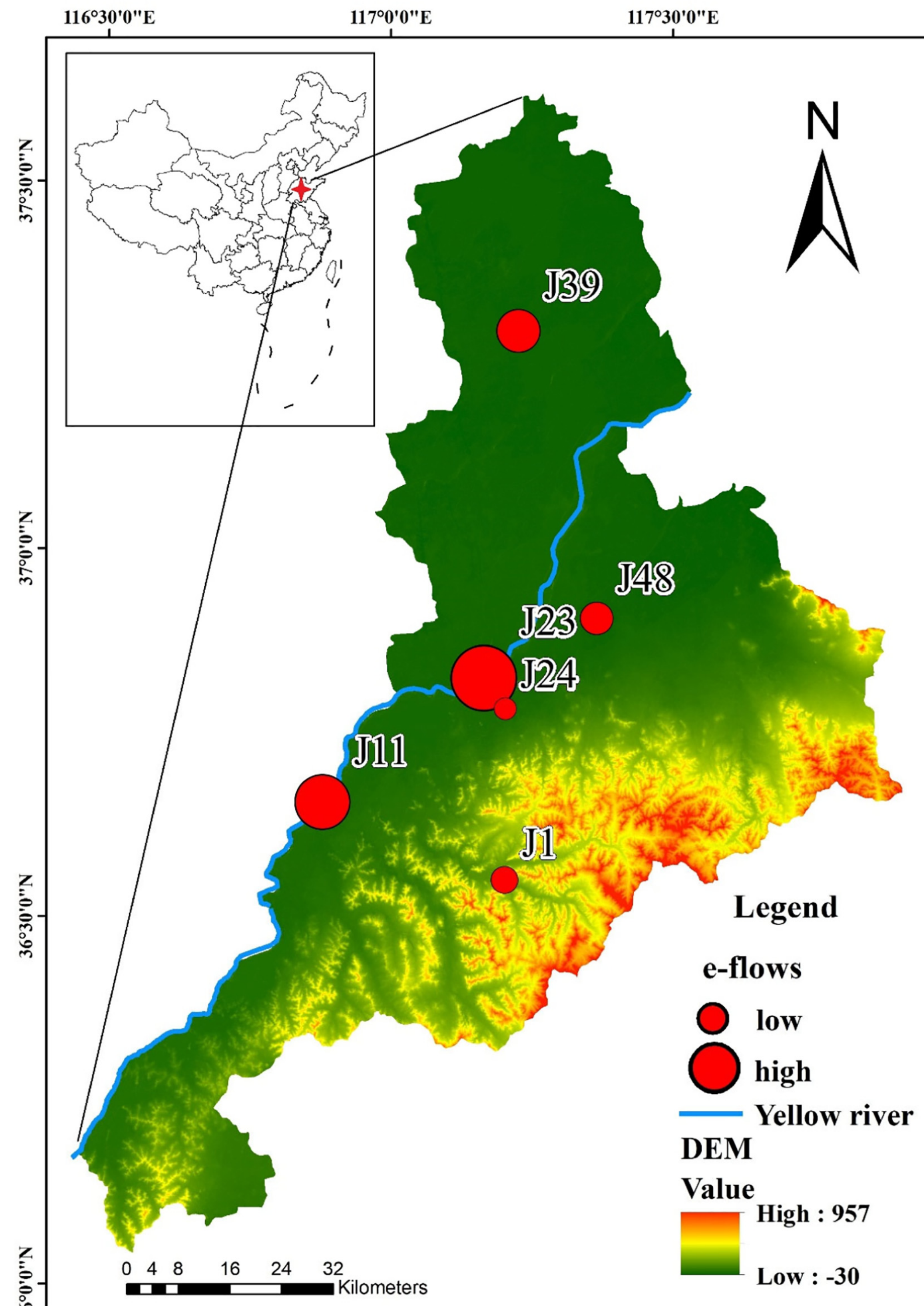

Fig. 6. Spatial distribution of e-flows.

5.3. Impact of hydrological and water quality factors on e-flows

From the correlation between the principal factors FL, RW, Tran and the mean value of e-flows, it can be concluded that there is a significant negative correlation between Tran and e-flows, while FL, RW and e-flows are positively correlated. The hydrological and water quality changes caused by human activities have an impact on the fish and the water ecosystem (Hemraj et al., 2017; Carvalho et al., 2016). A study conducted by Hemraj et al. (2017) in the Ramsar coastal lagoon of India showed that changes in streamflow and water quality affected the fish and the ecosystems. These results are consistent with the effects of FL, RW and Tran on e-flows obtained in our study. Changes in the hydrology and water quality affect the survival of aquatic organisms and further affect the e-flows. Sánchez-Carrillo et al. (2018) investigated

10 lakes around the world and found that temperature and altitude are principal factors leading to differences in aquatic organisms and ecosystem structure. Similarly, our study showed that there is a significant difference in the e-flows between mountain and plain ecosystems. Tunney et al. (2018) investigated 35 Canadian lakes and found that the water transparency is a principal factor affecting the predation relationship of the food web. A study by Lajus et al. (2015) in the Neva River and the Eastern Gulf of Finland has found that the number of fish decreased as transparency increased. There was a negative correlation between transparency and e-flows in our study. The reason is that an increase in transparency leads to a reduction in principal fish species, and ultimately leads to a reduction in the e-flows. The findings of these studies are generally consistent with our findings in Jinan City.

There are 21 large sewage treatment plants in Jinan, 16 in the central region, 2 in the southern region, 2 in the northern region, and 1 in the eastern region (Cai and Yang, 2019). Therefore, the sewage treatment capacity in the central region is much larger than that in other areas. The number of sewage treatment plants in each region has considerably affected river water quality. River water quality affects the living conditions of fish and eventually affects the determination of e-flows. The presence of sewage treatment plants will improve river water quality. Better water quality will help the survival of fish, which ultimately leads to an increase in the environmental flow calculated by the AEHRA method. Furthermore, in the southern mountain and the northern plain areas in Jinan, a large number of water projects have been constructed for water supply (Zhang et al., 2014). The construction of these water projects has reduced mean river flow velocity and led to river fragmentation. These changes have also affected the survival and breeding of fish, which have in turn affected the determination of e-flows. For example, in the central region of Jinan, there are more sewage treatment plants and less water projects, so the river water quality and connectivity are good, which is extremely beneficial for the survival of fish. Therefore, e-flows in the central region are high (Fig. 6). The construction of water projects will lead to a reduction in river flow velocity. Many fish will not survive due to the reduction of flow velocity, resulting in the decrease of the key fish species, and ultimately lead to a decrease in the calculated environmental flow of AEHRA. In brief, changes in hydrological and water quality factors affect the biodiversity of fish communities, leading to changes in the e-flows.

5.4. Limitations of the study

In this study, four methods were used to calculate e-flows. The impact of biological and environmental factors on e-flows was evaluated. The results of this study provide a strong foundation for the restoration and management of ecosystems. However, the time series of the hydrological data was short, resulting in some uncertainties in the e-flows calculated by the Tennant and wetted perimeter methods. In future work, it will be necessary to reinforce the development of new methods for the acquisition of hydrological and water quality factors in rivers to extend the hydrological data length of spatiotemporal changes at different hydrological frequencies in order to reduce the uncertainty in the calculation of e-flows. When applying the results of this study, long-term monitoring data should be guaranteed in the study area. Moreover, the analytical method should be chosen based on the hydrological, water quality, aquatic life and habitat data available.

6. Conclusions

In this study, four different methods were used to determine e-flows. The results show that the Tennant and wetted perimeter methods, which focus on the statistics of only streamflow, result in similar spatial distribution of e-flows; the AEHRA and integrated water quality method, which consider the effects of water quality and other hydrological factors such as flow velocity and water depth on fish, also result in a similar spatial variation. The spatial clustering results showed that there was no spatial distribution of hydrological factors. The water quality factors such as chlorine ions, sodium ions, conductivity, and transparency showed good spatial autocorrelation and significant agglomeration in their spatial distribution. Among the water quality factors, there was a significant negative correlation between transparency and e-flows, because the increase in transparency could impact the survival of principal fish species, resulting in a reduction in principal fish species and a decrease in e-flows. However, among the hydrological factors, there was a positive correlation between the streamflow, river width, and e-flows, because the increase in river width and streamflow could provide habitats and breeding sites for the fish, resulting in an increase in principal fish species and an increase in e-flows.

CRediT authorship contribution statement

C.S. Zhao: Methodology, Writing - original draft, Writing - review & editing. **Y. Yang:** Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **S.T. Yang:** Methodology. **H. Xiang:** Resources.**Y.R. Ge:**Resources. **Z.S. Zhang:** Investigation.**Y. Zhao:** Resources. **Q. Yu:** Investigation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.138695.

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