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Linking wilderness mapping and ecosystem services: Identifying integrated wilderness and ecological indicators to quantify ecosystem services of wilderness

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ABSTRACT

Wilderness has proven to provide a wide range of ecosystem services (ES). Wilderness have been shown to play an important role in preserving biodiversity and providing ES, which is indispensable to both nature and people. It is essential to integrate ES quantification into wilderness conservation and management. This study presents a method that combines the wilderness mapping and ecological indicators to measure ES of wilderness. The method was applied in 155,800 km^2 of Shandong province in China, across 23 types of land use. First, relative wilderness value (RWV) and ecosystem service capability (ESC) were quantified according to Weighted Linear Combination (WLC). Then, spatial autocorrelation between RWV and ESC were tested and analyzed using GeoDa software. Finally, the Redundancy analysis was used to investigate the primary drivers of RWV and ESC in different landscape types. The findings showed that, there were 27,263 km^2 of wilderness in Shandong province, of which 6,294 km^2 were high-quality wilderness. The region with the highest RWV was the Yellow River Delta (RWV = 0.82), and the area with the highest ESC was Laoshan Mountain (ESC = 0.76). Spatial autocorrelation analysis showed a positive correlation between RWV and ESC (Pearson's r = 0.637), both of which had significant spatial relevance (Moran's I = 0.589, $P < 0.005$). The RWV and ESC high-high clusters were found to cover 5,223 km^2 of high-quality wilderness areas. Regression analysis ($R^2 = 0.744$) showed that RWV can quantify ESC of urban area reliably. Population density (Explaining 33.9 %-49.3 %) was found to be a key indicator of RWV and ESC changes through the Redundancy analysis. In addition, we discussed key drivers of RWV and ESC of high-quality wilderness according to different landscape types. This approach can be used and adopted to support planning decisions dealing with wilderness conservation and management.

1. Introduction

The International Union for Conservation of Nature (IUCN) defines that wilderness are largely unmodified or slightly modified areas, retaining their natural characteristics and influence, without permanent or significant human habitation. As an important component of the natural environment, the wilderness can provide various ES such as supply services (provide water and food) (Allan et al., 2020; Ge et.al, 2024), regulatory services (air and climate regulation) (Asamoah et al., 2022), support services (biodiversity, self-sustaining ability) (Schumacher et al., 2018; Templer et al., 2015; Watson et al., 2016), and cultural services (spiritual value, aesthetic experience) (Zoderer et al., 2019). Based on the significant contribution of wilderness areas to biodiversity and maintaining ES, protecting the remaining wilderness areas is essential for both humans and nature (Zoderer and Tasser, 2021). With the acceleration of the process of urbanization and the reduction of wilderness, countries have begun to commit themselves to the protection and restoration of wilderness (Gandy, 2013; Vicenzotti and Trepl, 2009).

Support services are the basis for the continued provision of supply services, regulatory services, and cultural services by the wilderness (Xu et al., 2024). On the one hand, it provides a more suitable, more heterogeneous habitat for local wildlife and flora (Aznarez et al., 2022). On the other hand, urban wilderness can provide natural experiences and

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more opportunities for interaction with natural elements for residents (Rupprecht et al., 2015). The special aesthetic value of a wilderness landscape is also often correlated with its ecological value. In the wilderness, the range of stimuli triggered by sight, soundscape, and fragrance enhances the perception of biodiversity and creates a more unique aesthetic experience (Brant and Dunlap, 2023; Zhu et al., 2024). Moreover, interaction with natural elements such as wildlife and plants can relieve stress, promote positive emotions, and provide health benefits (Brun et al., 2018). Therefore, the conservation of the wilderness should focus more on natural elements, with a focus on supporting the natural and ecological value of the provided services.

Currently, there is still a lack of evaluation of support services in the wilderness area. Support services include a wide range of ecological indicators, which are related to ecological protection and regional ecological security, such as biodiversity, water conservation, soil conservation, wind prevention and sand fixation (Dong et al., 2021; Li et al., 2020), carbon storage, and coastal protection (Zong et al., 2021). In recent years, various models such as InVEST, ARIES, and SolVES have been developed for ES assessment. These models can be used to assess a variety of ecological indicators. Ecological indicators are often used to synergies/trade-offs studies among different ES (Wang et al., 2019; Zoderer et al., 2019), with little focus on the integrated ES of wilderness. We believe that combining multiple indicators can reflect the level of ecosystem service capability (ESC) better than a single indicator, and that an assessment of the non-monetary value of the wilderness can better reflect its intrinsic value, thereby can help to identify conservation priorities and develop guidance for action (Zhao et al., 2024). Referring to the ecological functions of the ecological red-line in Shandong Province, we found that biodiversity, water conservation, and soil conservation are the main conservation objectives(Chao et al., 2024). Concerns about carbon storage has increased with the propose of "carbon neutralization".

Wilderness mapping is an effective way to identify and evaluate the quality of the wilderness. The most commonly used method is to generate relative wilderness value (RWV) by combining a series of wilderness indicators using the Weighted Linear Combination (WLC) method (Cao et al., 2019; Carver et al., 2012; Müller et al., 2015). And the commonly used mapping indicators are land naturalness (Carver et al., 2012; Radford et al., 2019), distance deviation (Comber et al., 2010; Müller et al., 2018; Zoderer et al., 2020), and the degree of human interference (Müller et al., 2015; Zoderer et al., 2020). The land naturalness is determined by the biophysical composition of the land type, and expert scores (Cao et al., 2020). The distance deviation reflects the limited accessibility of wilderness areas and the distance from built-up areas and other artificial facilities. Indicators of the degree of human interference are the visibility of artificial structures and population density. Wilderness mapping had been proved to be effective to demonstrate the spatial distribution on different space scales (Tricker and Landres, 2018; Weng et al., 2024). However, the wilderness's conservation priorities at the provincial scale are poorly understood, which restricts conservation efforts.

Research has shown that there is a correlation between RWV and ES, but it is often limited to a certain ES, such as biodiversity, habitat quality. There is still lacks of space-related research of RWV with ESC, and the identification of key wilderness and ecological indicators. Based on the above considerations, the aim of this study is to present and test a method that can combine the wilderness mapping and ecological indicators to quantify ES of wilderness, in order to provide guidance for conservation and enhancement of wilderness ES. First, we quantified the RWV and ESC according to WLC approach. Then, spatial autocorrelation between RWV and ESC were tested and analyzed using GeoDa software. Finally, the Redundancy analysis was used to investigate the primary drivers of RWV and ESC in different landscape types.

2. Methods

2.1. Methodological framework

We have developed a methodological framework for quantifying the ES provided by wilderness areas using integrated indicators, including: (a) calculating RWV and ESC; (b) quantifying ES using RWV; (c) identifying key wilderness indicators and ecological indicators in different types of wilderness(Fig. 1). The mapping data is open source (Table A.1). The coordinate system of all mapping data and indicators is spatially calibrated to WGS_1984_UTM_Zone_51N with a resolution of 1000 m*1000 m.

2.2. Study area

In order to identify the relationship between ESC and RWV and explain the correlation between them, we selected Shandong Province as the study area (114°48′~122°42′E, 34°23′~38°17′N), which is located in the coastal region of the middle latitude of China, the north is the Bohai Sea, surrounded by the Yellow Sea in the east and south (Fig. 2a). The province's land area is 155,800 km^2, consisting of 16 cities. It's land use types present diversity (Fig. 2b) and construction intensity is unevenly distributed in space, providing the ideal study area to explore the correlation between wilderness indicators and ecological indicators. This article defines "build-up areas" as land used for urban, rural, and other types of development; "cultivated land" as paddy and dry fields; and "wilderness areas" as land containing natural landscapes (Fig. 2c).

2.3. Mapping of relative wilderness

Our work on the relative wilderness map is based on the wilderness continuum (Fig. A1). The wilderness continuum points to a gradual process of reducing human pressure from city to wilderness that emphasizes the fuzziness of the wilderness. Based on China's wilderness mapping research (Cao et al., 2019), we selected six indicators to map the relative wilderness: biophysical naturalness (BN), population density (PD), remoteness from settlements (RS), remoteness from roads/railways (RR), settlement density (SD), and roads/railways density (RD). Given the fuzziness of the wilderness, we used expert weight and fuzzy weight to map (Table A.2). The expert weight is the ratio of the average score for each wilderness indicator to the total score (Table A.2). The fuzzy analytical hierarchy process (FAHP) was used to calculate the fuzzy weight and to test the consistency ($I = 0.082$), with $I < 0.1$ indicating the weight is reliable. Specific methods of FAHP are contained in the appendix 2. The weighted formula (1) was used to overlap the indicators with different weights. All calculations were performed using ArcGIS 10.2. The data resolution of the indicator is uniformly processed to the size of 1000 m grid, which is consistent with the China wilderness map resolution. The appendix displays six indicators (Fig. A2).

$$\mathrm{RWV} = \sum_{1}^{n} X_i \times w_i \tag{1}$$

$$\mathrm{NI}_i = \frac{\lg(\alpha_i + 1)}{\lg(\alpha_{imax} + 1)} \tag{2}$$

BN reflects the degree of interference of human development and construction activities with the natural landscape and the naturalness of the landscapes themselves. We referred to the China Wilderness Map model's naturalness expert evaluation scale. (Table A.3). According to the expert rating sheet, the higher the score, the higher the naturalness.

PD refers to the amount of population distribution on the land area of the unit. This study selected Shandong province population distribution data in 2020 as the data source, using the kernel density filter to calculate the population density indicator.

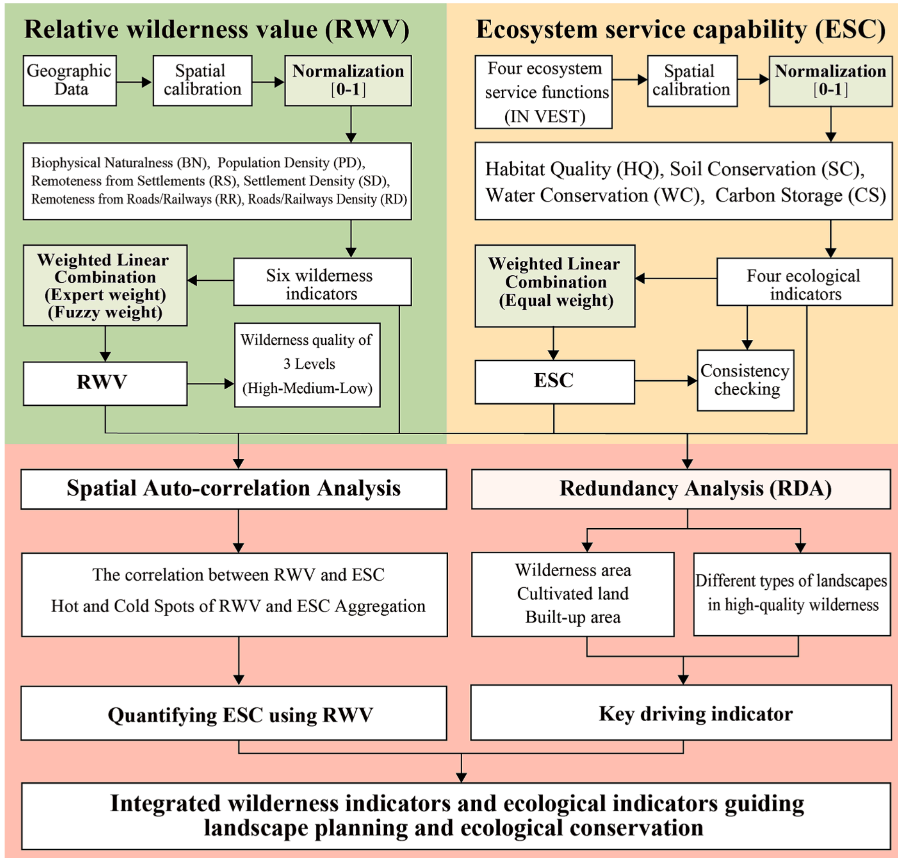

Fig. 1. Methodological framework for identifying integrated wilderness indicators and ecological indicators to measure ES of wilderness.

RS reflects the proximity of a grid in the study area to the existing urban construction area, urban gathering point, and rural settlement. The study selects data from the vectors of the settlements at levels 1, 2, and 3 of Shandong province in 2020 as a source of data and uses the Euclidean distance to calculate each indicator. The appendix (Table A.4) displays the specific weights. The higher the grid value, the farther the distance to the railway and the road.

RR reflects the proximity of motor vehicle roads to the grid of the study area. The study selected data from approximately 220,000 traffic network vectors, and divided the data into railroad, first, second, and third level roads. This is used as data sources to calculate the distance between the railway and the road by using the Euclidean distance. The appendix (Table A.5) displays the specifics of the weights.

SD refers to the number of settlements distributed on the land area of the unit. Taking the data of the first, second, and third levels of settlement as the data source, the kernel density filter was utilized to calculate the density indicator of the settlement in Shandong province. RD refers to the density of the railway and road. Using railway, primary, secondary, and tertiary roads as the data source, the kernel density filter was used for each calculation of rail and road density indicators.

Three of the indicators (SD, RD, and PD) do not match the wilderness of the cluster (e.g., the higher the RS, the higher the RWV it is; the higher the SD, the lower the RWV it is). The wilderness indicators were standardized using a normalization formula (2) such that value of all indicators range from 0 to 1, with the greater the score, the higher the RWV.

Sensitivity analysis was carried out to show the impact of indicator weights on the results. By calculating 25 sets of weights (reflecting each expert's opinion) as random weights. Then, by running 25 WLC models using different weight sets, 25 wilderness maps were created. To display the model's general sensitivity and pinpoint specific sensitive regions, the standard deviation of 25 result charts was computed.

2.4. Ecosystem service capability map

The Integrated Evaluation Model for Ecosystem Services and Weighing (InVEST) allows spatialization of quantitative evaluation of ES (X. X. Li et al., 2020; Qin et al., 2023). This study uses the InVEST and GIS models to quantify habitat quality (HQ), soil conservation (SC), water conservation (WC), and carbon storage services (CS). The four indicators were resampled to the 1000 m cell size, which is consistent with the relative wilderness map resolution. Using the normalization formula (2), the indicator results are treated as being between 0 and 1. Four indicators are shown in the appendix (Fig. A3).

Finally, adopting the equal-weighted strategy of the above four data points, we also constructed the ESC. Since there is no uncertainty about the weighting of ESC, we did not apply sensitivity analysis. Correlation analysis is also one of the methods of testing consistency, and we found that ESC is significantly positive with four indicators, so ESC can well represent the four ecological indicators.

2.4.1. Habitat quality (HQ)

The HQ model in InVEST is based on a combination of land use types and biodiversity threat factors (Qin et al., 2023). The model formula is:

$$Q_{xj} = H_J\left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z + k^z}\right)\right] \tag{3}$$

Q_{xj} denotes the HQ of x-grid in land use type j, with a value range of [0, 1]. The variables D_{xj} and H_j represent the degree of habitat degradation of the x-grid in land use type j and the suitability of the habitat for land use type j, respectively; z is typically set at 2.5 and k is a constant. Farmed and construction land are chosen as threat variables based on

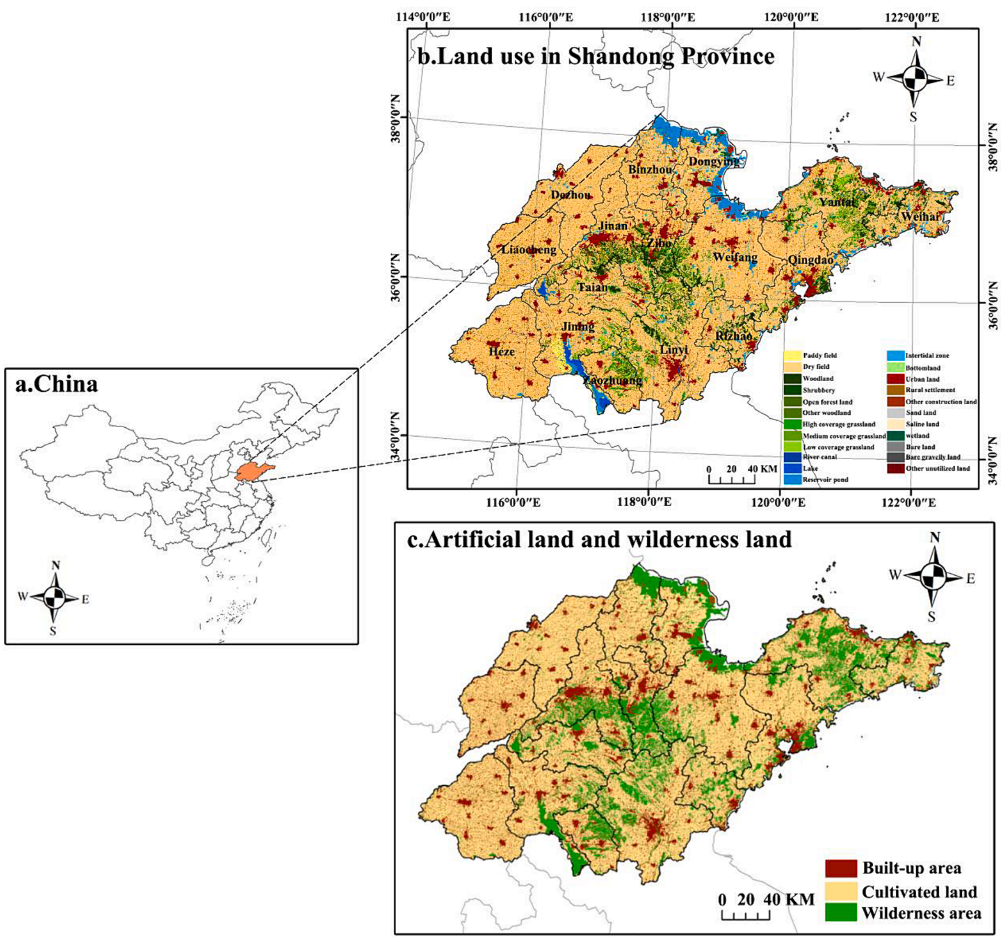

Fig. 2. Study area (**a.** China; **b.** Land use types in Shandong Province; **c.** Build-up area, cultivated land, and wilderness area.).

the analysis of the land use status. For information on the suitability of a given habitat for a certain type of land cover and the relative sensitivity of each type of habitat to threat factors, consult the InVEST model.

$$D_{xj} = \sum_{r=1}^{D}\sum_{y=1}^{Y_r}\left(\frac{W_r}{\sum_{r=1}^{R} W_r}\right) r_y i_{rxy} \beta_x S_{jr} \tag{4}$$

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}}\right) (Linear\ decay) \tag{5}$$

$$i_{rxy} = \exp\left[1 - \left(\frac{2.99}{d_{rmax}}\right) d_{xy}\right] (Exponential\ decay) \tag{6}$$

Y is the total number of grids containing threatening factors in the r, R is the number of threat factors, r is the type of threat factor, and β_x is the degree of land protection of cell x; W_r is weight; r_y is the number of threats on the grid; and i_{rxy} is the influence distance of the threat factor (Table A.6); The habitat type's sensitivity to threat factor r is denoted by S_{jr} (Table A.7), the distance between the x- and y-grids is $d_{xy,}$ and the threat factor r's maximal influence range is d_{rmax}.

2.4.2. Soil conservation (SC)

In the InVEST model, the Sediment Delivery Ratio (SDR) module is based on the universal soil loss equation ULSE (Li et al., 2017).

$$USLE_i = R_i \times K_i \times LS_i \times C_i \times P_i \tag{7}$$

Potential soil erosion (the formula for calculating soil erosion without taking into vegetation cover and SC measures):

$$RKLS_i = R_i \times K_i \times LS_i \tag{8}$$

Soil conservation:

$$SD_i = RKLS_i - ULSE_i \tag{9}$$

R_i represents the erosivity factor of rainfall for i-grid, K_i represents the soil erodibility factor for i-grid, LS_i represents slope degree and -length factor for the i-grid, C_i represents vegetation coverage and crop management factor for the i-grid, and P_i represents soil conservation measure for the i-grid.

$$R_i = 0.0534 \times P^{1.6548} \tag{10}$$

P is the annual rainfall (mm) (MJ·mm·/hm^2·h·a).

$$K_i = (-0.01383 + 0.51575Kepic) \times 0.1317 \tag{1}$$

$$\begin{aligned} Kepic = {} & \{0.20 + 0.3\exp[-0.0256SAN(1 - SIL/100)]\} \\ & \times [SIL/(CLA + SIL)]^{0.3} \times [1 - 0.25C/C + \exp(3.72 - 2.95C)] \\ & \times [1 - 0.7SN_1/SN_1 + \exp(22.9SN_1 - 5.51)] \end{aligned} \tag{12}$$

SAN is the contents of sand (%); SIL is the contents of silt (%); CLA is the contents of clay (%); SN_1 = 1-SAN/100; C is the organic carbon content (%). Slope degree and length factor: In the InVEST model, the LS has been embedded in the running program, just enter the Digital Elevation Models map and watershed map, no further calculations are required separately. Biophysics required for soil erosion modules contains C (vegetation coating factor) and P (soil conservation factor) were listed in table of Biophysical Coefficients (Table A.8).

2.4.3. Water conservation (WC)

The WC model uses the total water conservation quantity as a measurement indicator by the Water Balance Method. The formula is:

$$TQ = P_i - R_i - ET_i \tag{13}$$

$$R_i = P_i \times \alpha \tag{14}$$

TQ is the total water conservation quantity; P_i is the precipitation (mm); R_i is the surface runoff (mm); ET_i is the evapotranspiration (mm); α is the average surface runoff coefficient based on existing studies (Table A.9).

2.4.4. Carbon storage (CS)

The InVEST model can estimate the area's carbon reserves based on the corresponding carbon density values for different types of land use (Ma et al., 2019). References to the carbon density database are available (Table A.10). The formula for calculating the carbon reserve module for the InVEST model is as follows:

$$C = C_{above} + C_{below} + C_{soil} + C_{dead} \tag{15}$$

C is the total carbon storage (t/hm^2); C_{above} represents carbon reservoirs on the ground (t/hm^2); C_{below} represents subterranean partial carbon reserves (t /hm^2); C_{soil} represents soil carbon reserve (t/hm^2); and C_{dead} represents the dead organic carbon density (t/hm^2).

2.5. Data analysis

2.5.1. Spatial auto-correlation analysis

GeoDa is a spatial statistical tool that is mainly used in the qualitative assessment of the impact of urban development, the evaluation of land-value space distribution characteristics (Ma and Tong, 2022), and the vulnerability assessment of ecosystems. The spatial autocorrelation model is usually used to analyze the drivers of land coverage change (Wang et al., 2020), the spatial heterogeneity and its influencing factors (W. X. Liu et al., 2023), the coordination of ES and socioeconomic indicators, the spatial pattern of ES, and self-relevance (Yan et al., 2023). However, studies of the relevance of the application of spatial autocorrelation model to the exploration of RWV and ESC are not common. So we conducted spatial autocorrelation analysis of RWV and ESC, utilizing the Moran's I to evaluate the degree of space relevance, so that can represent spatial relevance with relevance maps and scatter plot intuitively.

2.5.2. Redundancy analysis (RDA)

RDA is a multi-analysis method based on the iterative process of corresponding relationships, ordering and multiple regression. This method has been widely used in the investigation of the relationship between ecological indices and their interpretative variables. RDA can statistically estimate the explanation and contribution of wilderness indicators and ecological indicators to RWV and ESC, which can help us determine what are the key factors that influence changes in RWV and ESC in different landscapes, such as lakes and forests, and the difference between key factors affecting changes in the RWV and the ESC, which are useful for wildlife conservation and rewilding actions in specific areas.

We used Canoco5 for redundancy analysis. Six wilderness indicators and four ecological indicators are used as independent variable, with RWA and ESC as dependent variable input procedures. The relevance and importance of the indicators in the wilderness, built-up areas and arable land were visualized respectively. According to the land type, we divided the high-quality wilderness into four types of landscape: forest, grassland, wetland, and water, and discussed the importance and relevance of indicators of these four types.

3. Results

3.1. Relative wilderness value (RWV)

The relative wilderness map has identified the RWV and fuzzy-relative wilderness value (F-RWV) in the study area (Fig. 3a; Fig. 3d). Comparing the two groups of weights, we found that the fuzzy weight is more inclined toward the BN and PD, ignoring the RR and RD. In the wilderness, roads are often the main source of human threat, and ignoring the road factors may lead to deviations in our assessment of the quality of the wilderness. In the wilderness, there are significantly more patches with high F-RWV values than with high RWV (Fig. 3e), which may mislead us to be more optimistic about the quality of the wilderness, so we chose to use expert weights for further data analysis.

From the whole study area, the lowest RWV is shown in the urban areas of each city, and the highest score of all landscape types is the Yellow River Delta wetlands (RWV = 0.82) in Dongying (Fig. 4a). Some of the forests and green space within the build-up areas has high RWV too, such as the Scenic Area of Laoshan Mountain (RWV = 0.61) in Qingdao, the tourist attraction of Ta Mountain in Yantai (RWV = 0.59), and the Scenic Area of Likoushan Mountain in Weihai (RWV = 0.50). Patches of 0.4–0.5 RWV were the most while 0.8–0.9 RWV were the least (Fig. 3b). Dongying is the city of highest RWV, and Liaocheng is the city of lowest RWV (Fig. 3c).

By running 25 WLC models using different weight sets, 25 wilderness maps were created (Fig. A4). The sensitivity of the WLC model to indicator weight uncertainty is shown in the appendix (Fig. A5). The results of the sensitivity analysis show the regions to be affected by the uncertainty associated with the weighting of the wilderness indicator, and the areas where the RWV are steadier and stronger. The Fig. A5 shows that the standard difference in all regions is less than 0.05, indicating a consistent and stable assessment of wilderness.

The RWV of wilderness was divided into three grades using the natural interruption method (Fig. A6): high-quality wilderness land (RWV:0.56–0.82); medium-quality wilderness area (RWV: 0.49–0.55); and low-quality wilderness area (RWV: 0.29–0.48). Table 1 represents the proportion of area of different level of wilderness. High-quality wilderness areas include a variety of types of land, the largest of which is a reservoir pond (1927 km^2), followed by woodlands (1277 km^2), lakes (587 km^2), and high-coverage grasslands (444 km^2).

Table A.11 lists the area of the wilderness within each municipal administrative division, sorted by the size of the high-quality wilderness. The largest area of high-quality wilderness is located in Dongying, which is 1298 km^2, mainly in the coastal wetlands of eastern and northern. Yantai has the largest wilderness area, which covers the tourist attractions of Tiangu Mountain (Fig. 4d), Ya Mountain National Forest Park (Fig. 4e), Zhaohu Mountain National Forest Parks (Fig. 4f), and Kunyu Mountain National Forest Park (Fig. 4g). The largest high-quality wilderness water area is Weishan Lake (Fig. 4h).

3.2. Ecosystem service capability (ESC)

The variations of the ESC are shown in Fig. 5a., with the concentrated regions of high ESC distributed in mountainous forests in the eastern and central southern regions. The lowest ESC areas are distributed on construction land in urban (ESC = 0.00). The areas with the highest ESC are located in the Laoshan Mountains (ESC = 0.76). Fig. 5b show that in the high-quality wilderness, forest lands can provide higher ESC than other landscape types. Through the four indicators (Fig. A3), we found that the spatial differences in the quality of habitat in Shandong provinces were significant, and areas with higher HQ show mountain, hill, and wetland accumulation characteristics. Forests had higher SC, WC, and CS than wetlands and lakes. Correlation analyses show that there is a significant positive correlation between ESC and the four ecosystem services, so the ESC model can reflect the overall ecosystem service capacity well (Fig. A10).

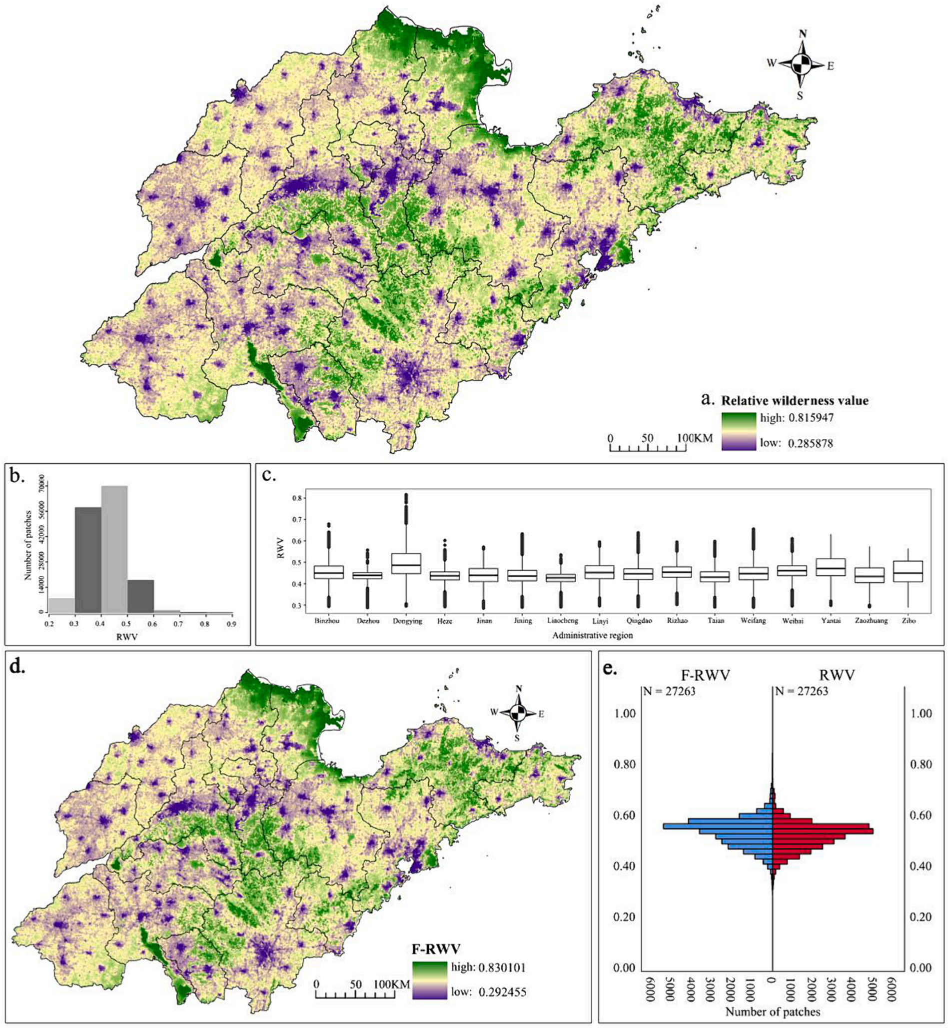

Fig. 3. Map and information of RWV and F-RWV (**a.** Relative wilderness map; **b.** Number of patches of RWV; **c.** Box plot of RWV in cities; **d.** Fuzzy-relative wilderness map; **e.** Number of patches of F-RWV and RWV in the wilderness area).

3.3. Spatial autocorrelation between RWV and ESC

3.3.1. Uni-variate analysis

We conducted an uni-variate spatial autocorrelation analysis of RWV (Moran's I = 0.824, P < 0.005), and the results showed that the data analysis was reliable (Fig. 6a). As shown in Fig. 6c, RWV had a significant spatial autocorrelation, with larger areas of high-high and low-low cluster areas. Among them, high-high cluster areas (32,718 km^2) were mostly in the wilderness areas and partly in cultivated land. 64.8 % of the wilderness is located in high-high cluster areas, and 91.1 % of the high-quality wilderness is located in high-high cluster areas. Low-low cluster areas were mostly in build-up areas. The cultivated land were the areas with no significant autocorrelation. The gradually decline tendency of the cultivated land from the border of the wilderness to the boundary of the built-up area (RWV:0.29–0.66), which serves a buffer zone between the wilderness and urban landscapes, may be the main reason for the lack of significant spatial autocorrelation.

3.3.2. Two-variable analysis

We conducted two-variable spatial autocorrelation analysis of RWV and ESC (Moran's I = 0.589, P < 0.005), and the results showed that the data analysis was reliable too (Fig. 6b). The scatter plot shows a positive correlation between RWV and ESC (Fig. 7a). As can be seen from the cluster distribution chart (Fig. 6d), RWV and ESC have significant spatial autocorrelation. The high-high cluster areas (25,079 km^2) are mostly in wilderness areas. 62.1 % of the wilderness is located in high-high cluster areas, and 83.0 % of the high-quality wilderness is located in high-high cluster areas. The low-low cluster is mostly located in the build-up area. The high-low and low–high cluster areas are smaller and fragmented. There are no significant concentration zones on the edge of arable land and the countryside. Among them, low–high cluster areas can indicate which grids of high ESC have been affected by severe human interference, cluster charts show that there are already 2,120 such grids. In addition, we conducted a spatial autocorrelation analysis of six wilderness indicators (Fig. A9), which showed that the strongest spatial relevance was PD and SD (Moran's I = 0.624, P < 0.005), and the weakest were BN and RR (Moran's I = 0.158, P < 0.005). We can find that within the wilderness, the degree of spatial autocorrelation between the different indicators is different. These results are especially important for wilderness conservation, which can provide guidance for policymakers.

We performed F-RWV spatial autocorrelation and regression analyses for comparison with the RWV (Fig. 6; Fig. 7). The results showed small differences between the results of the analysis produced by F-RWV and RWV. We believe that the reason for this result is that F-RWV has an approximately normal distribution with RWV because the fuzzy complementary judgement matrix for the establishment of vague weights is determined by expert scores. These results indicated that spatial correlation and linear regression were less sensitive to the weights obtained by different calculation methods.

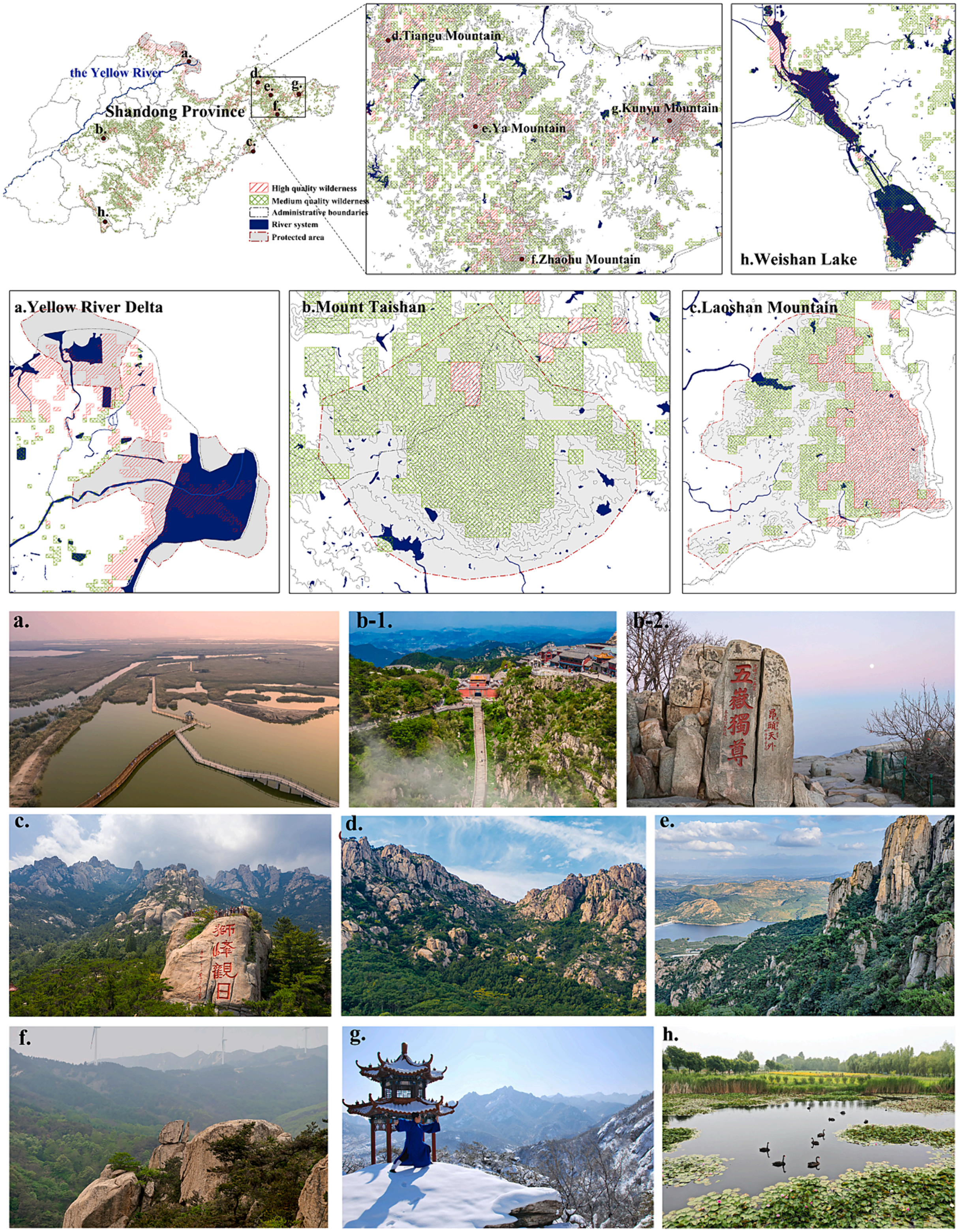

Fig. 4. High-quality wilderness of Shandong Province (**a.** Yellow River Delta; b. Taishan Mountain; **c.** Laoshan Mountain; **d.** Tiangu Mountain; **e.** Ya Mountain; **f.** Zhaohu Mountain; **g.** Kunyu Mountain; **h.** Weishan Lake). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The results of linear regression analysis (Fig. 7a) showed a positive correlation between RWV and ESC ($P < 0.01$, $R^2 = 0.405$, Pearson's $r = 0.64$). Since RWV and ESC show significant spatial concentration in built areas and the wilderness and show no significant concentration on most arable land, we predict that RWV is more suitable for assessing ESC in high-density cities. In order to validate our prediction, we selected grids from Qingdao's main district (Fig. A5) for regression analysis since there is hardly any cultivated land in this area. The regression analysis (Fig. 7b) of Qingdao's main urban area confirmed our prediction ($P < 0.01$, $R^2 = 0.744$, Pearson's $r = 0.86$).

Table 1
Wilderness classification and patches area.

Level	Area (km^2)	Number of patches	Proportion of the wilderness area (%)	Proportion of the total area(%)
High-quality	6294	862	23.09	4.09
Medium-quality	13,762	3523	50.48	8.94
Low-quality	7207	4755	26.43	4.69
Total	27,263	9140	100 %	17.72

When we consider the four ecological indicators separately, we found that they show significant spatial autocorrelation with RWV. However, there are differences between the Moran's I of the four indicators. The Moran's I between RWV and HQ, SC, WC, and CS are 0.560, 0.249, 0.484, and 0.353 respectively (Fig. A6). High-high cluster areas of HQ, WC, and RWV are distributed in wilderness areas. However, these areas of SC and CS are mainly distributed among various types of forest and grassland (Fig. 8).

3.4. Analysis of the importance of wilderness and ecological indicators in built-up area, cultivated land, and wilderness area

In RDA analysis, the stronger correlation between independent and dependent variables, the smaller the angle between them. Indicators have a positive correlation with the study object when the corner is at an acute angle, and have a negative correlation when it is at an obtuse angle. In addition, wilderness indicators are represented by green real lines, ecological indicators are represented by red real lines, RWV and ESC are represented by blue arrow lines; the length of the arrow indicates the size of the variable and index relationship; the longer the arrow, the greater the relevance.

The RDA results (Fig. A11) showed that wilderness and ecological indicators selected in built-up areas, cultivated land, and wilderness areas had an explanation of up to 70 % or more in the 1st axis and 2nd axis. Wilderness and ecological indicators in built-up areas can explain the changes in RWA and ESC more effectively than in arable and wilderness areas. In analyzing the explanation of a single indicator (Table 2), we found that PD (33.9 %–49.3 %) was a key wilderness indicator of the change of RWV and ESC of the wilderness, cultivated land, and built-up areas, which suggested that human activity was a critical indicator affecting the quality of the wilderness and ES.

In the discussion section, we analyzed the explanation and contribution of indicators in high-quality wilderness by landscape types. In forests and grasslands, the indicator's explanation of RWV and ESC is approximately 88 %; in wetlands, it is 73 %; and in waters, it is 77 %.

4. Discussion

4.1. RWV has the potential to quantify the ESC

China is a super-wild country with vast areas of wilderness, especially in the western uninhabited areas. However, in eastern coastal areas, such as Shandong Province, the wilderness has small, fragmented characteristics, but these areas have important natural benefits such as wildlife habitat and migration, plant populations, natural change, climate regulation, carbon storage, etc. (Cao et al., 2022). According to recent studies, there may be a clear link between improved ecosystem functioning and the quality of the wilderness, and improved quality can improve the availability of support services in the wilderness (Cao et al., 2022; Z. Xu et al., 2024). For example, the Laoshan Mountains have the highest ESC and are located in high-quality wilderness areas, thus having important ecological value, which is the basis for the cultural services provided by the area, such as wilderness aesthetics and experiences (Zhao et al., 2023). We found that RWV might serve as an alternative method of assessing the non-monetary value of the wilderness because the RVV combines multiple human interference factors to better represent the fuzziness and intrinsic value, and the InVEST model may be inaccurate (Müller et al., 2018).

There is a positive relationship between RWV and ecological indicators, such as HQ ($p < 0.01$, $R^2 = 0.441$, Pearson's $r = 0.61$), SC ($P < 0.01$, $R^2 = 0.079$, Pearson's $r = 0.21$), WC ($P < 0{,}01$; $R^2 = 0.283$; Pearson's $r = 0.54$), and CS ($P < 0.01$, $R^2 = 0.164$, Pearson's $r = 0.42$) (Fig. A10). Comparing R^2 and correlation indicators, the interpretation of HQ by RWV is superior to other indicators. Other studies have already found that urban-scale wilderness mapping and HQ can be applied to predict urban biodiversity (Aznarez et al., 2022; Müller et al., 2018). Therefore, in the absence of detailed data on species distribution, maps of relative wilderness can provide guidance for the delineation of the boundaries of protected areas, which can support biodiversity conservation.

4.2. Explanation and relevance of wilderness and ecological indicators in the high-quality wilderness

4.2.1. Forestland (Woodland, forest, shrubbery)

Forests are irreplaceable in sheltering biodiversity, stabilizing land carbon storage, hydrological regulation, and performing other ecological functions. In terms of the variety of ES they supply, forests which are the least influenced by human activity possess the highest protection

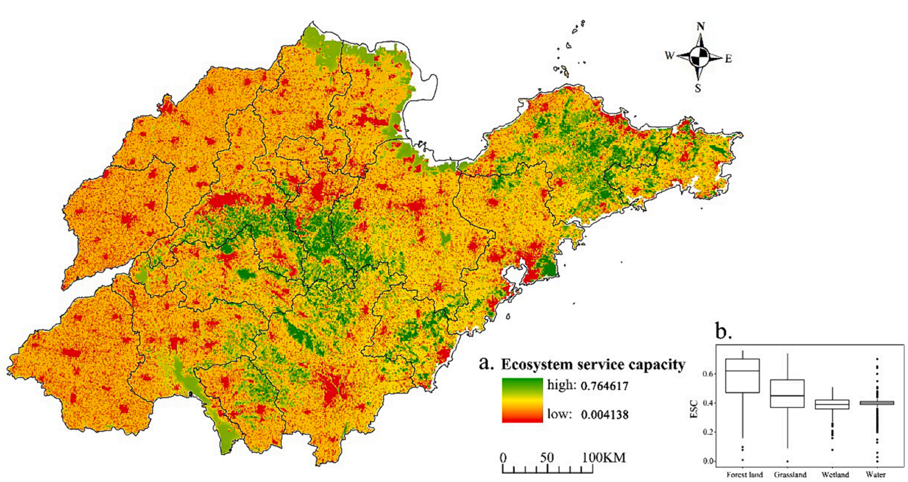

Fig. 5. Mapping of ESC (**a.** Ecosystem service capability map; **b.** Box plot of ESC in high-quality wilderness).

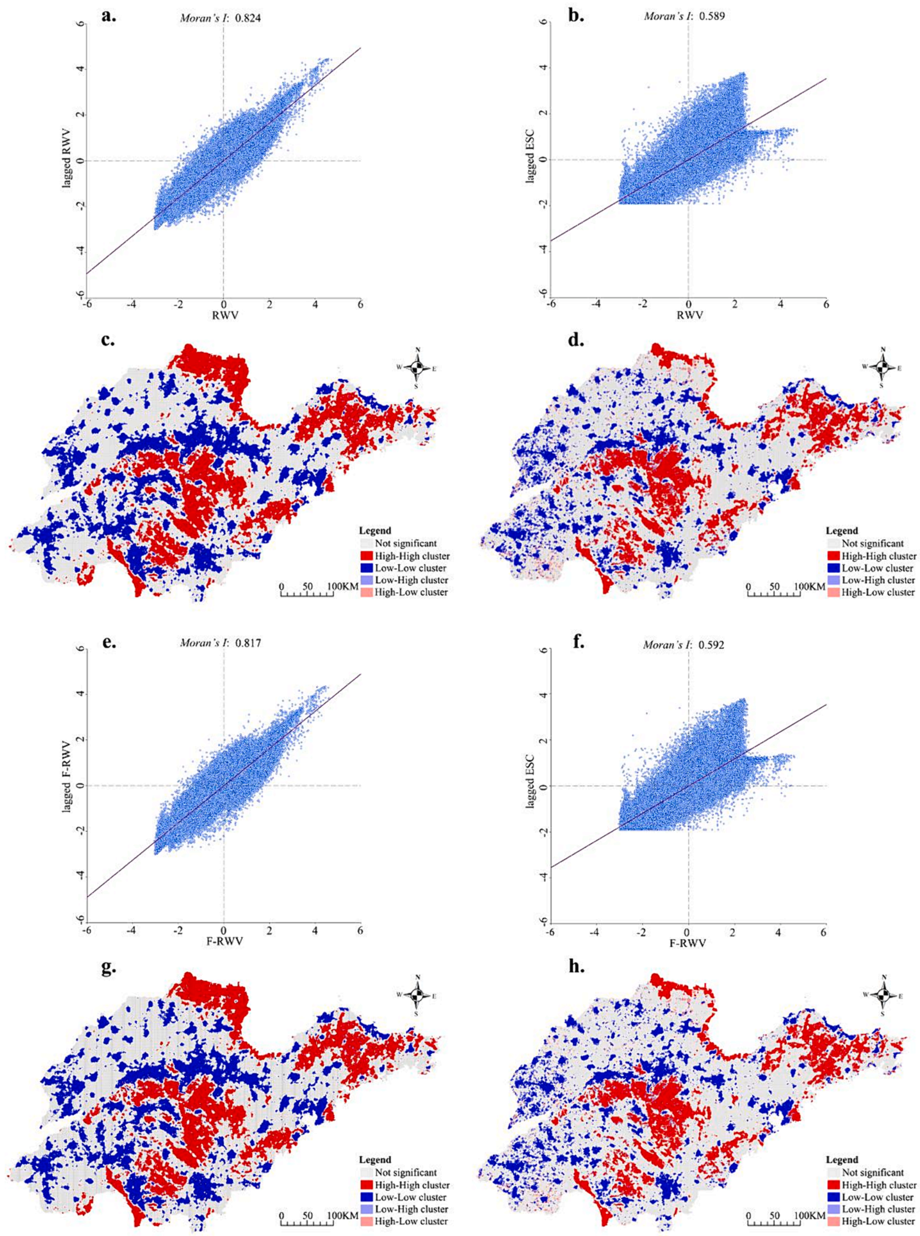

Fig. 6. Map of Moran's I and spatial autocorrelation (**a.** RWV; **b.** RWV and ESC; **c.** Spatial autocorrelation cluster of RWV; **d.** Spatial autocorrelation cluster of RWV and ESC; **e.** F-RWV; **f.** F-RWV and ESC; **g.** Spatial autocorrelation cluster of F-RWV; **h.** Spatial autocorrelation cluster of F-RWV and ESC).

value (Jie et al., 2021; Potapov et al., 2017; Zhao et al., 2024). In a study conducted in The Northeast Tiger-Leopard National Park (NTLNP) in China, forests were also considered to be the best provider of ES (Zhai et al., 2023). We found that CS is the key ecological indicator of the change in RWV and ESC in forest land (Explanation = 34.0 %) (Fig. A12). Therefore, in the forest wilderness, the spatial distribution characteristics and concentration of CS are effective indicators for visualizing the wilderness and ecological quality. In order to estimate CS, we used InVEST model based on land use, which may be a deviation with a more detailed calculation method. InVEST is more suitable for large-scale estimation because it reduces the workload of field tree surveys (Jie et al., 2021) and can visually reflect the space distribution and aggregation characteristics of CS. It is useful to apply our proposed method at large scales to support carbon peaking and carbon neutrality goals.

PD is the most critical wilderness indicator (Table A.12). Researches have indicated that the value of waste management, food production per unit area, soil creation and protection, gas adjustment, and biodiversity protection tends to decrease with an increase in population in the region. PD have been widely used to assess the extent of environmental human impact (Qian et al., 2023), wilderness (Cao et al., 2019), ES value, ES sustainability (Chen et al., 2020), supply and demand balance of ES.

4.2.2. *Grassland*

CS is a key driver indicator of RWV and ESC changes in grassland (Explanation = 31.7 %), which is consistent with forest land but less interpretative than forest land. Studies have shown that areas with a higher proportion of forest and grassland have a better capacity to provide ES and stronger carbon storage functions (Zhou et al., 2020; Zhu et al., 2021).

PD is a key wilderness indicator. Grasslands are more susceptible to human interference than forestlands and may be more vulnerable to destruction by human activities, leading to desertification, such as

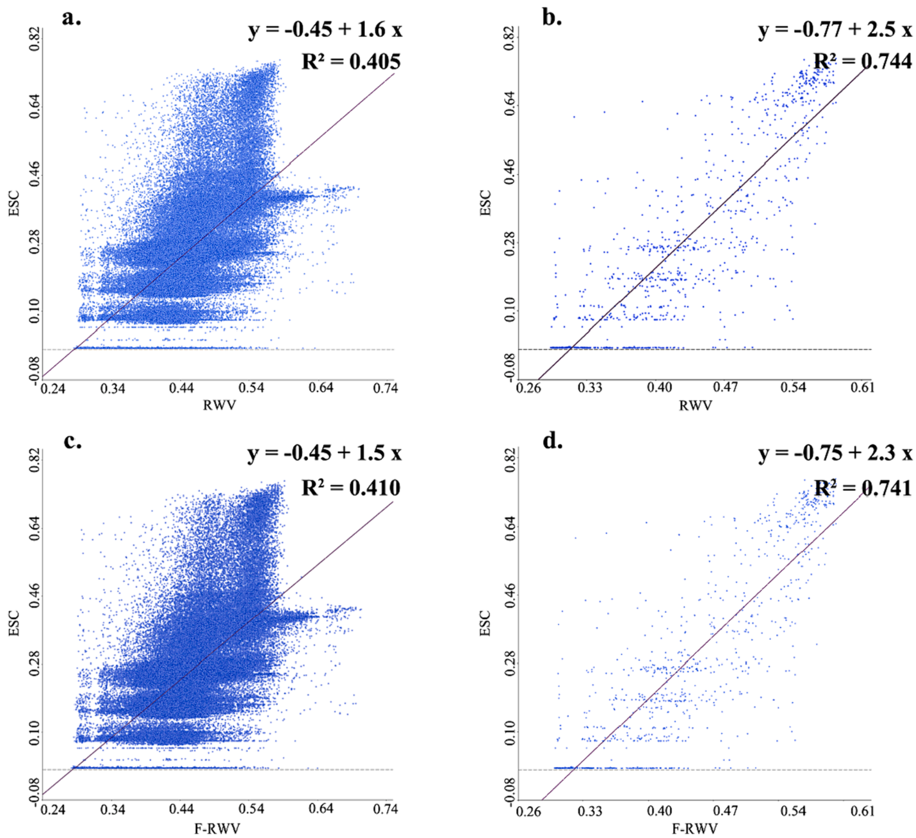

Fig. 7. Linear regression analysis (**a.** Overall RWV and ESC; **b.** Local RWV and ESC; **c.** Overall F-RWV and ESC; **d.** Local F-RWV and ESC).

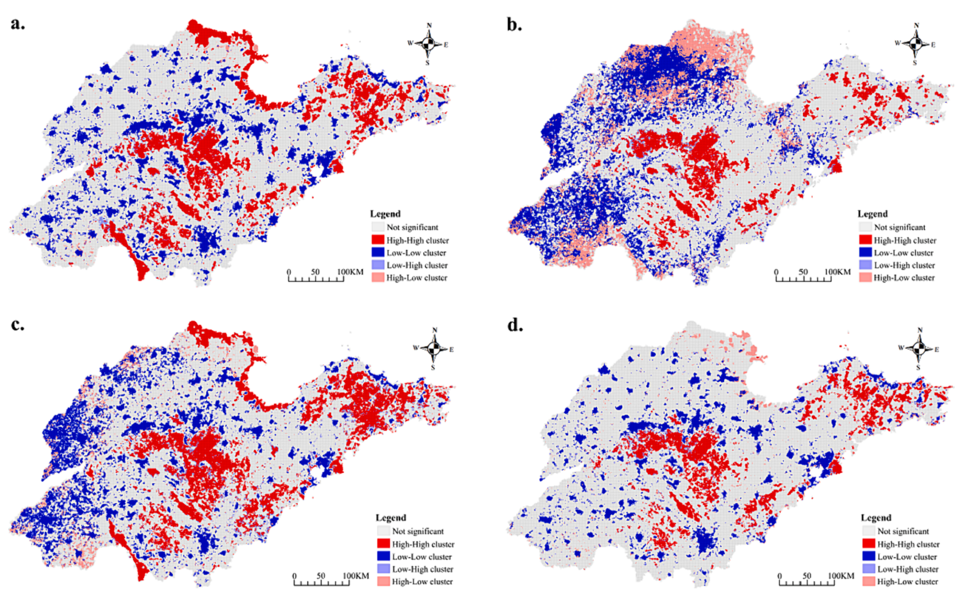

Fig. 8. Spatial autocorrelation cluster of RWV and ecological indicators (**a.** RWV and HQ; **b.** RWV and SC; **c.** RWV and WC; **d.** RWV and CS).

Table 2
Indicator explanation in built-up area, cultivated land, and wilderness area.

	Wilderness indicator						Ecological indicator			
	BN	PD	RD	RR	RS	SD	CS	HQ	SC	WC
Buit-up area	8.4	49.3	0.2	3.2	0.2	1.2	0.5	16.7	0.1	2.2
Wilderness area	12.5	35.2	0.2	5.6	0.3	1.0	2.3	16.7	0.1	4.1
Cultivated land	8.9	33.9	0.3	8.2	0.2	1.2	0.8	13.2	0.1	4.1

livestock, arable land, stumbling etc. (Neff et al., 2020). In grasslands, ESC has a negative correlation with RR (Explanation = 9.9 %), and regions with high ESC are known to have higher availability. Open and vegetatively scarce lawns are easier to access, and grassland in high-quality wilderness is more likely to have access to higher ES, especially cultural services. With regard to enhancing ES of forest and grassland, managers should focus on improving the BN of forests, planning roads according to the amount of the demand for ES and the actual capacity of the ecosystem, as well as logically controlling accessibility (Jiang et al., 2021), maintaining the stability of forests and grasslands, which can ensure a dynamic balance of regional CS, while improving HQ and SC, would produce more ES value.

4.2.3. *Wetland (Wetland, intertidal zone, bottomland)*

In wetlands, RD (Explanation = 35.9 %) is a key driving indicator, and wilderness indicators such as road densities have been studied as one of the indicators for assessing the ecological status of wetlands and showing a high correlation with water quality, indicating that comparative wilderness mapping also have the potential to evaluate wetland ecological conditions (Yang et al., 2021; Yang et al., 2016). In a study conducted in Shanghai's Chongming Wetland, road data has also been used as resistance to species migration.

HQ (15.1 %) is a key ecological indicator too, this is similar to some other research(Xu et al., 2023). The Yellow River Delta is the largest river wetland in China, providing important habitat for birds. With the rapid development of Shandong's economy, many networks of roads have been built. However, the expansion of transport roads has disrupted the connectivity of habitats, leading to the extinction of native species and the eradication of ecosystem structures and functions. Reducing the impact of human interference on the quality of habitats is critical to species conservation in the future.

4.2.4. *Water (Lake, reservoir pond)*

In water area, HQ (Explanation = 19.7 %) is a key driver indicator and positively correlated with RWV performance. The South Four Lakes area, where Weishan Lake is located, is the largest high-quality wilderness of the water area, providing a high-quality habitat for aquatic flora and fauna (Y. C. Liu et al., 2023). BN is a key wilderness indicator, large and complex lakes have a higher HQ and BN. The complexity of the shape of lakes is linked to the diversity of bird species. Biodiversity of birds is positively correlated with the surface area, the length of the lakes, and the distance to the habitat (Chukwuka et al., 2022). Therefore, the length and area of the lake can be considered as indicators for evaluating the lake's wilderness quality.

ESC is negatively correlated with RR, and RR has a higher explanation, which suggests that areas with higher ESC are impacted by roads. Research shows that the marginal effects of the presence of major road networks within a buffer zone of 500 m-1,000 m radius outside the lake wetlands not only damage the habitat range, but also increase the risk of environmental noise and traffic accidents caused by vehicles and directly affect the distribution and reproduction of certain species (Chukwuka et al., 2022; Sun et al., 2019). Meanwhile, RR can also be included in the assessment of HQ. In terms of wetland and waterbody improvement, managers should reduce SD and PD around wetlands, control access to wetlands, and convert broken reservoirs and pits into complete blue space to increase RWV.

4.3. *Some insights on the management of the wilderness*

In China, the Ecological Civilization Concept provides a solution to the protection of natural ecosystems, which includes many policies related to the conservation of the wilderness, such as the establishment of a "national park and protected area system." Ten national parks have now been built in China, and a target has been set for the selection of 49 national park candidate areas, which will protect 1.1 million square kilometers of wilderness area, reflecting the importance of policy guidance and the huge results of ecological civilization building. Our work is in line with the macro-context of ecological civilization policy and will contribute to ecological civilization construction.

Government policy is an important influencing factor of wilderness protection. In Shandong, higher-quality wilderness mountains have spectacular natural and cultural landscapes, such as the Taishan Mountains (Fig. 4b) and the Laoshan Mountain (Fig. 4c), which have been set up as tourist landscape areas and landmarks, providing recreational opportunities for the public and bringing well-being (Cao et al., 2019). Indeed, influenced by this policy, a large-scale, high-quality wilderness landscape has been preserved, and the stability of high-ESC regions has been enhanced, which is beneficial for wilderness conservation. These areas can be divided into different regions to match different demand, for example, setting up a core wilderness area that is not under human control and setting up buffer zones around them, allowing various degrees of wilderness entertainment activities and low-intensity land utilization (Cao et al., 2022).

The northern coastal wetlands, which are the Yellow River Delta region, have the highest RWV, indicating the effective conservation role played by the Yellow River Delta Conservation Area. Protected wetlands, streams, and surrounding areas can support high levels of biodiversity and can be used as ecological corridors to connect wilderness to larger ecosystems such as lakes or mountains (Sun et al., 2019). The Yellow River Delta National Reserve is currently in the planning phase for the establishment of the National Park, in order to achieve ecologically sustainable development and ecological civilization. Wilderness will therefore be an important component of the national parks (Zhao et al., 2022), and they will play a key role in protecting the existing wilderness.

Smaller wilderness spots are more threatened than large wilderness spots, and our study found that small areas near built-up areas are more prone to loss. The purpose of using the wilderness as an Nature-Based Solution(NBS) is to maximize ES from natural processes to improve the quality of life of urban inhabitants and thus be more suitable for small wilderness areas in cities (Sikorska et al., 2021). One of the wider applications of NBS is intended to abandon artificial cultivation and promote wilderness. Studies showed that the economic benefits of converting wasteland into wilderness may exceed those of land-centralized management. Thus, it is beneficial to allow some informal green spaces in towns to naturally move to the wilderness, introduce small infrastructure (micro-intervention), and prioritize ES and biodiversity (Luo and Patuano, 2023; Sikorski et al., 2021). Natural planting can increase biodiversity and improve CS. Sustainable management of blue and green spaces can be achieved by mapping high-quality wilderness as an NBS. By low-intensity controls on urban greenery with high wilderness level, or by deliberate reforestation, sustainable development goals can be realized and the resilience of cities can be enhanced (Zefferman et al., 2018).

5. Conclusion

The methodological framework presented in this study highlights the potential of combining and integrating wilderness indicators and ecological indicators on measurement ES of wilderness. In the future, this methodological framework, can be widely applied to identifying RWV and ESC hotspots on different scales, which will be also helpful to identify key ecological indicators in different wilderness areas. Furthermore, the research can provide a methodological basis for policymakers to define priority protected areas and formulate effective conservation policies, and promote effective ESC within a context of competing demands for preservation and for the use of scarce land under global urbanization.

There are a few limitations of this study. Firstly, the described study is a regional case study, and lacks international relevance. Secondly, the accuracy of the model needs further verification, especially using the InVEST model to quantify the non-monetary value of ecosystems serving. Thirdly, the study carried out only static data analysis, ignoring dynamic changes within the wilderness, such as climate change, vegetation change, wildlife migration, etc. The fuzziness of the wilderness requires broader social investigations, including the inherent values of the wilderness area, the wild flora and fauna, the views of environmentalists and landscape planners, and the opinions of the local indigenous population about it. It is advised to use more accurate data sources in the future when updated, because of the larger number of data selected and the incompatibility of the original data resolution. Fourthly, the study chose a fixed year and did not reflect changes in time between wilderness and ESC because there were some difficulties in obtaining historical data, and some of the data was not fixed updating, such as POI data. Moreover, there was no comparative study of urban-scale wilderness mapping with ESC, which we might need to do in the future.

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CRediT authorship contribution statement

Ruirui Zhu: Writing – review & editing, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Weiyi Liu:** Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Ruixin Xue:** Visualization, Software. **Shuo Teng:** Validation, Software. **Yefan Wang:** Visualization, Software. **Yanting Pan:** Data curation, Validation. **Weijun Gao:** Supervision, Resources.

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.

Data availability

Data will be made available on request.

Appendix 1

Table A1
Data sources.

Year	Layer	Resolution	Source
2020	Land use	30 m × 30 *m*	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (https://www.igsnrr.ac.cn/)
2020	Population density	100 m × 100 *m*	World Pop (https://hub.worldpop.org/)
2020	Railways and roads	Vector	Open Street Map (OSM) (https://download.geofabrik.de/asia.html)
2020	Settlements	Vector	
2020	Point of Interest (POI)	Vector	Baidu Map Open Platform
2020	Digital Elevation Model (DEM)	30 m × 30 *m*	Geospatial data cloud (https://www.gscloud.cn/)
2020	Precipitation	1000 m × 1000 *m*	the China Meteorological Science Data Sharing Service Network
2020	Evaporation		(https://data.cma.gov.cn/)
	Soil textile type	1000 m × 1000 *m*	Harmonized World Soil Database (HWSD) (https://www.fao.org/home/en/)

Table A2
Weighting of the six wilderness indicators.

	BN	PD	RS	RR	SD	RD
1	10	7	8	8	8	8
2	10	8	8	9	9	10
3	10	9	10	8	9	8
4	10	9	8	7	9	9
5	9	8	6	4	6	5
6	10	8	8	9	8	9
7	10	10	10	10	10	10
8	10	8	10	8	9	10
9	10	10	8	9	5	7
10	10	10	6	9	8	6
11	10	9	4	3	10	8
12	10	7	8	8	9	9
13	8	8	10	10	8	8
14	10	8	5	5	10	10
15	10	8	8	8	10	10
16	10	10	8	8	10	10
17	10	8	8	9	8	9
18	10	8	9	9	7	7
19	10	9	8	8	9	9
20	10	10	8	8	10	8
21	10	10	6	6	8	8
22	10	10	9	9	5	5
23	9	8	8	8	8	8
24	10	9	10	8	9	9
25	9	7	7	9	7	9
Mean Value	9.800	8.640	7.920	7.880	8.360	8.360
Expert Weights	0.192	0.170	0.155	0.155	0.164	0.164

(*continued on next page*)

Table A2 (*continued*)

	BN	PD	RS	RR	SD	RD
Fuzzy Weights	0.204	0.184	0.143	0.143	0.163	0.163

Table A3
Naturalness of land use.

Type of land use	Value	Type of land use	Value
Paddy field (11)	3.04	Intertidal zone (45)	8.76
Dry field (12)	2.88	Bottomland (46)	8.48
Woodland (21)	7.20	Urban land (51)	1.28
Shrubbery (22)	7.16	Rural settlement (52)	2.12
Open forest land (23)	6.88	Other construction land (53)	1.24
Other woodland (24)	4.72	Sand land (61)	8.68
High coverage grassland (31)	7.56	Saline land (63)	8.36
Medium coverage grassland (32)	7.48	Wetland (64)	8.84
Low coverage grassland (33)	7.44	Bare land (65)	7.48
River canal (41)	4.36	Bare gravelly land (66)	8.44
Lake (42)	8.12	Others (67)	9.52

Table A4
Weighting of different levels of settlements.

Settlement type	Weights
Level 1 settlement	0.388
Level 2 settlement	0.344
Level 3 settlement	0.268

Table A5
Weighting of railway and different levels of roads.

Road type	Weights
Railway	0.284
Level 1 Road	0.281
Level 2 Road	0.247
Level 3 Road	0.189

Table A6
Range and weighting of threat factors.

Threat factors	Influence distance(km)	Weights	Decay
Urban land (51)	10.00	1.00	Linear
Rural settlement (52)	5.00	0.70	Exponential
Other construction land (53)	8.00	0.80	Exponential
Paddy field (11) Dry field (12)	3.00	0.50	Exponential
Others (67)	8.00	0.40	Linear

Table A7
The habitat suitability of different types of land use and the relative sensitivity of each type of habitat to threat factors.

Type of habitat	Suitability	Urban land	Rural settlement	Other construction land	Paddy field/dry field	Others
Paddy field	0.60	0.50	0.35	0.40	0.35	0.40
Dry field	0.40	0.50	0.35	0.40	0.30	0.40
Woodland	1.00	0.85	0.65	0.60	0.60	0.60
Shrubbery	1.00	0.40	0.60	0.50	0.40	0.55
Open forest land	0.90	0.85	0.65	0.60	0.70	0.50
Other woodland	0.80	0.85	0.65	0.60	0.70	0.50
High coverage grassland	0.80	0.60	0.40	0.50	0.50	0.70
Medium coverage grassland	0.75	0.70	0.50	0.55	0.55	0.70
Low coverage grassland	0.70	0.80	0.60	0.55	0.60	0.70
River canal	0.80	1.00	0.70	0.80	0.65	0.30
Lake	0.80	1.00	0.70	0.80	0.65	0.30
Intertidal zone	1.00	1.00	0.80	0.80	0.70	0.40
Bottomland	1.00	1.00	0.80	0.80	0.70	0.40
Urban land	0.00	0.00	0.00	0.00	0.00	0.00
Rural settlement	0.00	0.00	0.00	0.00	0.00	0.00
Other construction land	0.00	0.00	0.00	0.00	0.00	0.00
Sand land	0.10	0.10	0.10	0.10	0.10	0.10
Saline land	0.10	0.10	0.10	0.10	0.10	0.10
Wetland	1.00	1.00	0.80	0.80	0.70	0.40
Bare land	0.10	0.10	0.10	0.10	0.10	0.10
Bare gravelly land	0.10	0.10	0.10	0.10	0.10	0.10
Others	0.10	0.10	0.10	0.10	0.10	0.10

Table A8
Biophysical Coefficients: C (vegetation coating factor) and P (soil conservation factor).

Type of land use	C	P
Paddy field /dry field	0.22	0.35
Woodland/forest land/shrubbery	0.06	1.00
Grassland	0.07	1.00
Wetland/intertidal zone/bottomland	1.00	0.00
River canal/lake	1.00	0.00
Urban land/rural settlement/other construction land	1.00	1.00
Others	1.00	1.00

Table A9
Average surface runoff coefficient.

Type of land use	coefficients
Paddy field /dry field	0
Woodland/forest land	4.65
Shrubbery	4.26
Grassland	3.94
Wetland/intertidal zone/bottomland	0
River canal/lake	0
Urban land/rural settlement/other construction land	0
Others	0

Table A10
Carbon density values for different types of land use.

	C_{above}	C_{below}	C_{soil}	C_{dead}
Paddy field /dry field	11.0	3.0	17.8	0.4
Woodland/forest land/shrubbery	34.2	21.0	19.1	2.8
Grassland	12.6	7.4	15.8	1.4
Wetland/intertidal zone/bottomland	3.2	0.7	15.3	0.2
River canal/lake	1.5	0.5	25.5	0
Urban land/rural settlement/other construction land	0	0	14.0	0
Others	0	0	14.6	0

Table A11
Wilderness area of cities.

	City	High-quality wilderness (km^2)	Medium-quality wilderness(km^2)	Low-quality wilderness(km^2)	Total(km^2)
1	Dongying	1298	450	149	1897
2	Yantai	1058	2580	911	4549
3	Binzhou	897	352	278	1527
4	Linyi	730	1640	896	3266
5	Weifang	635	1488	650	2773
6	Jining	580	917	604	2101
7	Qingdao	346	641	446	1433
8	Weihai	153	697	330	1180
9	Rizhao	147	540	323	1010
10	Taian	146	750	626	1522
11	Zibo	123	1385	420	1928
12	Jinan	98	1521	820	2439
13	Zaozhuang	81	711	344	1136
14	Heze	2	42	158	202
15	Dezhou	–	31	174	205
16	Liaocheng	–	17	78	95

Table A12
Indicator explanation of different types of landscapes in high-quality wilderness.

	Wilderness indicator						Ecological indicator			
	BN	PD	RD	RR	RS	SD	CS	HQ	SC	WC
Forestland	3.4	17.1	4.7	13	7.9	4.4	34.0	0.8	0.2	3.9
Grassland	5.9	18.2	3.6	9.9	7.3	5.8	31.7	0.7	0.4	4.2
Wetland	7.6	1.7	35.9	1.7	1.1	3.9	3.7	15.1	0.2	2.1
Water	13.7	6.9	5.2	10.8	6.4	2.3	2.6	19.7	0.1	8.2

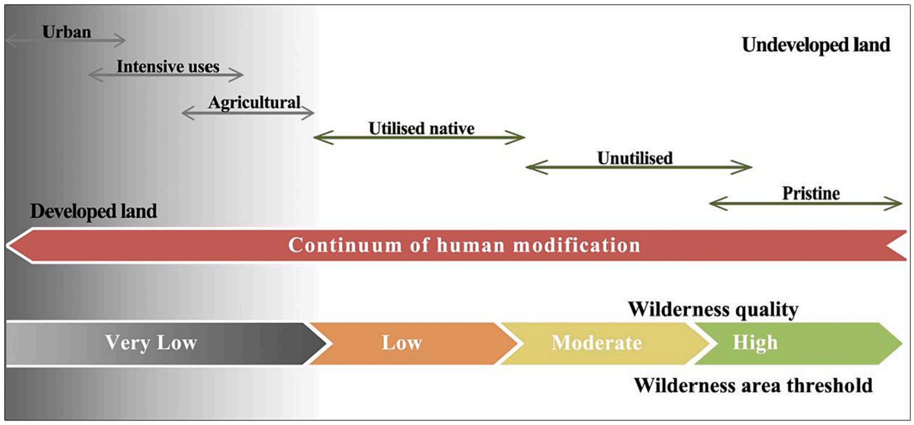

Fig. A1. Wilderness continuum.

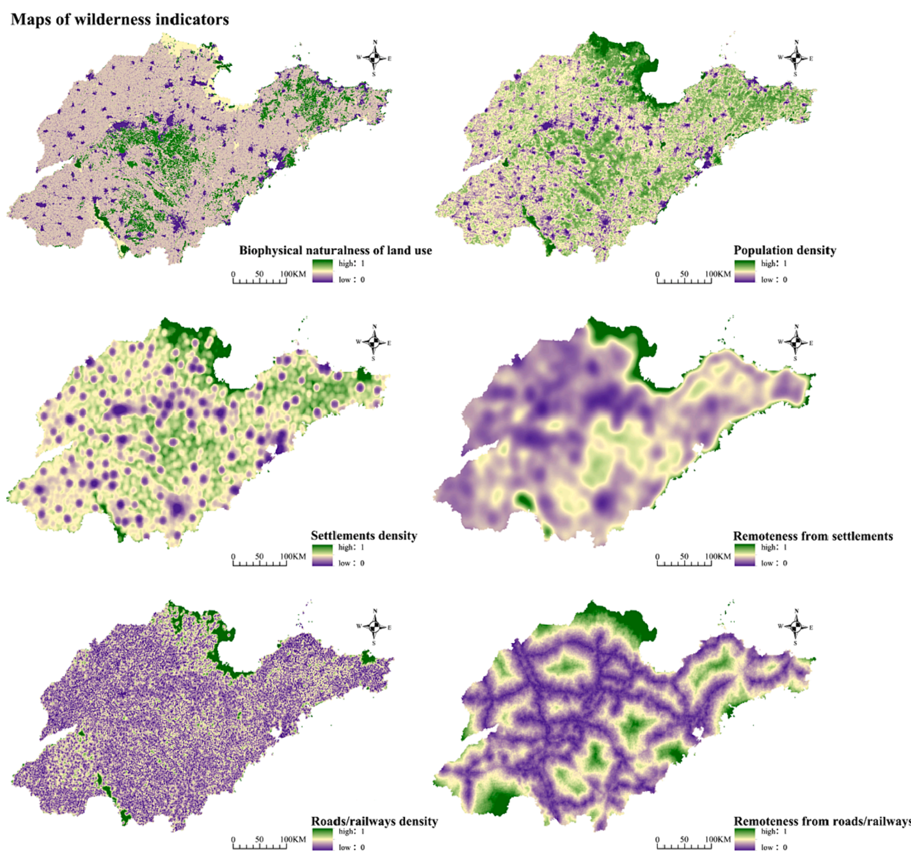

Fig. A2. Maps of Wilderness indicators.

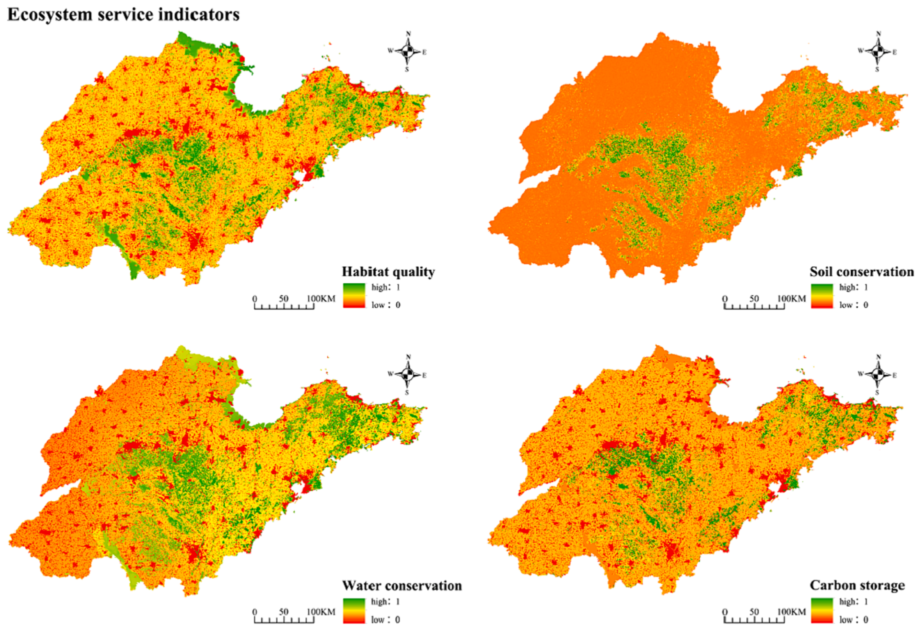

Fig. A3. Maps of Ecological indicators.

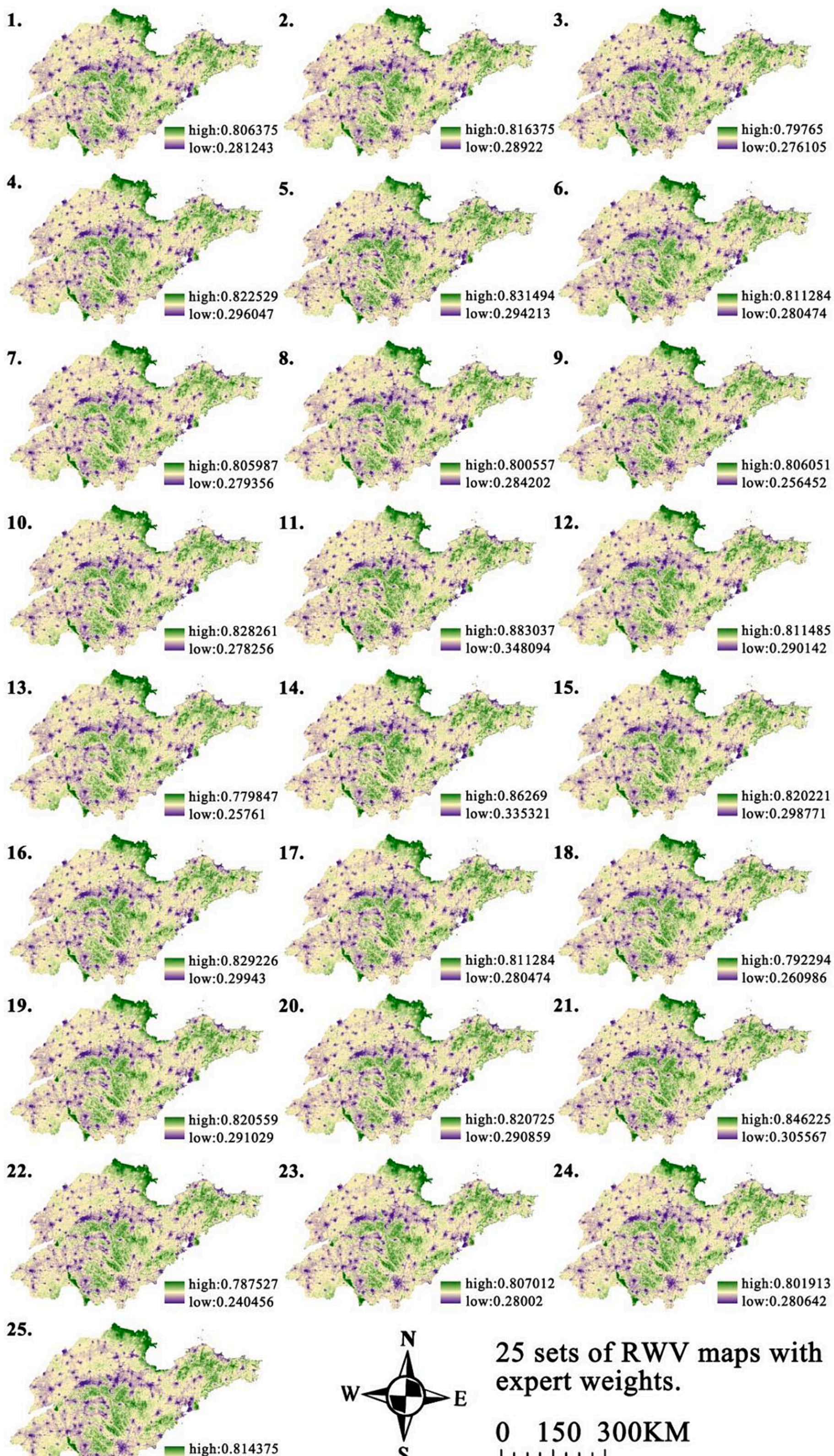

Fig. A4. 25 sets of RWV maps with expert weights.

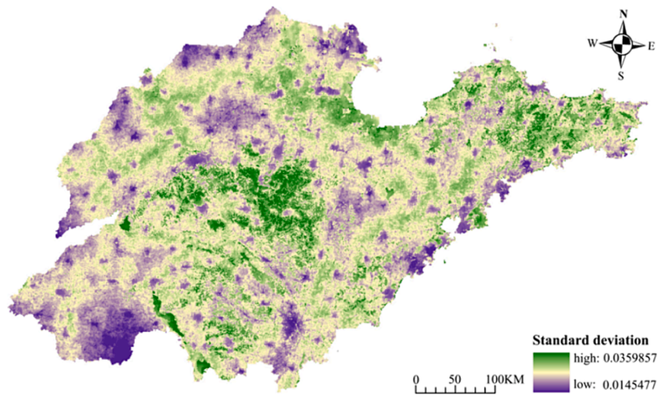

Fig. A5. Sensitivity to indicator weight uncertainty in the WLC model.

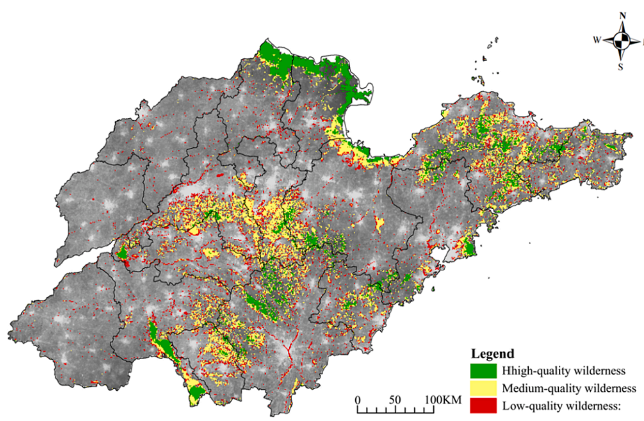

Fig. A6. Wilderness classification rating.

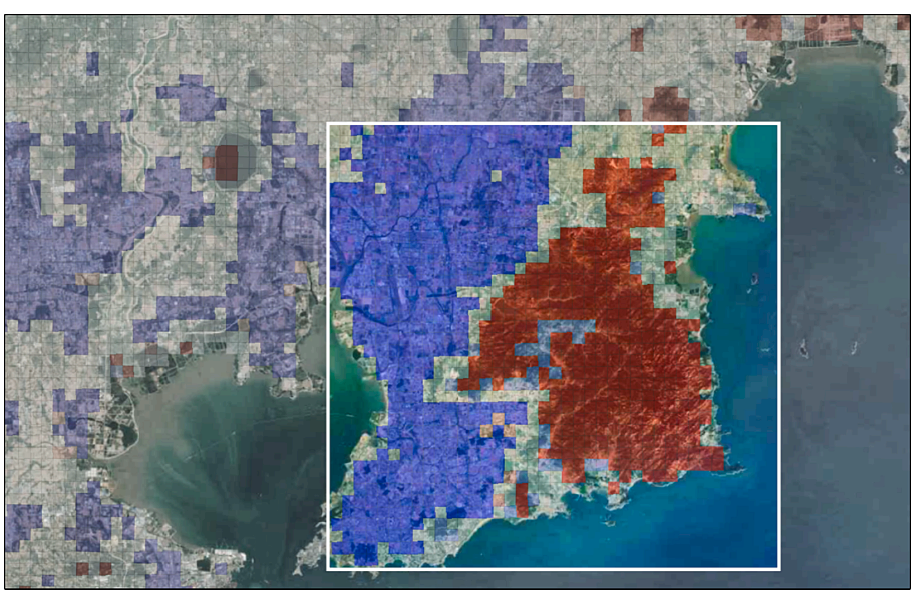

Fig. A7. The 1000 grids in the main urban area of Qingdao.

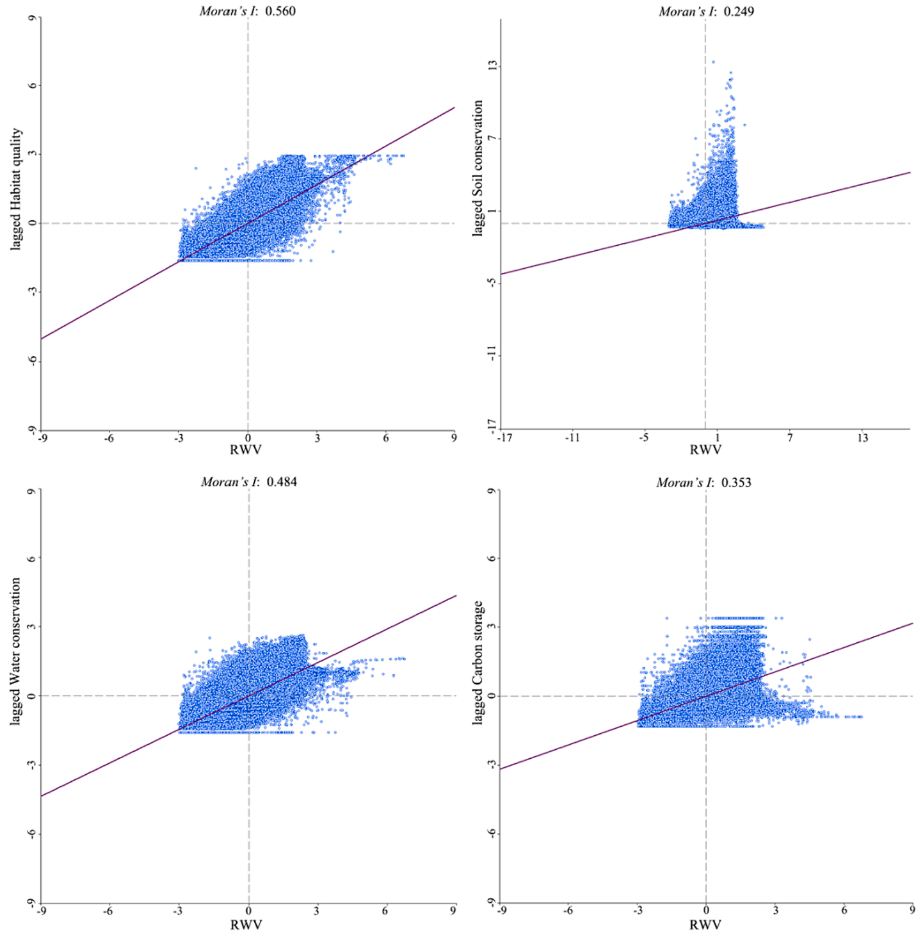

Fig. A8. The Moran's I between RWV and four ecological indicators.

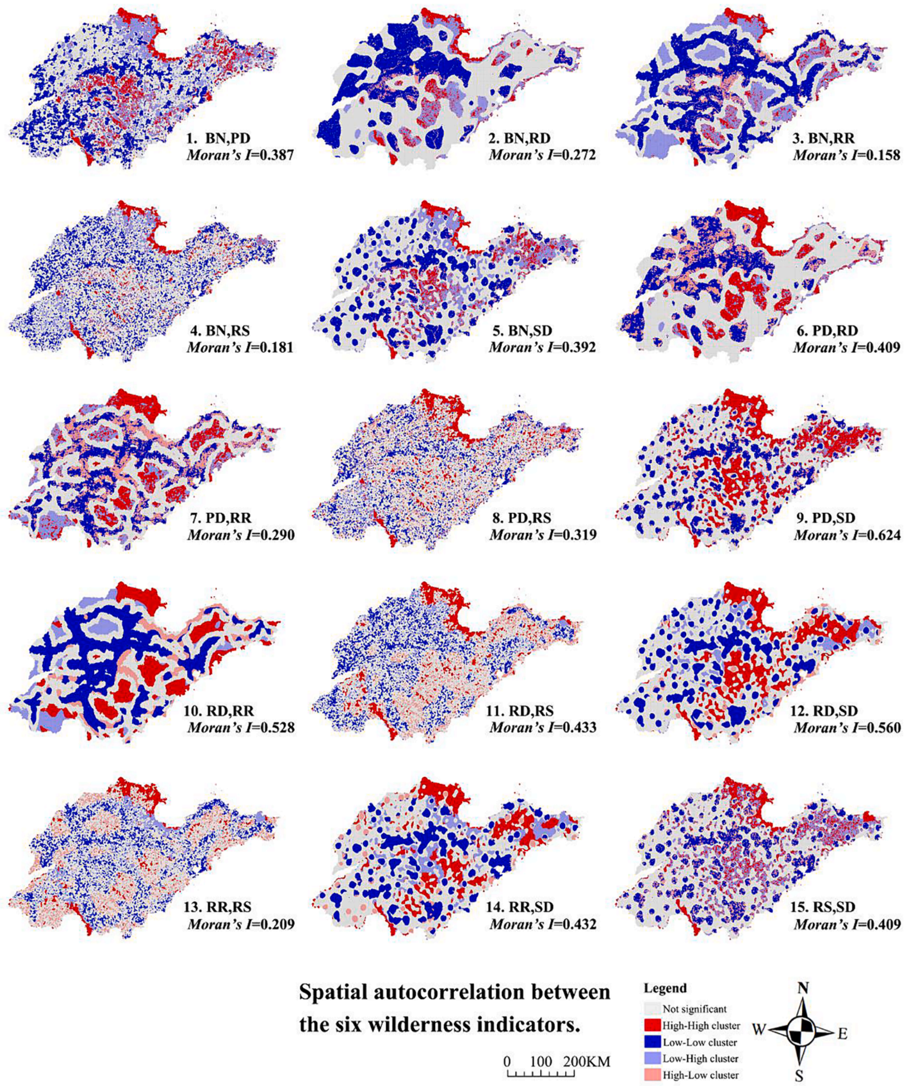

Fig. A9. Spatial autocorrelation between the six wilderness indicators.

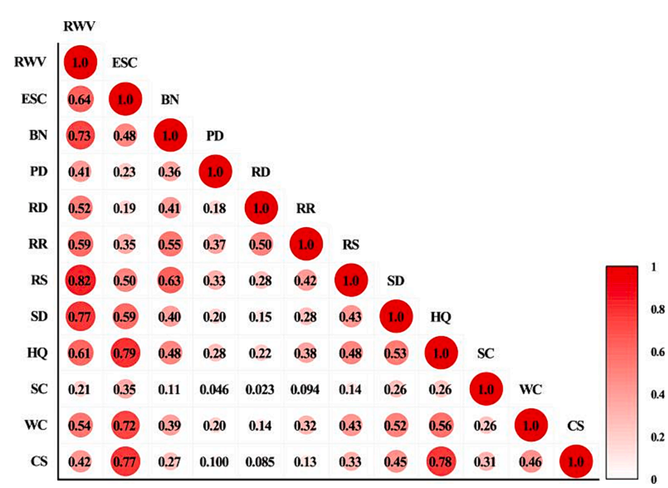

Fig. A10. Pearson's correlation between indicators.

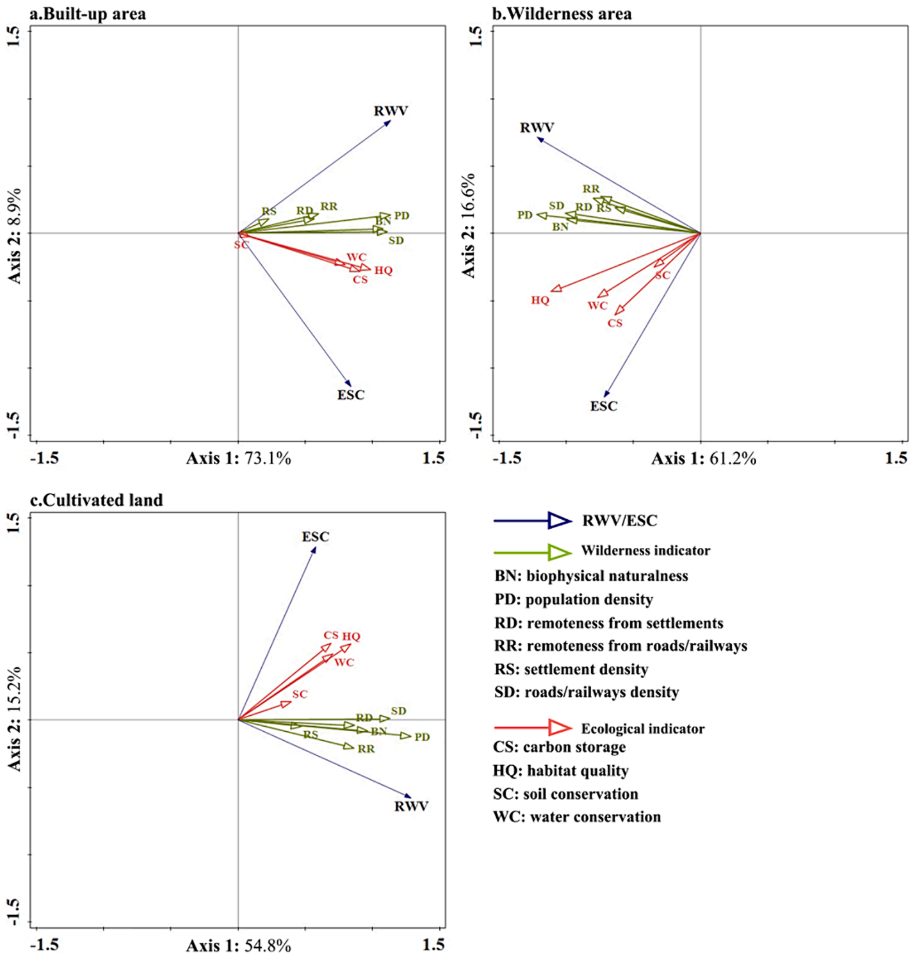

Fig. A11. RDA results for indicators in built-up area, cultivated land, and wilderness area.

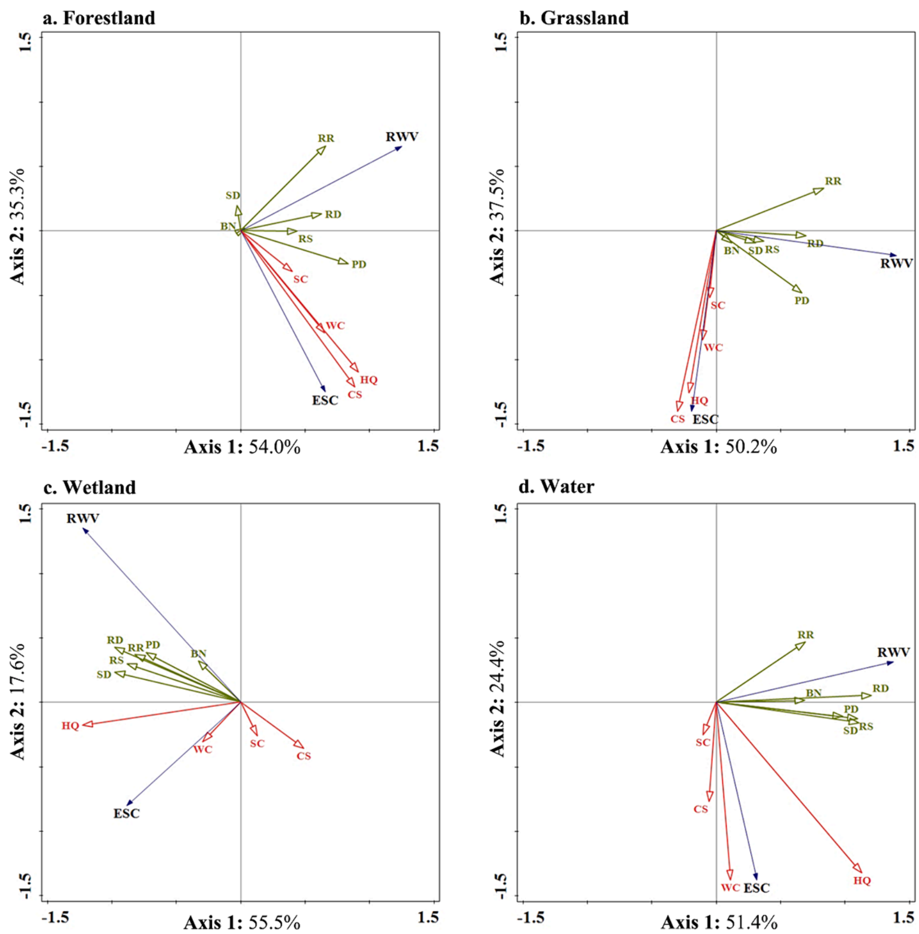

Fig. A12. RDA results for different types of landscapes.

Appendix 2

Fuzzy analytical hierarchy process (FAHP).

(1) Establish the fuzzy complementary judgement matrix (Table A14). By comparing the two factors, using the 0.2 ~ 0.8 measurement method shown in Table A13, the quantitative measurements were obtained with the fuzzy complementary judgement matrix $R = (r_{ij})\ n * n\ (i, j = 1, 2, 3, \ldots, n)$, in which $r_{ii} = 0.5$ indicates the factor r is equally important in comparison with its own; $r_{ij} \in [0.1, 0.5)$, indicates factor r_j is more important than factor r_i; $r_{ij} \in (0.5, 0.9]$, indicates factor r_i is more important than factor r_j.

(2) Weight calculation. If $R=(r_{ij})n \times n$ is the fuzzy complementary judgement matrix, and $w = (w_1, w_2, \ldots, w_n)$ is the weight vector of R, the formula (1) is used to calculate the weight of the fuzzy complementary judgment matrix as follows:

$$W_i = \frac{\sum_{i,j=1}^{n} r_{ij} + \frac{n}{2} - 1}{n(n-1)} \tag{1}$$

(3) Consistency test. A consistency test of the comparative judgment process is required to determine whether the weight calculated on the basis of formula (1) is reasonable. Based on the definition of matrix compatibility indicators I (A, W*) and characteristic matrix W* (Table A15), the compatibility of the judgement matrix with characteristic matrix is calculated and expressed as follows:

$$I(A, W*) = \frac{1}{n^2} \sum_{i,j=1}^{n} \left| a_{ij} + b_{ji} - 1 \right| \tag{2}$$

$$W_{ij} = \frac{w_i}{w_i + w_j} \tag{3}$$

$$A = (a_{ij})_{n*n}, W^* = (b_{ij})_{n*n} \tag{4}$$

A and W* are fuzzy complementary judgement matrix. If the compatibility indicator value I (A,W*) is less than a specific threshold of α (generally assumed as α = 0.1), the judgment matrix can be considered a satisfactory matrix of consistency. The smaller the α, the more reasonable it is for policymakers to make vague judgments.

Table A13
Reference table for fuzzy complementary judgment matrix.

Scale	Definition	Explanation
0.5	Equally important	The two factors are equally important
0.6	Slightly important	Comparing these two factors, the row factor is slightly more important than the column factor.
0.7	Clearly important	Comparing these two factors, the row factor is clearly more important than the column factor.
0.8	Much more important	Comparing these two factors, the row factor is much more important than the column factor.
0.2,0.3,0.4	Inverse comparison	If the factor r_i is compared with the factor r_j is judged $r_{ij} = 0.6$, then $r_{ji} = 0.5–0.6 = 0.4$.

Table A14
The fuzzy complementary judgement matrix.

	BN	PD	RS	RR	SD	RD
BN	0.5	0.6	0.8	0.8	0.7	0.7
PD	0.4	0.5	0.7	0.7	0.6	0.6
RS	0.2	0.3	0.5	0.5	0.4	0.4
RR	0.2	0.3	0.5	0.5	0.4	0.4
SD	0.3	0.4	0.6	0.6	0.5	0.5
RD	0.3	0.4	0.6	0.6	0.5	0.5

Table A15
The fuzzy complementary characteristic matrix.

	BN	PD	RS	RR	SD	RD
BN	0.5	0.5259	0.5866	0.5866	0.5546	0.5546
PD	0.4741	0.5	0.5612	0.5612	0.5289	0.5289
RS	0.4134	0.4388	0.5	0.5	0.4674	0.4674
RR	0.4134	0.4388	0.5	0.5	0.4674	0.4674
SD	0.4454	0.4711	0.5326	0.5326	0.5	0.5
RD	0.4454	0.4711	0.5326	0.5326	0.5	0.5

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