Front. Earth Sci. 2019, 13(2): 385–397
https://doi.org/10.1007/s11707-018-0726-8

RESEARCH ARTICLE

Ecological vulnerability analysis of Beidagang National Park, China

Xue YU, Yue LI, Min XI (✉), Fanlong KONG (✉), Mingyue PANG, Zhengda YU

College of Environmental Science and Engineering, Qingdao University, Qingdao 266071, China

Abstract Ecological vulnerability analysis (EVA) is vital for ecological protection, restoration, and management of wetland-type national parks. In this study, we assessed the ecological vulnerability of Beidagang National Park based upon remote sensing (RS) and geographic information system (GIS) technologies. To quantify the ecological vulnerability, 10 indices were collected by the 'exposure-sensitivity-adaptive capacity' model and spatial principal component analysis (SPCA) was then applied to calculate the ecological vulnerability degree (EVD). Based on the numerical values, EVD of the study area was classified into five levels: moderate, light, medium, strong, and extreme. Results showed that the average EVD value was approximately 0.39, indicating overall good ecological vulnerability in Beidagang National Park. To be specific, 80.42% of the whole area was assigned to a moderate level of EVD with the highest being the tourism developed areas and the lowest being the reservoirs and offshore areas. Ecological vulnerability of the region was determined to be affected by the natural environment and anthropogenic disturbance jointly. The primary factors included tourism disturbance, traffic interference, exotic species invasion, land use/land cover, and soil salinization. We expected to provide some insights of the sustainable development of Beidagang National Park and would like to extend the results to other wetland-type national parks in the future.

Keywords Beidagang National Park, ecological vulnerability degree, exposure-sensitivity-adaptive capacity, spatial principal component analysis

1 Introduction

National Park, as a new initiative to strictly protect the national landscape, rare species, and vulnerable systems and to rationally use natural and cultural resources, has attracted wide attention in these days (Zhai, 2014). As a fundamental step of development for national parks, ecological vulnerability analysis (EVA) has gained much attention in recent years. Its ability to correctly identify the driving factors and recognize the spatial distribution of vulnerability makes it crucial for the ecological protection and restoration of national parks. Previous studies on EVA of national parks were restricted to forest-type (Zou and Yoshino, 2017) and alpine mountainous-type National Parks (Nandy et al., 2015) and aimed solely at evaluating the vulnerability of forest fire (Mukti et al., 2016) and the ecological development zone (Nandy et al., 2015), which were relatively weak both in the objects and contents of EVA.

During the last two decades, a large number of wetland-type national parks were established to protect fragile wetland ecosystems, which are now facing deterioration due to human intrusion (Janssen et al., 2005). However, wetlands play an important role in biochemical transformation, production of biodiversity, and decomposition of organic matter (Ozesmi and Bauer, 2002). Therefore, in order to protect vulnerable wetlands, the international community has been emphasizing the importance of EVA in wetland conservation sites (Ma et al., 2015). Moreover, ecological vulnerability is an indicator that integrates multidimensional and multivariate attributes which contains natural, human, economic, and social elements (Buotte et al., 2016; Stevenazzi et al., 2017). Hence, to evaluate the ecological vulnerability comprehensively and spatially by considering all such elements is vital for the EVA in wetland-type national park.

Various methods such as the fuzzy analytic hierarchy process (Li et al., 2009), artificial neural networks (Fu et al., 2011), comprehensive evaluation methods (Boori and Amaro, 2011), landscape evaluation (Qiu et al., 2007), and global sensitivity analysis (Herman et al., 2013) have been widely used for EVA. Such methods are limited to rather small numbers of principal components or eigen-

Received January 19, 2018; accepted July 10, 2018

E-mails: ximin@qdu.edu.cn (Min XI); kongfanlong@qdu.edu.cn (Fanlong KONG)

vectors when modeling the variation. Another alternative approach is based on the principal component analysis (PCA) and the spatial feature extraction method (Takane, 2016), namely, the spatial principal component analysis (SPCA). One upside of this approach is that SPCA adds a spatial restriction on the traditional PCA, accounting for the spatial dependence in sets of geo-reference data (Córdoba et al., 2013; Gavioli et al., 2016). It also converts multiple indicators to a new set of uncorrelated synthetic variables named principal components (PCs) from the original variables through certain transformations (Li et al., 2011). SPCA has become a focus of attention in evaluating ecological vulnerability, proposed and implemented by Ma et al., (2015), Nandy et al., (2015), and Zou and Yoshino (2017).

Beidagang National Park, located in the south of Binhai New Area of Tianjin, was the first national park constructed to protect wetlands in China. Previous studies on Beidagang mainly focused on biodiversity evaluation (Liu et al., 2002), wetland dynamics (Ma et al., 2012), and ecological restoration (Guo et al., 2011). However, no ecological vulnerability assessment in this area has been reported yet. Therefore, in this study, an EVA model using SPCA, remote sensing (RS), and GIS was developed to assess the ecological vulnerability of the Beidagang National Park. The main objectives were: (i) to identify the vulnerability influential factors; (ii) to quantitatively calculate the ecological vulnerability and to reveal its spatial distribution in Beidagang National Park; and (iii) to enrich the methodological system of ecosystem assessment and provide a reference for other National Park and related researches by proposing targeting spatial management measures.

2 Materials and methods

2.1 Study area

Beidagang National Park is located in the south of Binhai New Area of Tianjin, covering an area of 3.7×10^4 hectares. It includes Beidagang reservoir, the downstream of Duliujian River, Qianquan reservoir, Lierwan reservoir, Shajingzi reservoir, Guangang Park, Beitang reservoir, and Huanggang reservoir, etc. (Fig. 1). The region has temperate continental monsoon climatic conditions with an average annual temperature of 11.3°C and total precipitation of about 600 mm. Additionally, Beidagang National Park is well known for its rich biodiversity. The dominant vegetation species are *Phragmites australis* and *Suaeda salsa*. They provide shelter to many scheduled and endangered birds such as the Oriental White Stork, *Ichthyaetus relictus,* and *Larus saundersi.*

Wetlands account for approximately 79.6% of the Beidagang National Park. In recent years, the rapidly increasing population and development of anthropogenic activities pose great threats to the ecosystem, for example through the inland wetland fragmentation, coastal habitat shrinking, exotic species invasion, ecological water shortage, and pollution. The above problems lead to low

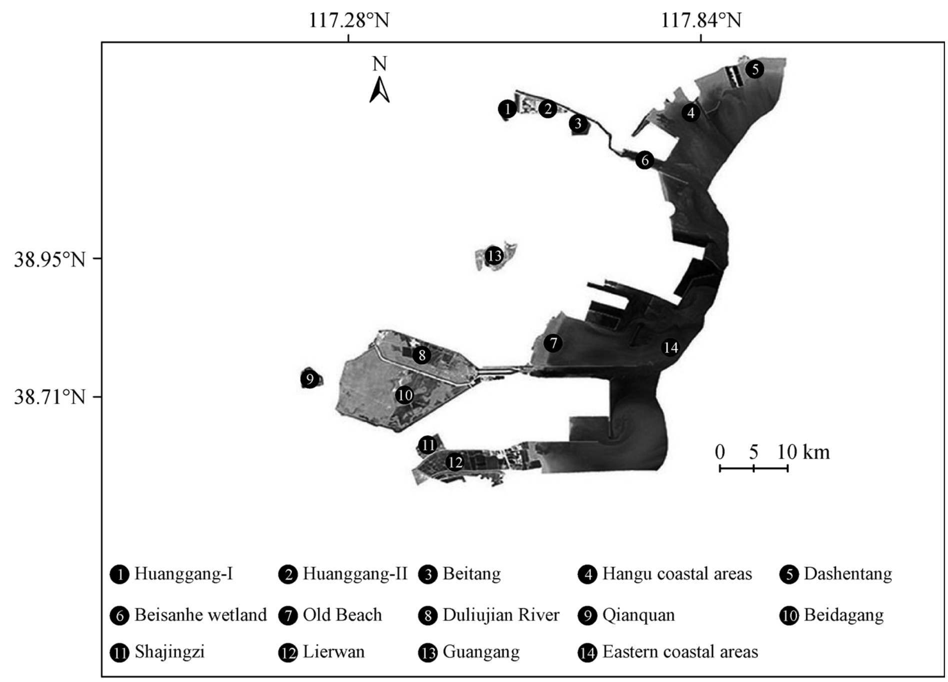

Fig. 1 Location of the study area.

resistance and high exposure in Beidagang National Park and increase the ecological vulnerability. Once the wetland ecosystem is destroyed, the recovery would take a long time.

2.2 Vulnerability evaluation model

As proposed by the Intergovernmental Panel on Climate Change (IPCC), the vulnerability evaluation model is frequently established based on the 'exposure-sensitivity-adaptive capacity' framework combined with the regional characteristics (Džeroski, 2001; Li and Tong, 2008; Sano et al., 2015). This framework, dependent on the interaction between the natural and human systems, has been widely recognized by researchers (Aretano et al., 2015), and can provide scientific evidence for sustainable development of the ecosystem.

The exposure unit is the coupled human-natural system that may be vulnerable to the hazard (Polsky et al., 2007). Habitat reduction, environmental pollution, and land reclamation lead to a decline in wildlife populations. The invasion of exotic species poses a serious threat to native species. The development of tourism causes damage to natural wetlands. Therefore, we chose the land use/land cover, traffic interference, tourism disturbance, and exotic species invasions as the evaluation factors of exposure. Here, the distance to roads, tourist attractions, and the center of exotic species were used to describe the traffic interference, tourism disturbance, and the exotic species invasion, respectively, because these interferences become more remarkable when they are closer to the center of roads, attractions, and exotic species (Zhang et al., 2010).

Ecological sensitivity is used to measure the instability of ecosystems (Luers et al., 2003). With the rapid urbanization and industrialization, wetlands in Binhai New Area have been becoming increasingly unhealthy. The development of agriculture and industry and the loss of a large number of natural wetlands have destroyed the integrity of the wetland ecosystem and caused serious fragmentation of the wetlands. Additionally, the infiltration and interaction between land and surface water, groundwater, and seawater resulted in serious salinization in Binhai New Area. Therefore, we chose soil salinization, water pollution, and landscape fragmentation (perimeter-area ratio (PARA) as factors of the sensitivity (Xi et al., 2016).

Ecological adaptive capacity indicates the ability of an ecosystem to maintain its structures and functions when experiencing an external disturbance (Hong et al., 2016; Zou and Yoshino, 2017). It depends on the vegetation, topography, hydrology, climate, and soil in a specific area (Engle, 2011). In this paper, the annual average temperature, the annual average precipitation, and NDVI were applied to reflect the ecological adaptive capacity (Fig. 2).

In short, we can conclude that the ecological exposure and sensitivity have positive relationships with ecological vulnerability, meaning that a higher exposure and sensitivity lead to a higher vulnerability. In contrast, the ecological adaptability has a negative correlation with ecological vulnerability, meaning that a higher adaptive capacity results in a lower vulnerability.

2.3 Data collection

The basic data of meteorology, hydrology, soil, tourism, and transportation in Beidagang National Park were collected to construct the ecological vulnerability evaluation model (Table 1). RS were taken from OLI images of Path 122/Row 33 of Landsat 8 in America (http://www.gscloud.cn/). Then, in order to extract the NDVI and land use/land cover, ENVI software was used to process the images by radiometric calibration, atmospheric correction, geometrical rectification, image enhancement, and image clipping. Next, PARA was obtained by processing land use patches. Finally, all data were imported into ArcGIS for spatial analysis. Due to the inconsistency of projection modes and scales between different data, it was necessary to spatially quantify the selected indices before using and to make geometrical registration and data resampling for each map. In this study, raster was the basic evaluation unit and all spatial data were unified into 30 m×30 m raster data.

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{nir}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{nir}} + \rho_{\mathrm{red}}}, \tag{1}$$

where the ρ_{nir} is the spectral reflectance in near-infrared

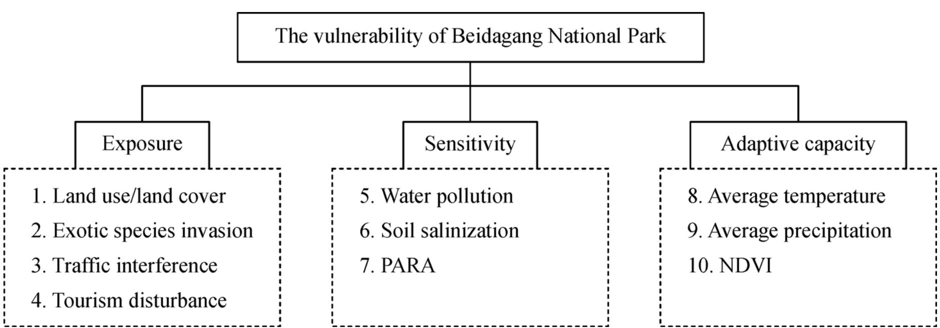

Fig. 2 Ecological vulnerability evaluation model in Beidagang National Park.

Table 1 Indicator's classification and source

Type	Indicator	Source
Remote sensing	Land use/land cover	Forest, grassland, water, mudflat, rearing pond, agricultural land, constructed land
	NDVI	Eq. (1)
	Landscape fragmentation	Eq. (2)
Monitoring data	Average temperature	Chinese Meteorological Data Sharing Service System (http://cdc.cma.gov.cn)
	Average precipitation	Chinese Meteorological Data Sharing Service System (http://cdc.cma.gov.cn)
	Water pollution	Water monitoring data
Socio economic survey data	Traffic interference	Social and economic investigation
	Tourism disturbance	Wetland ecotourism investigation
Wetland survey data	Exotic species invasion	Wild plant investigation
	Soil salinization	Wetland soil survey

band and $\rho_{\rm red}$ is the spectral reflectance in red band.

$$\mathrm{PARA}_i = \frac{\mathrm{TP}_i}{\mathrm{TA}_i}, \tag{2}$$

where the PARA_i is the perimeter-area ratio of the ith land use type; TP_i is the total perimeter of the ith land use type. TA_i is the total area of the ith land use type.

2.4 Spatial principal component analysis

2.4.1 Data standardization

Ecological vulnerability degree (EVD) characterizes the ecological conditions and is commonly used for EVA (Jin and Meng, 2011). Due to the differences of dimension and the physical meaning between each evaluation index, it is impossible to evaluate the EVD directly, so we need to standardize the evaluation indices (Liu et al., 2017). Different methods were applied to separately standardize the qualitative and quantitative indices. The values were between 0–1.

Quantitative indices: According to the relationship with ecological vulnerability, indicators were divided into positive and negative indicators. Positive indices indicated that the higher the index value, the higher the degree of ecological vulnerability. In contrast, the high value of the negative indices represented the lower degree of ecological vulnerability. In this study, average temperature, water pollution, soil salinization, and landscape fragmentation were positive indicators standardized by Eq. (3) while average precipitation and NDVI were negative indicators standardized by Eq. (4).

$$\text{Positive indicators: } Y_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \times 100\%, \tag{3}$$

$$\text{Negative indicators: } Y_i = \frac{X_{\max} - X_i}{X_{\max} - X_{\min}} \times 100\%, \tag{4}$$

where Y_i and X_i represented the standardized value and actual value of an indicator, respectively. $X_{\min}$ was the minimum actual value and $X_{\max}$ was the maximum actual value.

Qualitative indices: grade-weighted method was used for standardization where high value meant the high EVD. Qualitative indices included land use/land cover, traffic interference, tourism disturbance, and exotic species invasion (Table 2). According to the expert knowledge and the actual characteristic, these above qualitative indices were directly assigned the value by the grade-weighted method.

2.4.2 Calculation of EVD

There was a certain correlation among the evaluation indices, and the accuracy of the evaluation results would be interfered by the index repetition because the ecological vulnerability was influenced by many factors (Lei et al., 2013). The powerful spatial analysis function of RS and GIS was an effective method to solve the multivariate problems (Arianoutsou et al., 2011). Supported by the GIS spatial analysis tool, SPCA converted the relevant multi-variable spatial data into a few unrelated comprehensive indicators through orthogonal transformation (Wang et al., 2004). Through this method, more original variables could be reflected by fewer PCs. In this study, ArcGIS 10.2 were used to calculate the EVD through the following equation.

$$\mathrm{EVD} = \sum_{j=1}^{n} P_{ij} W_j, \tag{5}$$

where W_j was the weight of each index that calculate by Eq. (6).

$$W_j = \sum_{i=1}^{m} \lambda_{ij}^2 / \sum_{j=1}^{n-1} \sum_{i=1}^{m} \lambda_{ij}^2, \tag{6}$$

where m was the number of PCs, $m = 5$; λ_{ij} was the eigenvalue of variable j in grid cell i.

The contribution ratio r_i was obtained using Eq. (7):

Table 2 Grade-weighted method

Standardized value	2	4	6	8	10
Land use/land cover	Forest, grassland, water	Mudflat	Rearing pond	Agricultural land	Constructed land
Traffic interference	> 4000	3000–4000	2000–3000	1000–2000	0–1000
Tourism disturbance	> 4000	3000–4000	2000–3000	1000–2000	0–1000
Exotic species invasion	> 6000	3000–6000	1500–3000	500–1500	0–500

$$r_i = \lambda_i / \sum_{i=1}^{n} \lambda_i. \tag{7}$$

2.5 Classification of EVD

The classification of ecological vulnerability was of great significance to the overall understanding of the ecological condition of the study area. In our study, the EVD value was classified into five levels (moderate, light, medium, strong, and extreme), based on the characteristics of ecological vulnerability (Table 3). Meanwhile, the exposure, sensitivity, and adaptive capacity were also divided to five levels (I, II, III, IV, and V).

Table 3 Classification of EVD

EVD	Range
Moderate	< 0.42
Light	0.42–0.51
Medium	0.51–0.60
Strong	0.60–0.69
Extreme	> 0.69

3 Results

3.1 The ecological vulnerability factors

Through the SPCA, multiple PCs were identified for exposure (3), sensitivity (2), adaptive capacity (2), and comprehensive ecological vulnerability (5), respectively, depending on the cumulative contribution of each PC (Table 4). The detailed loading of each variable for the PCs can be seen in Table 5, Table 6, Table 7, and Table 8. The heaviest loadings are in boldface. For PC1, factors with the highest eigenvalue were tourism disturbance (0.61) and traffic interference (0.54) while the highest contributing factor to PC2 was land use/land cover (0.77), followed by exotic species invasion (−0.50). For PC3, the indicator with the heaviest eigenvalue was tourism disturbance (0.79) (Table 5). As shown in Table 6, the highest contribution to PC1 was soil salinization (0.92) while in PC2, landscape fragmentation (−0.85) and water pollution (0.52) had the heaviest eigenvalues. Table 7 shows average temperature (−0.78) and NDVI (0.76) were the largest contributors to PC1 and PC2, respectively. Among the comprehensive vulnerability analysis (Table 8), tourism disturbance (0.53) and land use/land cover (0.53) had the

Table 4 The eigenvalue and contribution ratio of each PC

Principle component		Aspects			
		Ecological vulnerability	Exposure	Sensitivity	Adaptive capacity
PC1	Eigenvalue	0.06	0.05	0.02	0.02
	Contribution ratio/%	37.73	59.55	50.43	58.32
	Cumulative contribution/%	37.73	59.55	50.43	58.32
PC2	Eigenvalue	0.03	0.02	0.02	0.01
	Contribution ratio/%	20.72	17.30	37.74	26.54
	Cumulative contribution/%	58.45	76.85	88.17	84.86
PC3	Eigenvalue	0.03	0.01		
	Contribution ratio/%	17.21	12.97		
	Cumulative contribution/%	75.66	89.82		
PC4	Eigenvalue	0.01			
	Contribution ratio/%	7.03			
	Cumulative contribution/%	82.69			
PC5	Eigenvalue	0.01			
	Contribution ratio/%	5.37			
	Cumulative contribution/%	88.06			

Table 5 The detailed loading of exposure

Item	PC1	PC2	PC3
Tourism disturbance	**0.61**	−0.07	**0.79**
Exotic species invasion	0.28	**−0.50**	−0.21
Traffic interference	**0.54**	−0.39	−0.49
Land use/land cover	0.51	**0.77**	−0.31

Note: – represented negative correlation. The heaviest loadings are in boldface.

Table 6 The detailed loading of sensitivity

Item	PC1	PC2
Landscape fragmentation	−0.26	**−0.85**
Soil salinization	**0.92**	−0.07
Water pollution	−0.30	**0.52**

Note: – represented negative correlation. The heaviest loadings are in boldface.

Table 7 The detailed loading of adaptive capacity

Item	PC1	PC2
Average temperature	**−0.78**	0.56
Average precipitation	0.52	0.32
NDVI	0.36	**0.76**

Note: – represented negative correlation. The heaviest loadings are in boldface.

Table 8 The eigenvalue and weight of each factor

Item	PC1	PC2	PC3	PC4	PC5	Weight
Landscape fragmentation	0.23	−0.23	**−0.47**	−0.01	0.27	0.08
Tourism disturbance	**0.53**	0.25	0.15	**0.78**	−0.14	0.20
Exotic species invasion	0.17	**0.42**	0.10	−0.10	**0.71**	0.14
Traffic interference	0.43	**0.38**	0.24	−0.57	−0.44	0.18
Land use/land cover	**0.53**	−0.04	−0.44	−0.21	0.17	0.11
Soil salinization	−0.26	**0.57**	−0.32	0.07	−0.11	0.10
Water pollution	0.05	−0.01	**0.48**	−0.08	0.30	0.07
Average temperature	0.15	**−0.41**	0.30	0.01	0.03	0.06
Average precipitation	−0.24	0.22	−0.11	0.07	0.03	0.02
NDVI	−0.17	0.17	0.25	−0.01	0.27	0.04

Note: – represented negative correlation. The heaviest loadings are in boldface.

heaviest eigenvalues in PC1. In PC2, soil salinization (0.57), exotic species invasion (0.42), average temperature (−0.41), and traffic interference (0.38) contributed the highest. In PC3, indices with the heaviest eigenvalues were water pollution (0.48) and landscape fragmentation (−0.47). In addition, tourism disturbance (0.78) contributed most to PC4, while exotic species invasion (0.71) heavily affected PC5.

Among the 10 ecological vulnerability factors, the highest weight focused on tourism disturbance (0.20), followed by traffic interference (0.18), exotic species invasion (0.14), land use/land cover (0.11), soil salinization (0.10), landscape fragmentation (0.08), water pollution (0.07), average temperature (0.06), NDVI (0.04), and average precipitation (0.02). Moreover, the weights of tourism disturbance, traffic interference, and exotic species invasion added up to 0.53, accounting for more than half of all factors (Table 8).

3.2 Spatial distribution characteristics

3.2.1 Exposure

As shown in Fig. 3, the exposure in Beidagang National Park mainly ranked at the I level. Additionally, the southern and northeastern parts of Lierwan, the Old Beach, and Dashentang had the highest exposure values. The areas of I, II, III, IV, and V were 804.10 km^2, 319.43

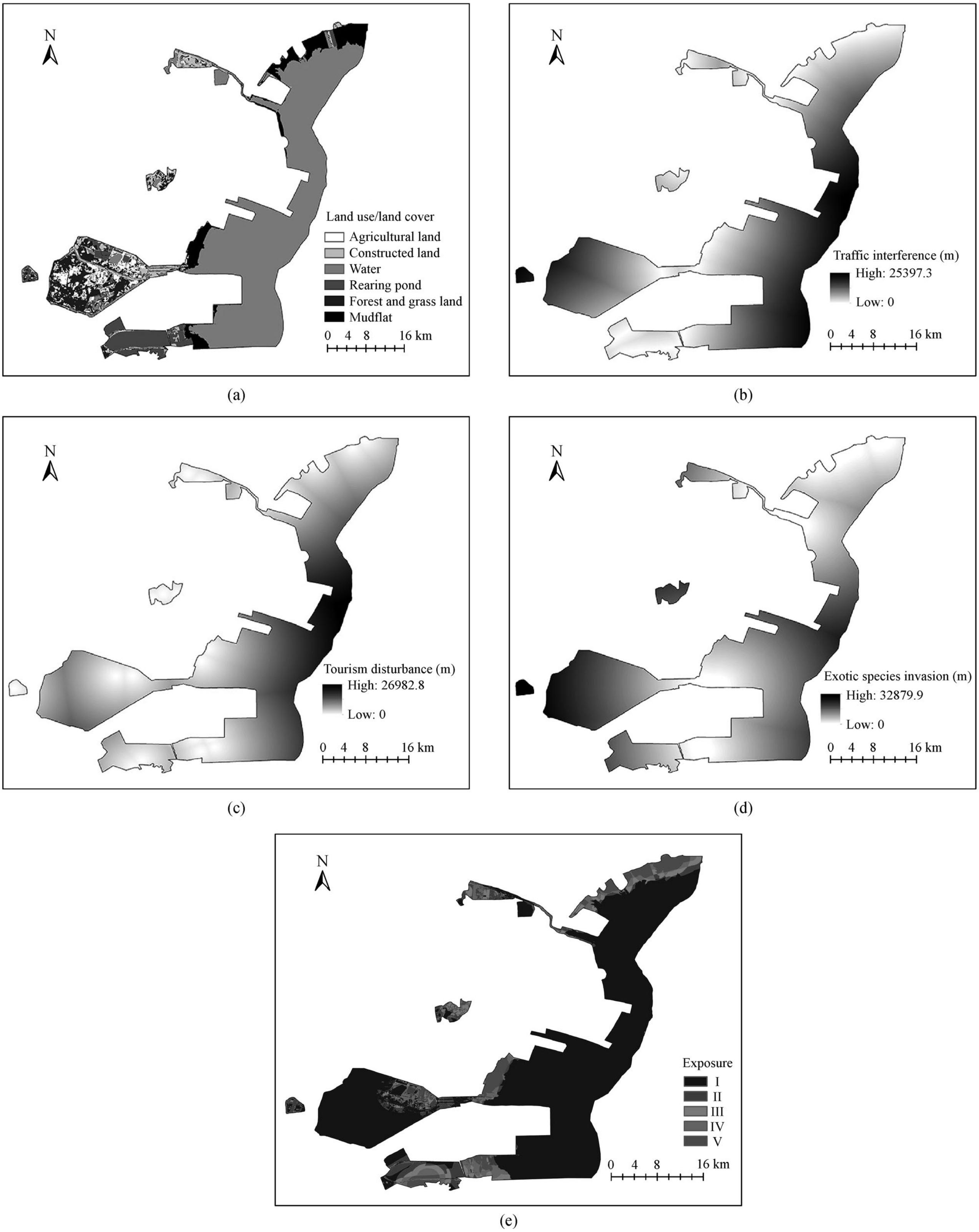

Fig. 3 The distribution of (a) land use/land cover, (b) traffic interference, (c) tourism disturbance, (d) exotic species invasion, (e) exposure index.

km^2, 67.72 km^2, 5.40 km^2, and 6.70 km^2, respectively, accounting for 66.82%, 26.55%, 5.63%, 0.45%, and 0.56% of the total area (Table 9).

3.2.2 Sensitivity

The overall sensitivity was relatively low with the highest value mainly at the northeastern part of the Duliujian River, some areas of Guangang Park and the Huanggang-II reservoir (Fig. 4). In addition, the areas of I, II, III, IV, and V were 976.13 km^2, 69.76 km^2, 55.39 km^2, 58.77 km^2, and 73.21 km^2, respectively, accounting for 81.12%, 5.80%, 4.60%, 4.88%, and 6.08% of the total area (Table 9).

3.2.3 Adaptive capacity

As shown in Fig. 5, the adaptive capacity in Beidagang National Park was not very high. The areas with the highest adaptive capacity were distributed in the Beidagang reservoir and the Duliujian River with high NDVI. Moreover, the areas of I, II, III, IV, and V were 23.91 km^2, 157.23 km^2, 419.43 km^2, 270.88 km^2, and 341.26 km^2, respectively, accounting for 1.97%, 12.96%, 34.59%, 22.34%, and 28.14% of the total area (Table 9).

3.2.4 Comprehensive ecological vulnerability

The average value of EVD in Beidagang National Park was 0.39, ranking at the moderate degree. As shown in Fig. 6, the areas of moderate vulnerability were located in the Beidagang, Qianquan, and Shajingzi reservoirs, the northwestern part of the Duliujian River, northwestern Lierwan, the western part of Beitang reservoir, and the eastern portion of the coastal area. Areas of light vulnerability occurred in the center of Lierwan, the western part of the Huanggang-II Reservoir, the eastern part of Beitang Reservoir, and the southwestern portion of Guangang Park. The medium vulnerability mainly focused on the southern of Lierwan, the eastern of Duliujian River, the northwestern of Huanggang-I reservoir, the northeastern of Guangang Park, and the coastal area at Hangu district. The strong vulnerability was at the western of Old Beach, the northeastern of Lierwan, and the peripheral zone of Dashentang. The extreme vulnerability areas distributed in Beisanhe wetland and Dashentang.

Through analyzing the distribution of EVD, the areas of the moderate, light, medium, strong, and extreme vulnerability were 961.64 km^2, 97.62 km^2, 68.94 km^2, 47.21 km^2, 20.34 km^2, respectively, accounting for 80.42%, 8.16%, 5.77%, 3.95%, and 1.70% of the total area (Table 9).

Table 9 The areas of each degree of exposure, sensitivity, adaptive capacity, and vulnerability

Item		Evaluation index			
		EVD	Exposure	Sensitivity	Adaptive capacity
Moderate	Areas/km^2	961.64			
	Percent/%	80.42			
Light	Areas/km^2	97.62			
	Percent/%	8.16			
Medium	Areas/km^2	68.94			
	Percent/%	5.77			
Strong	Areas/km^2	47.21			
	Percent/%	3.95			
Extreme	Areas/km^2	20.34			
	Percent/%	1.70			
I	Areas/km^2		804.10	976.13	23.91
	Percent/%		66.82	81.12	1.97
II	Areas/km^2		319.43	69.76	157.23
	Percent/%		26.55	5.80	12.96
III	Areas/km^2		67.72	55.39	419.43
	Percent/%		5.63	4.60	34.59
IV	Areas/km^2		5.40	58.77	270.88
	Percent/%		0.45	4.88	22.34
V	Areas/km^2		6.70	73.21	341.26
	Percent/%		0.56	6.08	28.14

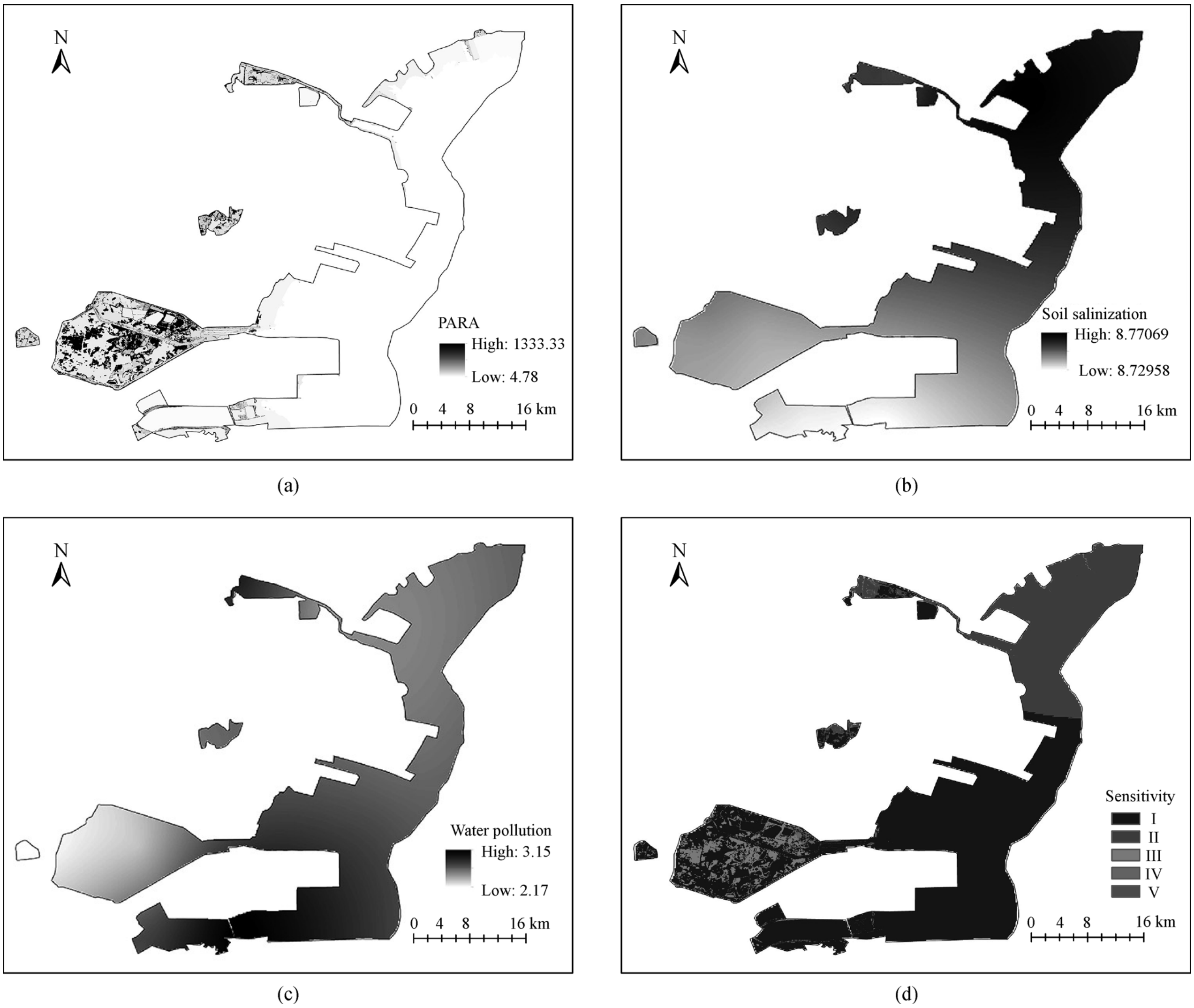

Fig. 4 The distribution of (a) landscape fragmentation, (b) soil salinization, (c) water pollution, (d) sensitivity index.

4 Discussion

4.1 Ecological vulnerability was subjected to a double impact by natural and human disturbance

Coastal wetland covers a large amount of areas of Beidagang National Park, where the ecological vulnerability was highly stressed due to natural and ever-increasing human pressure (Huang et al., 2009; Zhang et al., 2009). Anthropogenic activities have been a significant indicator for the ecological vulnerability assessment. For example, in the coastal wetland of eastern Fujian, land reclamation rate and pollution had the heaviest weight (You et al., 2013). In Hangzhou Bay wetland, urbanization, industrialization, the distance to cities and roads, as well as other human activities accounted for 45% of all the factors. In Qilihai wetland, the human population density and human disturbance index were used as the evaluation index of ecological pressure (Qin et al., 2013). In our study, 10 indicators were selected with comprehensively considering the natural-social system and the obvious environmental problems in Tianjin coastal wetland. In particular, tourism disturbance, traffic interference, and land use/land cover were mainly related with human activities. Landscape fragmentation, exotic species invasion, soil salinization, and water pollution were the main environmental problems under the pressure of human disturbance. And average temperature, average precipitation, and NDVI belonged to the natural condition of the study area.

The contribution degree of factors to ecological vulnerability was determined by the weight coefficient, indicating that the high weight coefficient had a higher ecological vulnerability. As shown in Table 8, the factors whose weight coefficient were greater than 0.1 were tourism disturbance (0.20), traffic interference (0.18), exotic species invasion (0.14), land use/land cover (0.11) and soil salinization (0.10). This implied the ecological vulnerability of the Beidagang National Park was not only

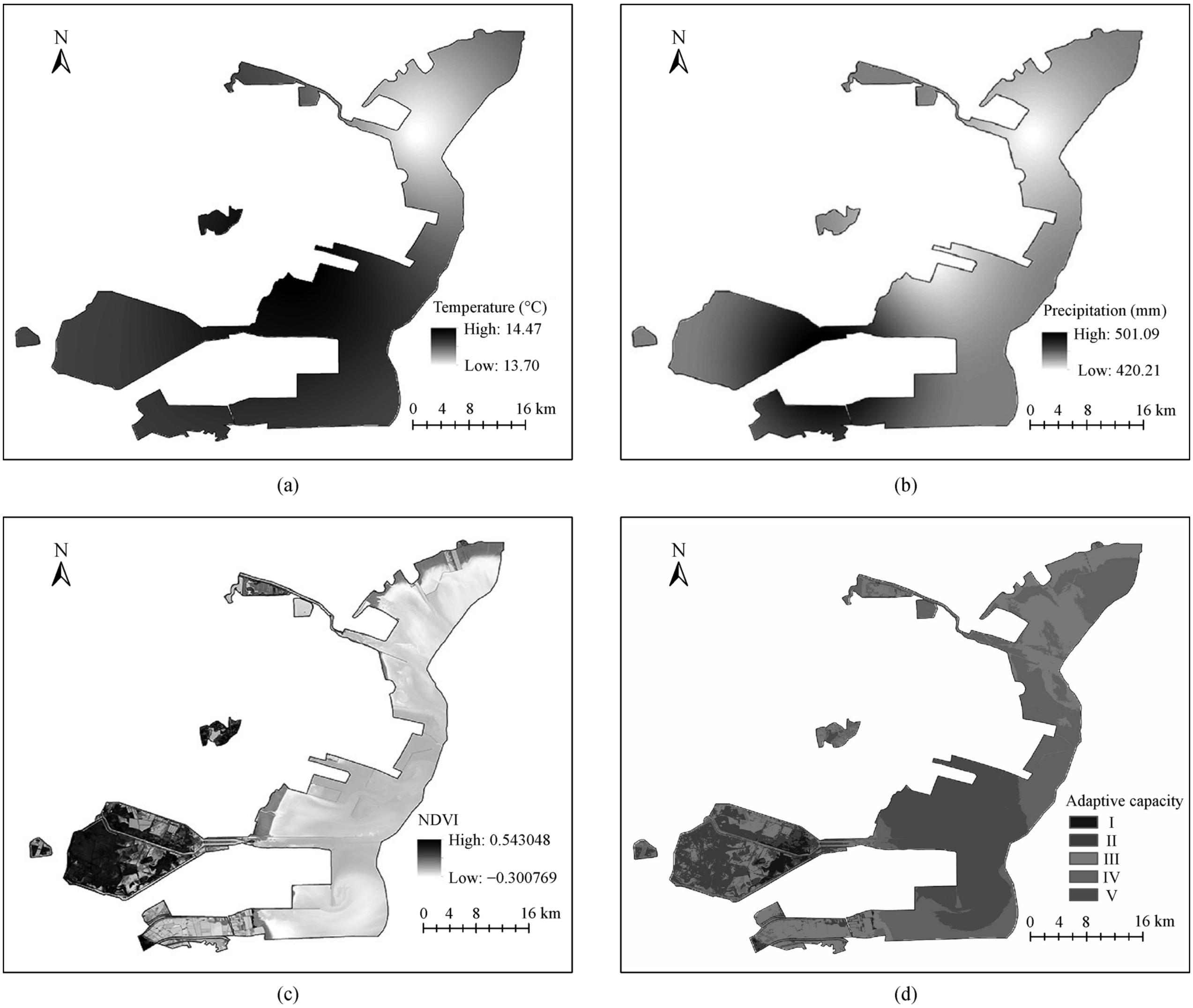

Fig. 5 The distribution of (a) average temperature, (b) average precipitation, (c) NDVI, and (d) adaptive capacity.

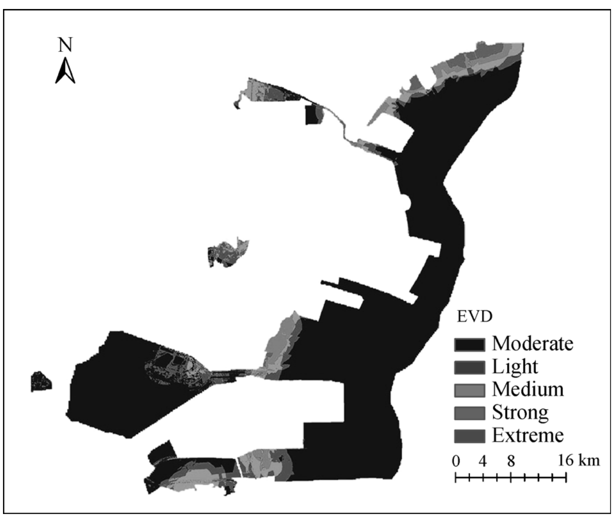

Fig. 6 The spatial distribution of EVD.

affected by the natural environment, but also heavily influenced by the surrounding community production and visitor activities (Xiao et al., 2017). Through the local investigation, the invasive species (i.e., *Spartina alterniflora)* were mainly distributed in the coastal wetlands of Hangu, such as the peripheral zone of the Dashentang and Beisanhe wetland in Tanggu. They competed for materials with the native plants and posed a great threat to the local biodiversity and the structure and function of the ecosystem (Gong et al., 2016). Additionally, in Binhai New Area, the high primary salt content in the soil and phreatic water, with the shallow groundwater level and strong evaporation, resulted in a large amount of salt accumulating in the topsoil, which created the secondary salinization of the soil (Wang et al., 2015). Moreover, Beidagang National Park was seriously affected by anthropogenic activities. Li (2014) indicated that the human disturbance index had the greatest impact on the ecosystem health of the Tianjin coastal wetlands, including the following: 1) some natural wetlands are gradually replaced by urban land and transport area (Wang et al., 2008), and a large amount of industrial waste water is directly discharged into the wetland without treatment leading to water pollution (Wang et al., 2018); 2) tourist activities, especially the discharged sewage and garbage as well as the excessive exploitation of wetland resources threaten the sustainable development of the environment, culture, and economic ecosystem (Zhuang et al., 2003); and 3) fertilizers from aquaculture and agriculture with high nitrogen, phosphorus, and potassium cause wetland pollution through surface runoff into the water system (Chen et al., 2014; Hansen et al., 2014).

4.2 The driving factors to exposure, sensitivity, adaptive capacity, and comprehensive ecological vulnerability

The PCs of exposure, sensitivity, adaptive capacity, and comprehensive vulnerability were extracted separately using the SPCA model. Three PCs of exposure indices were identified that accounted for 89.82% of the total variance (Table 4), so they could reflect the composition of the spatial distribution of exposure. As shown in Table 5, the first PC was heavily loaded on tourism disturbance, traffic interference, and land use/land cover. The second PC had a positive correlation with land use/land cover but was negatively related to exotic species invasion and traffic interference. The third PC was positively correlated with tourism disturbance and traffic interference, while negatively correlated with traffic interference.

Two PCs of sensitivity indices accounted for 88.17% of the total variance, suggesting only 11.83% of the information was lost. Therefore, they could reflect the spatial distribution of sensitivity (Ma, 2014). As shown in Table 6, PC1 mainly included soil salinization and the PC2 was positively correlated with water pollution and negatively loaded on landscape fragmentation. Two PCs of adaptive capacity indices accounted for 84.86% of the total variance, so they could represent the distribution of the adaptive capacity. Average temperature was the main contribution to the first PC, while NDVI heavily contributed the second PC (Table 7). Five PCs of comprehensive indices with a cumulative contribution ratio greater than 85% were extracted with the SPCA model. Moreover, PC1 and the PC2 contained 60% of the information carried by the original variables, suggesting that ecological vulnerability was mainly affected by PC1 and PC2. As shown in Table 8, PC1 was positively correlated with tourism disturbance, traffic interference, and land use/land cover, meaning that a higher tourism disturbance, traffic interference, and land use/land cover had higher ecological vulnerability. The PC2 loaded positively on exotic species invasion, traffic interference, and soil salinization, and negatively loaded on average temperature, indicating that the more serious environmental problems were closer to the main roads and that the lower average temperatures led to the higher EVD.

The protection objectives of Beidagang National Park were (i) to ensure regional security by protecting and restoring the natural attributes of wetlands; (ii) to restore the bird habitats and maintain biodiversity; and (iii) to develop ecotourism and become a demonstration base of natural experience and scientific research. Among the comprehensive vulnerability driving factors, human interference (tourism disturbance, traffic interference, and land use/land cover) and environmental problems (invasive species and soil salinization) positively affected PC1 or PC2. All of them have negative impacts on the natural attributes of the wetlands, habitats, and biodiversity, and the wetland tourism resources, which was not consistent with the protection target of Beidagang National Park. Therefore, tourism, transportation, land reclamation, and invasive species should be fully taken into consideration in future development.

4.3 Spatial distribution analysis of EVD

Poor stability, weak ecological resilience, and serious environmental problems led to strong vulnerability. Figure 6 showed that there were high EVD in the tourism developed areas, where the population density was high and the impacts of the environmental pollution caused by anthropogenic pressure were wide, such as the Dashentang village, Beisanhe wetland, Tianjin Waterworld, Mazu Culture Park, and the National Oceanic Museum. In these areas, on the basis of the combination of regional policy and practice, it was recommended to: 1) investigate the wetland characteristics comprehensively, including those zones into the ecological red line with a relatively high ranking, and improve the eco-compensation system; 2) prohibit development activities unrelated to ecological protection and other human disturbance, such as reclamation and tourism. Except for necessary ecological monitoring and scientific examination, it was not permitted to enter the core area without approval; and 3) improve the conservation and rehabilitation technology for the habitat and important water bodies.

Low scoring vulnerable areas are mainly distributed in reservoirs and offshore areas. In these areas, a relatively higher salinization and lower NDVI were found, whereas the human population density and disturbance were comparatively low, leading to a relatively lower vulnerability. Moreover, rich water resources and strong self-purification capacity improved the anti-interference ability and recovery ability of the wetland ecosystem and reduced the EVD. In these areas, the EVD was not high, but some reservoirs such as Beidagang and Beitang are drinking water sources. Disordered urban expansion and excessive reclamation should be forbidden along those few remaining parts of the natural coastline.

5 Conclusions

In this study, we selected 10 factors associated with the characteristics of both natural processes and anthropogenic activities of coastal wetlands and the actual exposure, sensitivity, and adaptive capacity of Beidagang National Park to build an ecological vulnerability evaluation model and then quantitatively evaluated the resulting EVD. RS, GIS, and SPCA were applied in this paper. Based on the results, the following conclusions can be drawn:

1) The ecological vulnerability of the National Park was subjected to a double impact by natural and human disturbance. Moreover, tourism disturbance, traffic interference, exotic species invasion, land use/land cover, and soil salinization contributed heaviest to EVD.

2) It could be found that the average EVD value was 0.39 and the overall ecological vulnerability in Beidagang National Park was not very high. From the point of view of spatial distribution, the moderate vulnerability areas occupied 80.42% of the whole area. And the highly vulnerable areas were concentrated in tourist attractions with large population density and the coastal areas with serious exotic species invasions as well as the larger pollution areas caused by anthropogenic disturbance. Areas with low vulnerability concentrated in reservoirs and offshore areas. The 'exposure-sensitivity-adaptive capacity' model was used to select vulnerability indices. However, the driving factors of vulnerability of wetland-type national parks were complex and changeable. Therefore, in the future research, more indicators should be collected to evaluate ecological vulnerability, such as discharge amount of industrial waste water, intensity of pesticide application, and soil organic carbon content.

Acknowledgements The authors greatly appreciate the State Forestry Administration of the People's Republic of China for providing basic data and investigation reports. This work is financially supported by the National Natural Science Foundation of China (Grant No. 41771098) and Shandong Natural Science Foundation (Nos. ZR2014DQ028 and ZR2015DM004).

References

Aretano R, Semeraro T, Petrosillo I, De Marco A, Pasimeni M R, Zurlini G (2015). Mapping ecological vulnerability to fire for effective conservation management of natural protected areas. Ecol Modell, 295: 163–175

Arianoutsou M, Koukoulas S, Kazanis D (2011). Evaluating post-fire forest resilience using GIS and multi-criteria analysis: an example from Cape Sounion National Park, Greece. Environ Manage, 47(3): 384–397

Boori M S, Amaro V E (2011). Natural and eco-environmental vulnerability assessment through multi-temporal satellite data sets in Apodi valley region, Northeast Brazil. J Geogr Reg Plan, 4: 216–230

Buotte P C, Peterson D L, Mckelvey K S, Hicke J A (2016). Capturing subregional variability in regional-scale climate change vulnerability assessments of natural resources. J Environ Manage, 169: 313–318

Chen Y, Fang L, Yang J (2014). The cropland pollution in China: status and countermeasures. Chinese Journal of Agricultural Resources and Regional Planning, 35: 1–5 (in Chinese)

Córdoba M, Bruno C, Costa J L, Balzarini M (2013). Subfield management class delineation using cluster analysis from spatial principal components of soil variables. Comput Electron Agric, 97: 6–14

Džeroski S (2001). Applications of symbolic machine learning to ecological modelling. Ecol Modell, 146(1–3): 263–273

Engle N L (2011). Adaptive capacity and its assessment. Glob Environ Change, 21(2): 647–656

Fu B, Jiang Q, Ren C, Xie Z (2011). Ecological vulnerability assessment of wetland based on neural network. Journal of Northeast Normal University (Natural Science Edition), 43: 140–143 (in Chinese)

Gavioli A, de Souza E G D, Bazzi C L, Guedes L P C, Schenatto K (2016). Optimization of management zone delineation by using spatial principal components. Comput Electron Agric, 127: 302–310

Gong L, Zhang R, Li R, Shi F (2016). Study on community dynamics of *Spartina alterniflora* at the intertidal zone in Tianjin. Acta Sci Natur Univ Nankaiensis, 49: 43–51

Guo T, Zhang X, Cheng T (2011). Evaluation of wetland ecological restoration project based on SD: a case study on Qilihai wetland in Tianjin. Procedia Environ Sci, 10: 2587–2593

Hansen A J, Piekielek N, Davis C, Haas J, Theobald D M, Gross J E, Monahan W B, Olliff T, Running S W (2014). Exposure of U.S. National Parks to land use and climate change 1900–2100. Ecol Appl, 24(3): 484–502

Herman J D, Kollat J B, Reed P M, Wagener T (2013). From maps to movies: high-resolution time-varying sensitivity analysis for spatially distributed watershed models. Hydrol Earth Syst Sci, 17(12): 5109–5125

Hong W, Jiang R, Yang C, Zhang F, Su M, Liao Q (2016). Establishing an ecological vulnerability assessment indicator system for spatial recognition and management of ecologically vulnerable areas in highly urbanized regions: a case study of Shenzhen, China. Ecol Indic, 69: 540–547

Huang B, Ouyang Z, Zhang H, Zhang L, Zheng H (2009). Assessment of eco-environmental vulnerability of Hainan Island, China. Chinese Journal of Applied Ecology, 20: 639–646 (in Chinese)

Janssen R, Goosen H, Verhoeven M L, Verhoeven J T A, Omtzigt A Q, Maltby E (2005). Decision support for integrated wetland management. Environ Model Softw, 20(2): 215–229

Jin Y, Meng J (2011). Assessment and forecast of ecological vulnerability: a review. Chinese Journal of Ecology, 30: 2646–2652 (in Chinese)

Lei B, Jiao F, Wang Z, Liu Y, Zhu L (2013). Eco-environment vulnerability evaluation and characteristics analysis in Yanhe river watershed. Journal of Northwest Forestry University, 28: 161–167 (in Chinese)

Li B, Tong L (2008). Vulnerability and sustainable development mode of coal cities in Northeast China. Chin Geogr Sci, 18(2): 119–126

Li L, Shi Z, Yin W, Zhu D, Ng S L, Cai C, Lei A (2009). A fuzzy analytic hierarchy process (FAHP) approach to eco-environmental vulnerability assessment for the Danjiangkou reservoir area, China. Ecol Modell, 220(23): 3439–3447

Li X (2014). Ecosystem health assessment in Tianjin coastal wetland based on the 'PSR' model. Ocean Development and Management, (4): 39–43 (in Chinese)

Li Y, Tian Y, Li C (2011). Comparison study on ways of ecological vulnerability assessment—a case study in the Hengyang Basin. Procedia Environ Sci, 10: 2067–2074

Liu D, Cao C, Dubovyk O, Tian R, Chen W, Zhuang Q, Zhao Y, Menz G (2017). Using fuzzy analytic hierarchy process for spatio-temporal analysis of eco-environmental vulnerability change during 1990–2010 in Sanjiangyuan region, China. Ecol Indic, 73: 612–625

Liu S, Zhu L, Feng Y (2002). Biodiversity evaluation on wetland—a case study form Paleocoast and Wetland Nature Reserve Zone in Tianjin. Chin J Eco Agric, 10: 76–78

Luers A L, Lobell D B, Sklar L S, Addams C L, Matson P A (2003). A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. Glob Environ Change, 13(4): 255–267

Ma C, Zhang G, Zhang X, Zhao Y, Li H (2012). Application of Markov model in wetland change dynamics in Tianjin Coastal Area, China. Procedia Environ Sci, 13: 252–262

Ma J (2014). Dynamic evaluation of ecological vulnerability in the Three Gorges Reservoir Region in Chongqing section, China. Dissertation for Master degree. Chongqing: Southwest University, 1–66

Ma J, Li C, Wei H, Ma P, Yang Y, Ren Q, Zhang W (2015). Dynamic evaluation of ecological vulnerability in the Three Gorges Reservoir Region in Chongqing Municipality, China. Acta Ecol Sin, 35: 7117–7129

Mukti A, Prasetyo L B, Rushayati S B (2016). Mapping of fire vulnerability in Alas Purwo National Park. Procedia Environ Sci, 33: 290–304

Nandy S, Singh C, Das K K, Kingma N C, Kushwaha S P S (2015). Environmental vulnerability assessment of eco-development zone of Great Himalayan National Park, Himachal Pradesh, India. Ecol Indic, 57: 182–195

Ozesmi S L, Bauer M E (2002). Satellite remote sensing of wetlands. Wetlands Ecol Manage, 10(5): 381–402

Polsky C, Neff R, Yarnal B (2007). Building comparable global change vulnerability assessments: the vulnerability scoping diagram. Glob Environ Change, 17(3–4): 472–485

Qin L, Han F, Song G, Li L, Wang Z, Zhang B, Jiang S (2013). EVA of Qilihai wetland based on the 'PSR' model. Soil and Water Conservation in China, (5): 59–72 (in Chinese)

Qiu P, Xu S, Xie G, Tang B, Bi H, Yu L (2007). Analysis on the ecological vulnerability of the western Hainan Island based on its landscape pattern and ecosystem sensitivity. Acta Ecol Sin, 27(4): 1257–1264

Sano M, Gainza J, Baum S, Choy D L, Neumann S, Tomlinson R (2015). Coastal vulnerability and progress in climate change adaptation: an Australian case study. Reg Stud Mar Sci, 2: 113–123

Stevenazzi S, Bonfanti M, Masetti M, Nghiem S V, Sorichetta A (2017). A versatile method for groundwater vulnerability projections in future scenarios. J Environ Manage, 187: 365–374

Takane S (2016). Effect of domain selection for compact representation of spatial variation of head-related transfer function in all directions based on Spatial Principal Components Analysis. Appl Acoust, 101: 64–77

Wang B, Cao Z, Zhang Z (2008). Ecological environment evaluation on Beidagang Wetland Nature Reserve. Environmental Science and Management, 33: 181–184 (in Chinese)

Wang S, Wang G, Chen Z (2004). Eco-environmental evaluation and changes in Yellow River Basin. Journal of Mountain Research, 22: 133–139 (in Chinese)

Wang W, Li G, Hou J, Liu Y (2015). Salinization characteristics of soil profile in coastal areas of Tianjin and its affecting factors. Geophys Geochem Explor, 39: 172–179

Wang X, Cai X, Wang Z, Sun T (2018). Factors and countermeasures of wetland pollution in China. Applied Chemical Industry, 47: 399–403 (in Chinese)

Xi M, Kong F, Li Y, Yu X (2016). Analysis on characteristics of soil salinization in coastal wetlands of Jiaozhou Bay. Bulletin of Soil and Water Conservation, 36: 288–292

Xiao L, Zhong L, Zhou R, Yu H (2017). Review of international research on national parks as an evolving knowledge domain in recent 30 years. Progress in Geography, 36: 244–255 (in Chinese)

You W, He D, Lin L, Wang R, Cai J, Wang P, Zhang Z, Xiao S, Zheng X (2013). Dynamics assessment on ecological vulnerability of coastal wetland in eastern Fujian Province. Fujian Agriculture and Forestry University, 42: 649–653 (in Chinese)

Zhai H (2014). Perspectives on establishment of national parks system in China. China Forest Products Industry, 41: 11–16

Zhang H, Liu P, Hu D, Sui J (2010). Influence of ecotourism disturbance on habitation and survival of Black Stork in Shidu Nature Reserve. Chinese Journal of Wildlife, 31: 13–16 (in Chinese)

Zhang X, Wang K, Zhang W, Chen H, He X (2009). The quantitative assessment of eco-environment vulnerability in karst regions of Northwest Guangxi. Acta Ecologica Sinica, 29: 749–757

Zhuang D, Ding D, Ren X (2003). Research on ecological tourism resources protection and exploitation of the wetland resources in China. Econ Geogr, 23: 554–557

Zou T, Yoshino K (2017). Environmental vulnerability evaluation using a spatial principal components approach in the Daxing'anling region, China. Ecol Indic, 78: 405–415