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Topographic Gradient Differentiation and Ecological Function Zoning Based on Ecosystem Services: A Case Study of Fuping County

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ABSTRACT

Scientifically delineating ecological function zones is essential for national territory spatial planning and comprehensive management. In this study, we evaluated five ecosystem services, habitat quality, water yield, carbon sequestration, soil conservation, and food production, in Fuping County, China, and introduced the application of the topographic position index in exploring the topographic gradient effect of each service. We next applied the K-means clustering algorithm to identify the ecosystem services bundles and analyze the dominant type of ecosystem service in these bundles. A particle swarm optimization-support vector machine model was also constructed to identify the boundaries of ecological function zones and complete the ecological function zoning. The results are as follows: (1) In Fuping County, the high-value areas of habitat quality are distributed in the west, north, and southeast; those of soil conservation are in the northwest, northeast, and southwest; those of water yield are in the east and south; those of carbon sequestration are in the west, and those of food production is in the east. (2) The habitat quality first decreases and then increases with an increasing topographic gradient; food production and water yield decline with increasing topographic gradient; carbon sequestration and soil conservation increase with increasing topographic gradient. (3) Four types of ecosystem services bundles were identified. The dominant ecosystem functions of Type I, II, and III bundles are food production and water yield, carbon sequestration, and soil conservation, respectively. Type IV bundles generally have low levels of ecosystem services in the study area. (4) Four ecological function zones were delineated: food production zone, ecological conservation zone, potential restoration zone, and critical restoration zone. The research findings can provide a theoretical and practical basis for formulating and implementing ecological spatial management policies in the Taihang Mountains of China.

INTRODUCTION

According to the report to the 19th National Congress of the Communist Party of China, establishing a resource-conservative and environment-protective spatial pattern should be a priority in ecological civilization construction. Delineating ecological function zones is not only fundamental for developing natural resources, restoring ecological functions, and protecting the environment, but also for supporting socio-economic development and coordinating human-land relationships (Hong et al. 2019).

In recent years, ecological function zoning based on ecosystem services has gradually become mainstream in ecological zoning studies. Identifying ecosystem service bundles based on their service assessment and spatial distribution is significant for exploring the regional ecological security pattern. The concept of an ecosystem service bundle, first proposed by Kareiva et al. (2007), refers to a combination of ecosystem services recurring in a specific region during a certain period and is a crucial criterion for delineating ecological zones (Raudsepp-Hearne et al. 2010). Scholars worldwide have mainly applied the K-means clustering algorithm (Peng et al. 2021), SOFM neural network (Yan et al. 2021), and PAM clustering algorithm (Pan et al. 2021) to identify and delineate the ecosystem service bundles at various scales, such as national (Turner et al. 2014) and regional scales (Crouzat et al. 2015). Such studies have also been combined with investigations in different fields, including urban spatial management (Riechers et al. 2018), land resource allocation (Balzan et al. 2018), and food security (Bommarco et al. 2013).

Identifying ecological function zone boundaries is the key to ecological function zoning. In previous studies, most scholars delineated the zones according to either the geographical locations of the boundaries between identified ecosystem services bundles and their research experience or by directly clustering the administrative and watershed units (Niu et al. 2020). Although this method can clarify the delineated zone boundaries, it is highly subjective, ignores the consistency of ecological functions within each zone, and does not follow any unified classification standard. To address this problem, a few scholars have standardized and automated ecological zoning in recent years by applying machine learning methods to delineate the ecological function zones. Mao et al. (2019) used the support vector machine (SVM) to mine grid data through machine training and employed the grid search algorithm to optimize the parameters and obtain the optimal classification plane that serves as the decision boundaries for ecological function zoning. This method can effectively eliminate subjectivity in ecological function zoning and quantitatively convert the classification to zoning. However, the SVM model based on the grid search optimization algorithm is not applicable to large-scale datasets, and its training efficiency and accuracy decline with expanding sample size (Xu 2014). In comparison, SVM combined with the particle swarm optimization (PSO) algorithm displays greater suitability for large-sample datasets because of its higher accuracy and steady operation (Xu 2014) and has been widely applied in geoscience research. Du et al. (2018) used the PSO-based SVM model to classify wetlands in remote sensing images and reported higher classification accuracy than the conventional SVM model. In ecological regionalization, the PSO-SVM model has not yet been applied to ecological function zoning studies.

Fuping County in Hebei Province, China, a region with typical topographic and geomorphological features of the Taihang Mountains, was selected as the study area. With the aim to provide technical reference for improving the eco-environmental quality of Fuping County and the Taihang Mountains, we first evaluated various ecosystem services of the county based on the InVEST model to explore their topographic gradient effect, used the K-means clustering algorithm to identify the ecosystem service bundles, and attempted to construct a PSO-SVM model on the MATLAB platform to obtain the optimal boundaries of the ecological function zones.

DATA AND METHODS

Study Area

Fuping County, covering an area of 2527.14 km^2, is situated in the middle of the Taihang Mountains and west of Hebei Province (Figs. 1 and 2). The geomorphological features of this county reflect those of the Taihang Mountains. The terrain is inclined from the northwest to southeast, with the highest and lowest elevations of 2282 m and 192 m in the northwest and southeast, respectively. The landform is dominated by mid- and low-altitude mountains and hills. Fuping County is in the warm temperate zone, with a semi-humid and semi-arid continental monsoon climate. The study area contains developed water systems and rich biological resources, making it a key ecological function zone.

Data Sources

The land use data were retrieved from the 2018 Land Change Survey Database of Fuping County; DEM data were

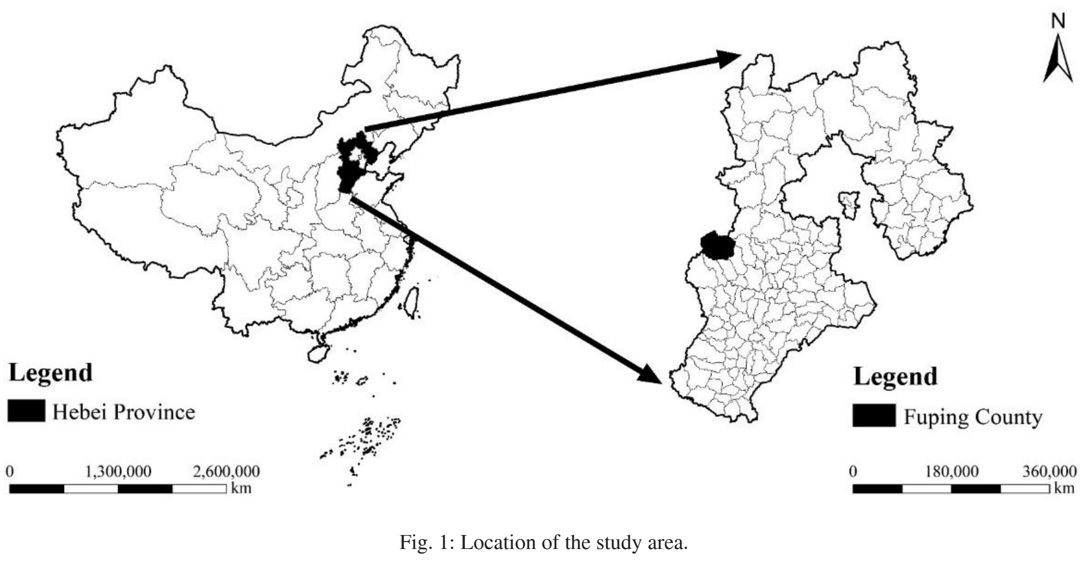

Fig. 1: Location of the study area.

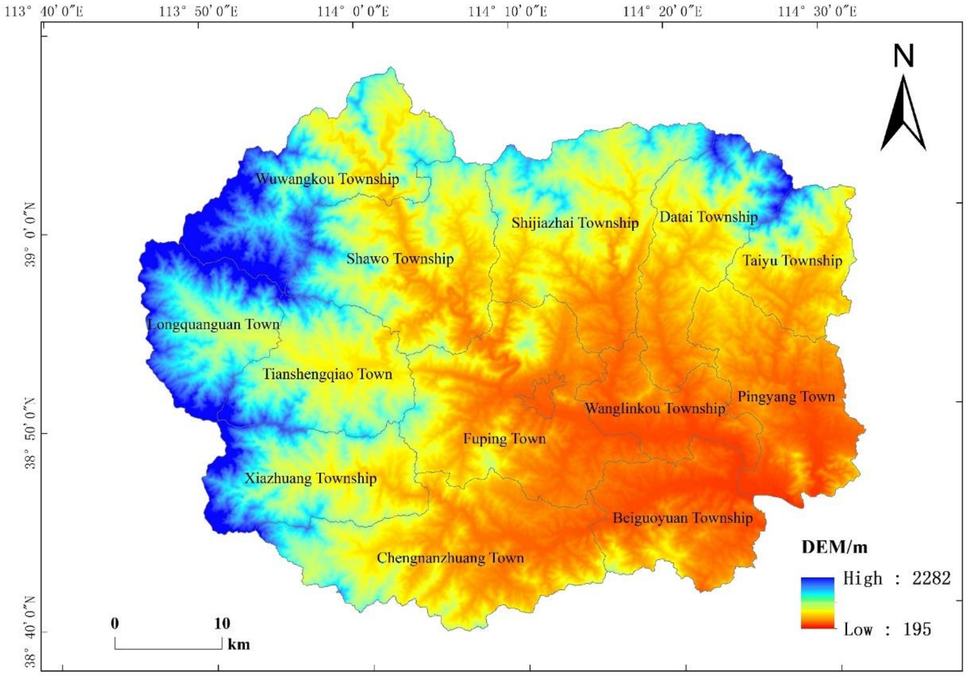

Fig. 2: Topographic map of the study area.

downloaded from the Geospatial Cloud (http://ww.gscloud.cn/) with a spatial resolution of 30 m; precipitation and meteorological data were obtained from the observations of 16 meteorological stations in Fuping County for the year 2018; soil data were collected from the China soil dataset of the Harmonised World Soil Database (HWSD); population and food production data were sourced from the 2018 Hebei Rural Statistical Yearbook.

Research Methods

Ecosystem Service Assessment

We used the InVEST model to evaluate five ecosystem services in Fuping County, including habitat quality, water yield, carbon sequestration, soil conservation, and food production (Table 1). The model parameters were obtained referring to the InVEST User's Guide (Sharp et al. 2020)

Table 1: Calculation methods of ecosystem services.

Ecosystem service	Calculation formula	Variable interpretation
Habitat quality	$Q_{xj} = H_j\left[1-\left(\frac{D_{xj}^z}{D_{xj}^z+K^z}\right)\right]$	Q_{xj} is the habitat quality of grid x of land-use type j; Hj is the habitat suitability of land-use type j; Dxj is the habitat stress suffered by grid x of land-use type j; K is the half-saturation coefficient, usually half of the grid cell; z is a normalisation constant, generally considered as 2.5.
Water yield	$Y_i = \left(1-\frac{AET_i}{P_i}\right)\times P_i$	Y_i, AET_i, and P_i are the annual water yield, evaporation, and precipitation on grid I, respectively, in mm.
Carbon sequestration	$C_{tot} = C_{above} + C_{below} + C_{soil} + C_{dead}$	C_{tot} is the supply of carbon sequestration service in t/hm^2; C_{above} and C_{below} are the carbon densities of aboveground and belowground biomass, respectively, in t/hm^2; C_{soil} and C_{dead} are the carbon densities of soil and dead organic matter, respectively, in t/hm^2.
Soil conservation	$SC_i = RKLS_i - USLE_i$ $RKLS_i = R_i \times K_i \times LS_i$ $USLE_i = R_i \times K_i \times LS_i \times C_i \times P_i$	SC_i is the amount of soil conserved; $RKLS_i$ is the degree of potential erosion; $USLEi$ is the amount of actual erosion; R_i is the rainfall erosivity factor; K_i is the soil erodibility factor; LS_i is the slope length factor; C_i is the vegetation cover and management factor; P_i is the soil and water conservation practice factor.
Food production	$G_{ij} = \frac{G_{agr}}{S_i}\times G$	G_{ij} is the food production capacity (t) of grid i in the j-th administrative unit; G_{agr} is the cultivated land area in grid i (hm²) obtained by superimposing the grid map of each administrative unit onto the map of cultivated land; S_i is the total area of grid i (hm²); G is the food production per unit area of cultivated land in the administrative unit (t/hm²).

and available research results (Chen et al. 2019, Guo et al. 2008, Han et al. 2008, Liu et al. 2018, Liu et al. 2019, Liu et al. 2021, Wu et al. 2008, Zhao 2020, Zhu et al. 2019).

Topographic Gradient Classification

The topographic position index refers to the comprehensive elevation and slope gradient for a random point in a certain area and can reflect the terrain complexity comprehensively. It is calculated as:

$$T = ln[(E/E_0 + 1) \times (S/S_0 + 1)] \quad ...(1)$$

Here E and E_0 denote the elevation at the point and regional average elevation, respectively; S and S_0 represent the slope gradient at the point and regional average slope gradient, respectively.

Combined with the actual landform of Fuping County and an available study (Xu et al. 2020), we adopted the quantile method in ArcGIS to classify the topographic position index.

Identification of Ecosystem Service Bundles

In this study, we used the K-means clustering algorithm to identify the ecosystem service bundles in the study area based on the SPSS 26 platform. We set the five ecosystem services as variables and 500 m grids as evaluation units. The Z-scores of ecosystem services in each evaluation unit were standardized and clustered, and a total of six clustering results, each containing 2-7 types of clusters, were output for representing the actual situation of the study area. To avoid excessive subjectivity in the clustering process, we employed the Fragstats 4.2 software to calculate and analyze the contagion and patch cohesion indices of each clustering result and determine the optimal number of clusters based on the results (Peng et al. 2021).

Ecological Function Zoning Based on the PSO-SVM Model

1. **SVM:** SVM is a supervised learning algorithm first proposed by Boser (1992) with statistical theory. It can be used for classification, regression, and outlier detection. The classification is achieved by constructing an optimal hyperplane in the eigenspace. Theoretically, this model can optimally classify high-dimensional data. The SVM data processing steps are as follows.

   Assume that the sensory feature data are of N dimensions, with total L sets, that is, $(x_1,y_1), \ldots, (x_1,y_1) \in R^n$.

   The decision plane can be expressed as:

   $$f(x) = \varpi \cdot g(x) + b \quad ...(2)$$

   Here ϖ is the weight coefficient of the decision plane, $g(x)$ a nonlinear mapping function, and b the threshold.

   The optimal classification hyperplane needs to fulfill the following condition:

   $$y_i(\varpi \cdot g(x_i) + b) \geq 1 \quad ...(3)$$

   A non-negative slack variable ξ_i is introduced to restrict the classification error within a specified range, and the optimization problem is converted to:

   $$\begin{cases} min\frac{1}{2}\|\varpi\|^2 + c\sum_{i=1}^{n}\xi_i, c \geq 0 \\ s.t \quad y_i[(\varpi \cdot g(x_i) + b)] \geq 1 - \xi_i, \xi_i \geq 0 \end{cases} \quad ...(4)$$

   Here, c is a penalty factor that controls the complexity and generalisation ability of the model.

   The Lagrangian algorithm is introduced to transform the optimisation problem into a dual problem:

   $$\begin{cases} min\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j a_i a_j K(x_i, x_j) - \sum_{i=1}^{n} a_i \\ s.t \quad \sum_{i=1}^{n} y_i a_i = 0, 0 \leq a_i \leq c \end{cases}, \quad ...(5)$$

   Where,

   $$K(x_i, x_j) = \left(g(x_i) \cdot g(x_j)\right) \quad ...(6)$$

   The RBF kernel is introduced as follows:

   $$K(x_i, x_j) = exp(-g\|x_i - x_j\|)^2 \quad ...(7)$$

   Here g is the kernel function parameter that controls the range of the input space.

   The above optimisation problem is converted into:

   $$\begin{cases} min\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j a_i a_j \, exp(-g\|x_i - x_j\|)^2 - \sum_{i=1}^{n} a_i \\ s.t \quad \sum_{i=1}^{n} y_i a_i = 0, 0 \leq a_i \leq c \end{cases} \quad ...(8)$$

2. PSO Algorithm: The PSO algorithm is a parallel search technique based on the evolution of swarm intelligence. It searches for the optimal solution by sharing information among different individuals in the swarm (Zhang 2005). First, m particles are assumed in the N-dimensional search space. The position and velocity of the i-th particle are defined as $X_k^i = (X_1^i, X_2^i, \cdots, X_n^i)$ and $V_k^i = (V_1^i, V_2^i, \cdots, V_m^i)$, respectively. Each particle is treated as a possible solution. Then, a fitness function is defined to calculate the fitness value corresponding to each particle. Finally, $P_k^i = (P_1^i, P_2^i, \cdots, P_n^g)$ denotes the optimal solution found by each particle, that is, the individual extremum, and $P_k^g = (P_1^g, P_2^g, \cdots, P_n^g)$ represents the global extremum of the entire particle swarm obtained from the optimal solutions. The velocity

and position of the particles are calculated using the following formulae.

$$V_{k+1}^{i} = \omega_k V_k^i + c_1\phi_1\left(P_k^i - \chi_k^i\right) + c_2\phi_2\left(P_k^g - \chi_k^i\right) \quad ...(9)$$

$$\chi_{k+1}^{i} = \chi_k^i + V_{k+1}^i \quad ...(10)$$

Here ω_k is the inertia factor, c_1 and c_2 are the learning factors, and ϕ_1 and ϕ_2 are random numbers between 0 and 1. The parameter values were determined referring to the relevant literature (Zhang 2005, Ding et al. 2011), and the parameters were optimised accordingly.

3. Ecological Function Zoning: The accuracy of the SVM model depends on two critical parameters, the penalty factor c and the kernel function parameter g. In this study, the PSO-SVM model was established on the MATLAB platform, and the optimal parameter combination was determined by integrating the PSO and SVM algorithms.

RESULTS

Spatial Distribution of Ecosystem Services

Each ecosystem service was evaluated based on the land use map of Fuping County (Fig. 3). The natural breaks classification method in ArcGIS was applied to classify the low value, relatively low value, relatively high value, and high value areas of each ecosystem service and obtain their spatial distribution patterns (Fig. 4). The detailed analysis is as follows.

1. The habitat quality is high in the west, north, and southeast but low in the center. The landform in the west and north is dominated by mid-altitude mountains, with an elevation above 800 m. That region has high forest coverage and scarce cultivated land. In the southeast, the terrain is flat, with high grassland coverage, rich water sources, and high habitat quality. The low value areas are concentrated in central Fuping County, where the dominant land-use type is unused land, with low vegetation coverage.
2. The soil conservation level is high in the northwest, northeast, and southwest but low in the southeast. Woodland is the predominant land-use type in the high value and relatively high value areas of soil conservation, with high vegetation coverage. The southeast part of the study area has relatively low elevation and flat terrain, with low vegetation coverage and a large proportion of cultivated land. Intense erosion caused by rivers and rainfall results in weak soil conservation capacity.
3. The water yield level is high in the east and south and low in the north and west. The water yield service is mainly affected by precipitation, and its spatial

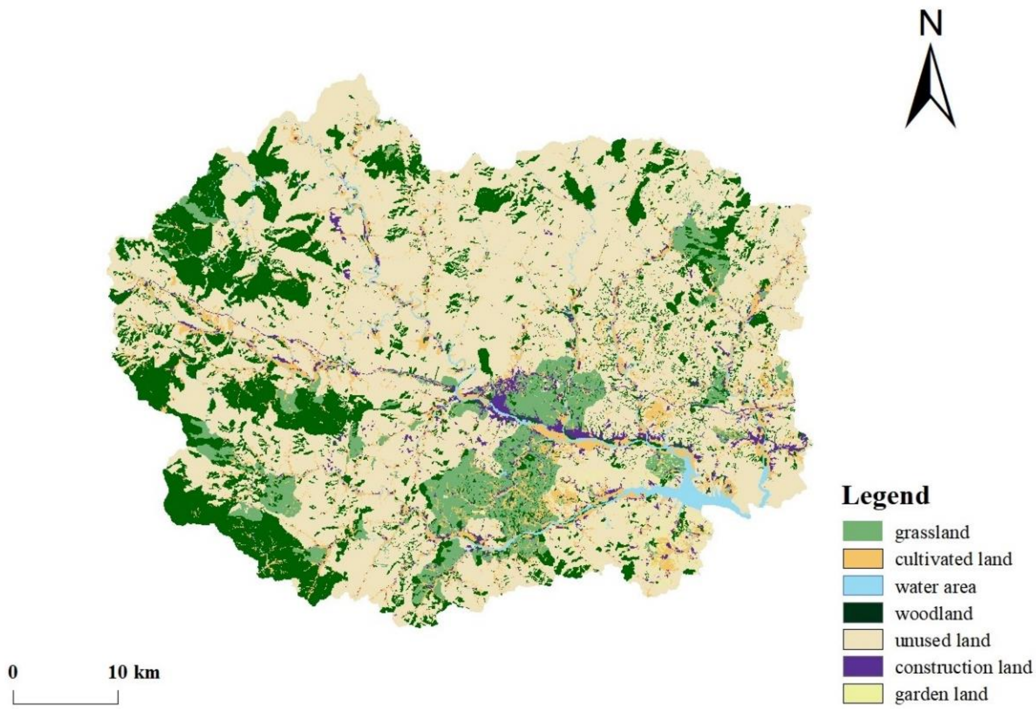

Fig. 3: Land use map of Fuping County.

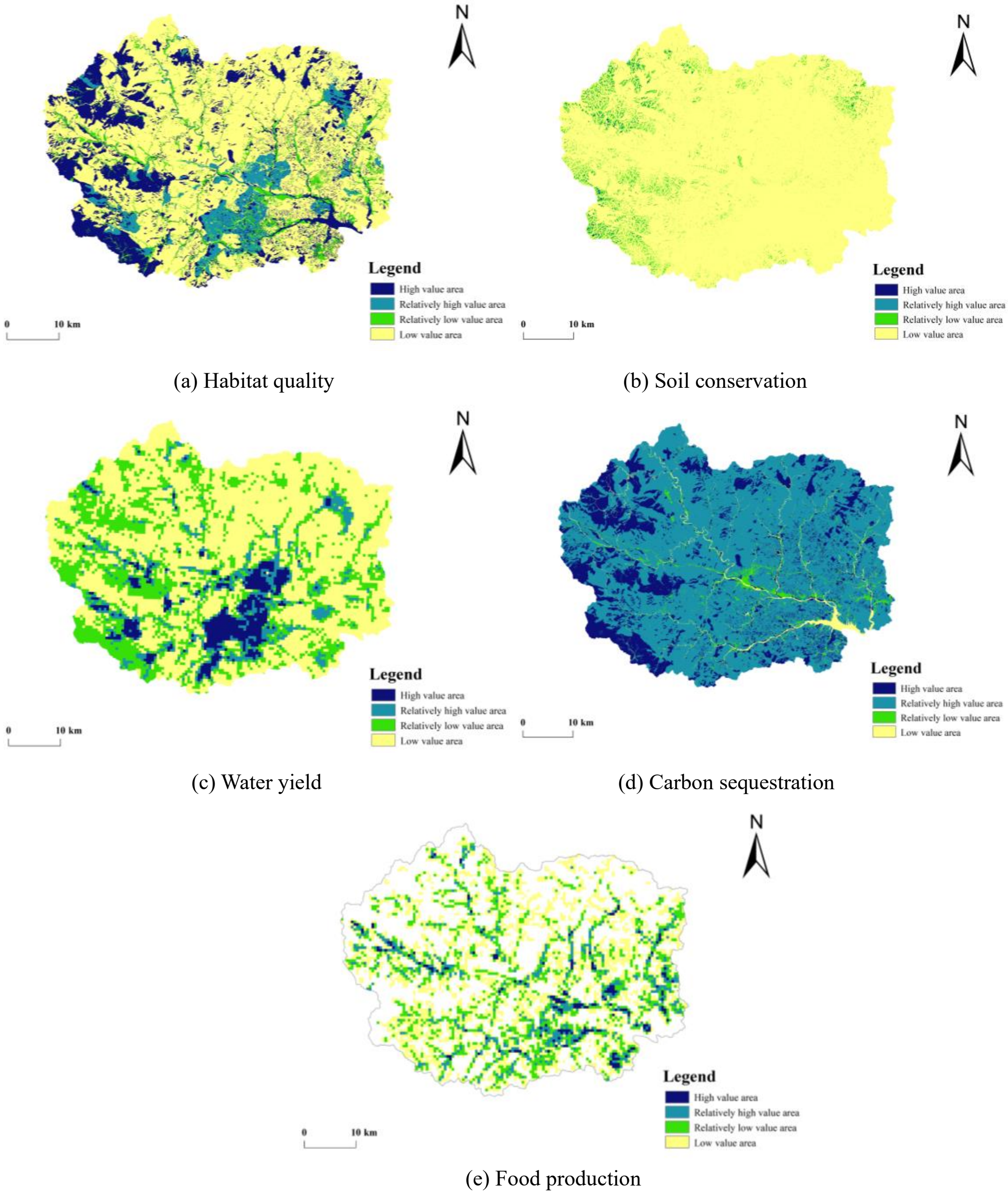

Fig. 4: Spatial distribution of ecosystem services.

distribution pattern is consistent with that of annual precipitation. Influenced by water areas and reservoirs in the county, the high value areas are concentrated in the central part, with a few scattered in the northwest and southeast.

4. The carbon sequestration capacity is high in most parts of the study area. The carbon sequestration service is mainly related to the area and coverage of woodland. The proportion of both woodland and vegetation coverage is high in the western part of Fuping County, with correspondingly higher carbon sequestration ability. The eastern area has relatively abundant cultivated land resources, with several rural settlements and low vegetation coverage, and low carbon sequestration capacity.

5. Food production service is restricted by the cultivated land area, with low overall production capacity. Generally, food production is high in regions with flat terrain, excellent irrigation conditions, and high

quality cultivated land; conversely, it is low in areas with high elevation, steep slopes, and limited irrigation conditions.

Topographic Gradient Effect of Ecosystem Services

The topographic position indices of different locations in the study area were calculated using Eq. (1) and categorized into Classes I to V (Fig. 5). Class I is mainly distributed in the southeast of Fuping County; Classes II, III, and IV are found mostly in the central Fuping County; Class V is concentrated in the western and northern parts of Fuping County. Combined with the distribution of land-use types, we can see that cultivated land, grassland, garden land, water areas, and construction land are dominant in Class I topographic positions, and their area decreases gradually with the increasing class number of topographic positions. Woodland is dominant in Class V topographic positions, and its area shrinks with decreasing class of topographic positions. Unused land is dominant in topographic positions of Classes II–IV (Fig. 6).

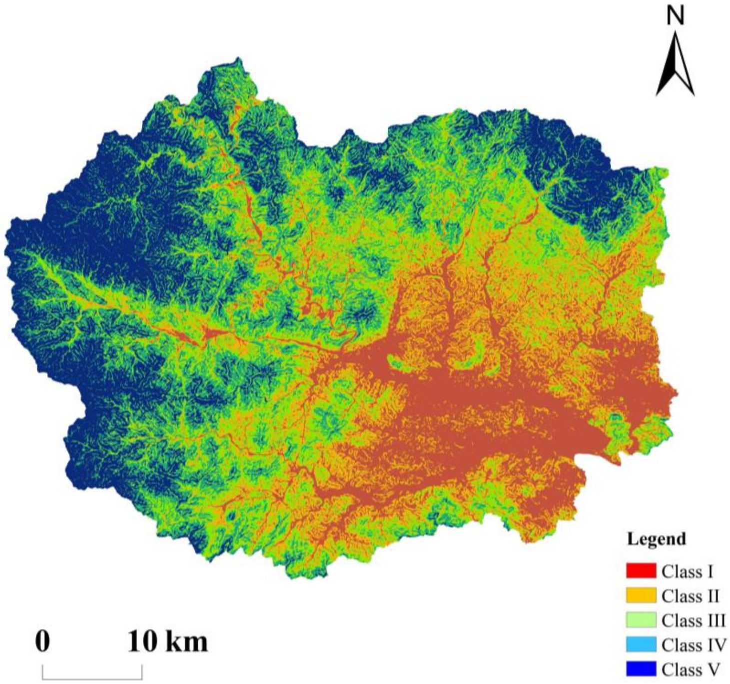

Fig. 5: Distribution of topographic position indices.

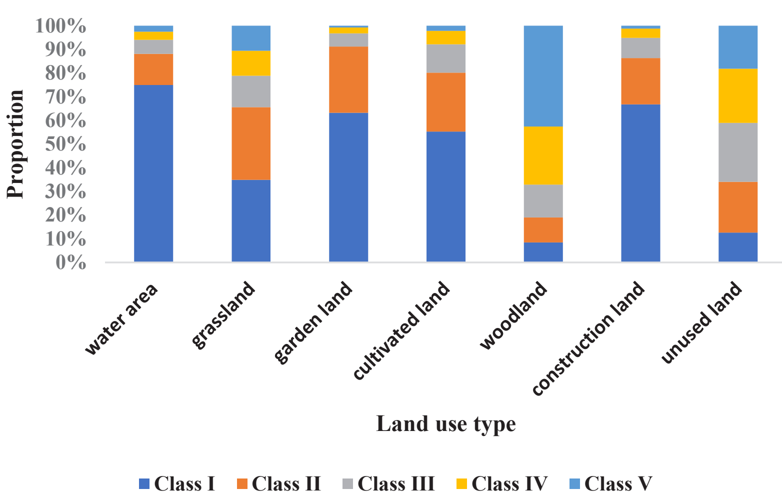

Fig. 6: Distribution of land-use types by topographic position classes.

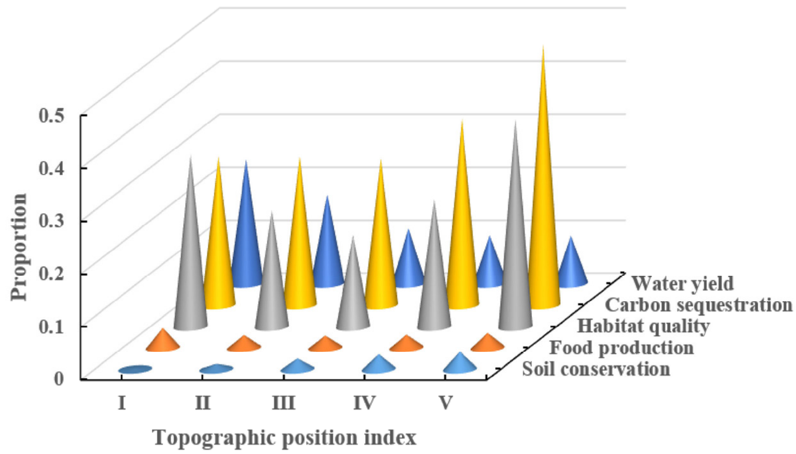

Fig. 7: Variation trends in ecosystem services with the topographic position index.

We analyzed the ecosystem service statistics according to the class of topographic positions (Fig. 7). We found that high value zones of average habitat quality are distributed in topographic positions of Classes I and V, and the level of habitat quality declines first and then increases with the increasing class number; high value areas of average carbon sequestration and soil conservation are distributed in Class V topographic positions, and service levels increase with the increasing class number; high value areas of average food production and water yield are distributed in Class I topographic positions, and service levels decrease with increasing class number.

Ecological Function Zoning

Identification of Ecosystem Service Bundles

We adopted the K-means algorithm to cluster the five ecosystem service indicators, and the resulting cluster types were numbered 2, 3, 4, 5, 6, and 7, respectively. All these results passed the significance test. The Fragstats 4.2 software was applied to calculate the contagion index and the patch cohesion index for each clustering result, and four types of optimal ecosystem services bundles were determined according to the calculation results (Fig. 8).

Type I bundle is mainly distributed in the central and southern parts of Fuping County, with high capacities of water yield and food production; type II bundles are mostly distributed in the west and northeast of Fuping County, with high levels of habitat quality and carbon sequestration service; type III bundles are predominantly distributed in the northeast, northwest, and southwest, with a high soil conservation capacity; type IV bundles are mainly distributed in the central and eastern part of

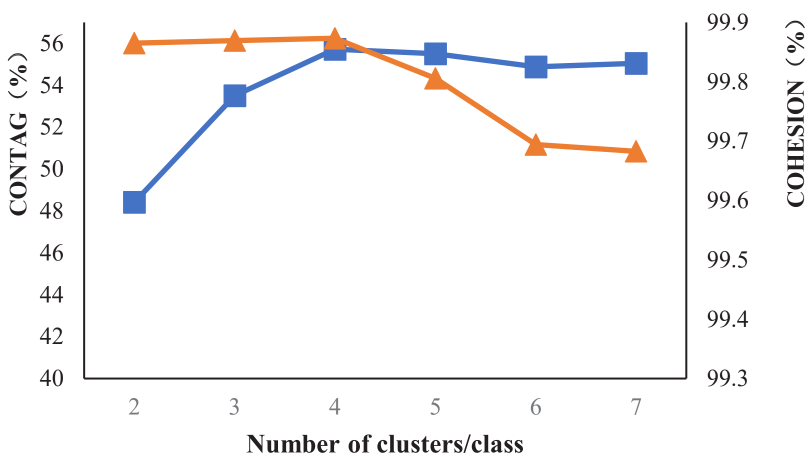

Fig. 8: Calculation results of the landscape index.

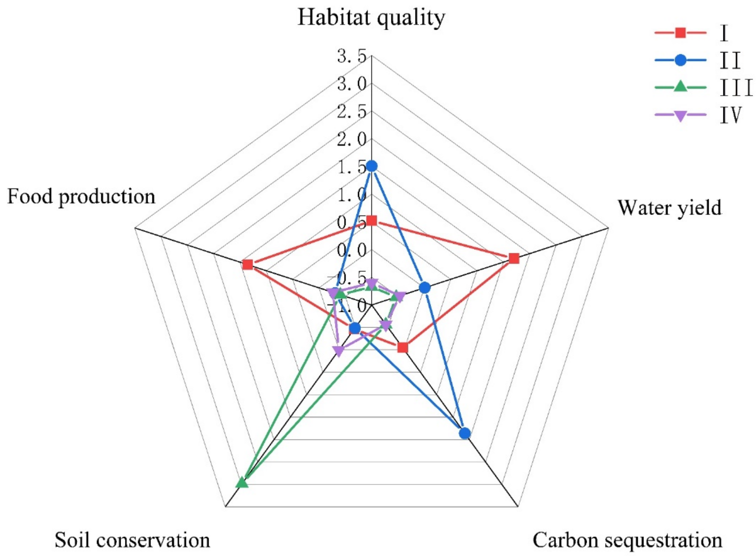

Fig. 9: Functional structures of the ecosystem services bundles.

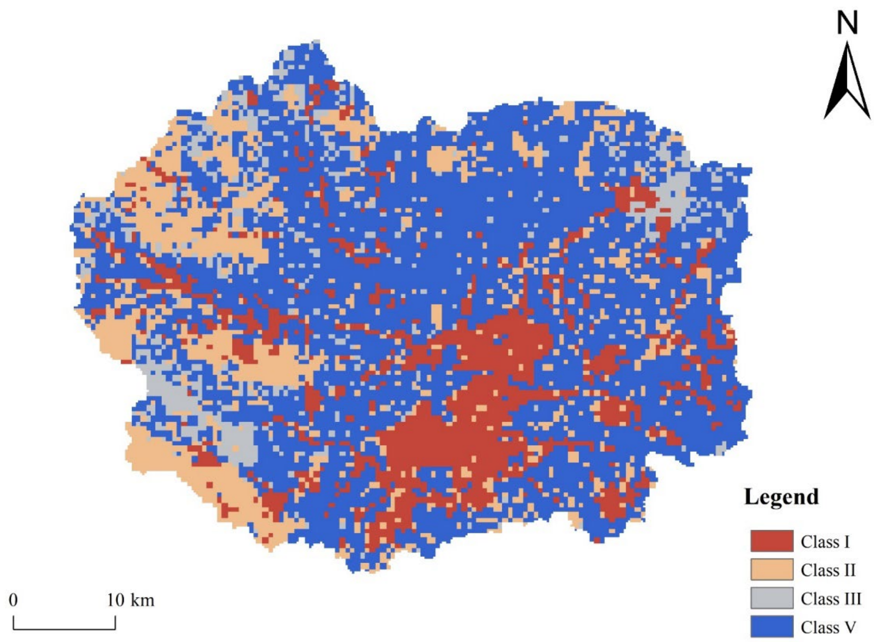

Fig. 10: Ecosystem services bundles in Fuping County.

Fuping County, with generally low ecosystem service levels (Figs. 9 and 10).

Identification of Ecological Function Zone Boundaries

We applied the PSO algorithm to explore the optimal solutions of the penalty factor c and the kernel function parameter g on the MATLAB platform (Fig. 11). The optimal parameters were then used to complete the SVM training and determine the subregion boundaries. The small patches in the SVM training results were eliminated and smoothed in ArcGIS, and finally, Fuping County was divided into four ecological function zones (Fig. 12). These ecological function zones were superimposed on the map of topographic position classes to obtain the topographic position index of each zone (Fig. 13).

According to the characteristics of each type of ecosystem services bundle and the geographical location and ecological

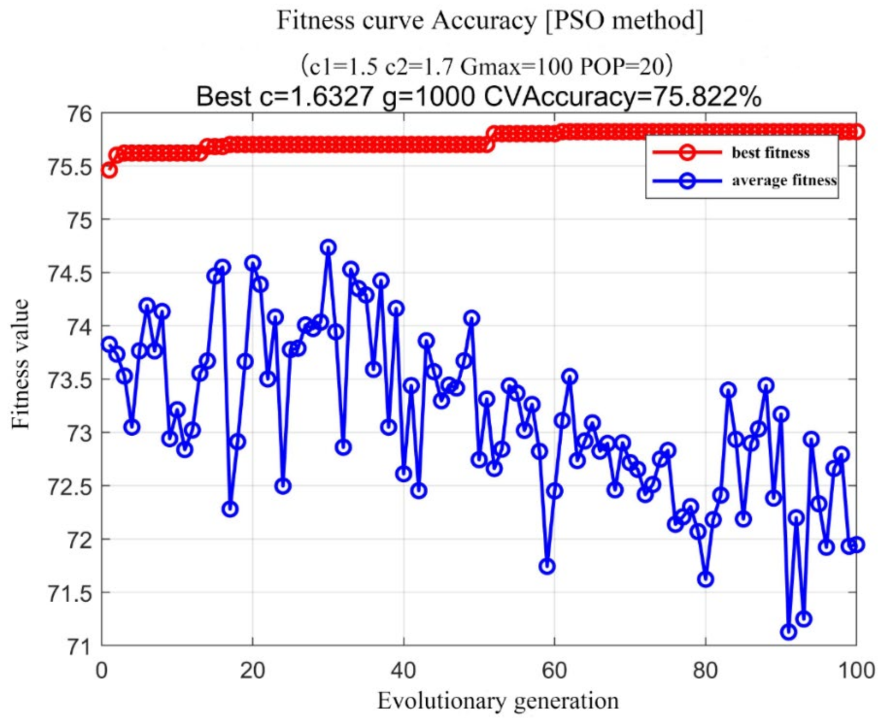

Fig. 11: PSO fitness curve.

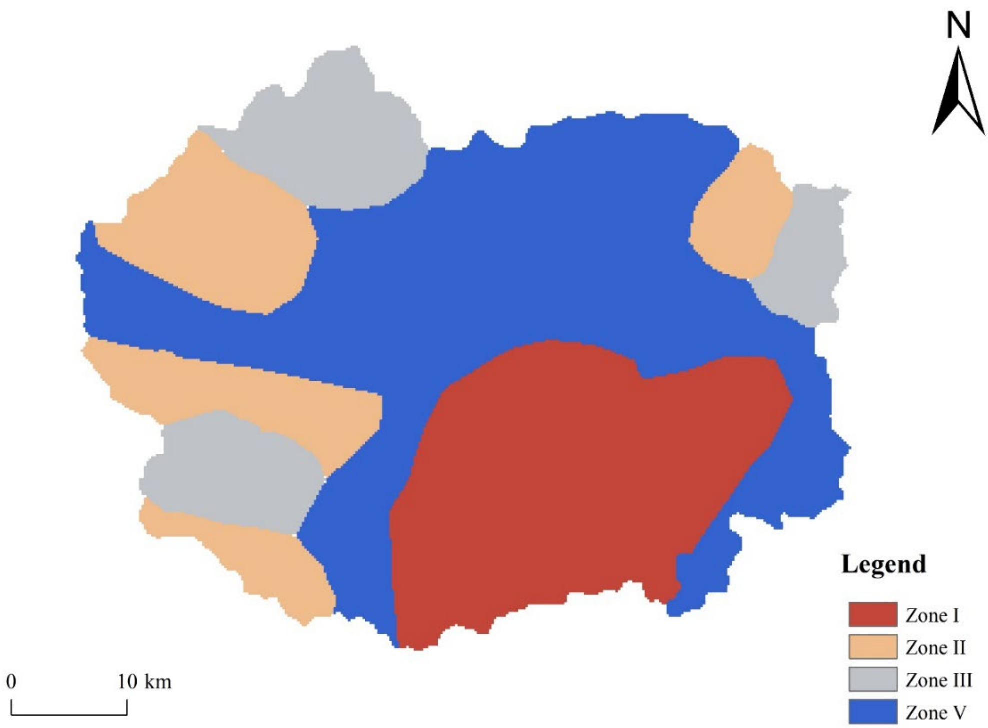

Fig. 12: Ecological function zoning in Fuping County.

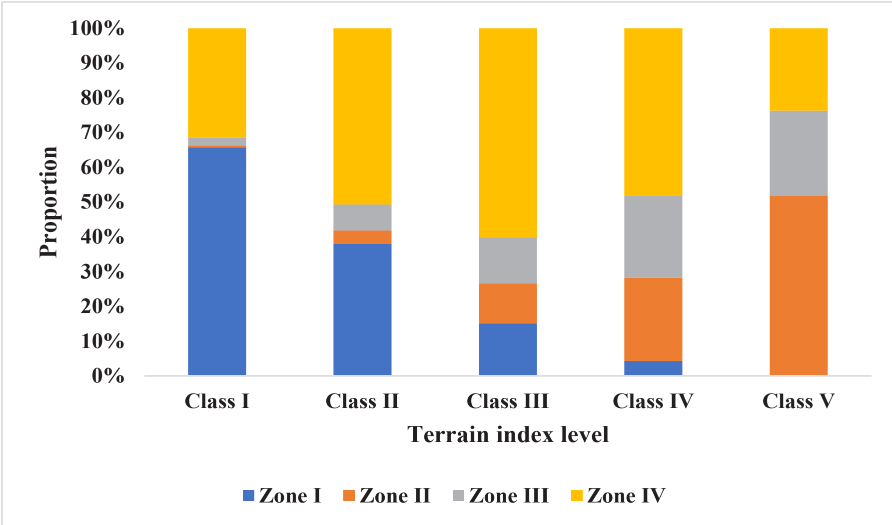

Fig. 13: Composition of topographic position index in each ecological function zone.

functions of each subregion, the ecological function zones are divided as follows.

1. Food production zone (I). It is located in the south-central part of Fuping County, accounting for 24.9% of the total area. The zone has high levels of water yield and food production services but low habitat quality and carbon sequestration capacity. This zone is mainly concentrated in the topographic positions of Class I, with a flat terrain and high average annual precipitation. It is surrounded by several water areas and reservoirs and is the main food production region in Fuping County.
2. Ecological conservation zone (II). It is located in the high-altitude regions in the west and northeast of Fuping County, accounting for 19.6% of the total area. Its habitat quality and carbon sequestration capacity are high, whereas the food production and soil conservation capacities are low. This zone is mainly distributed in the topographic positions of Class V, with high vegetation coverage and minor anthropogenic interference.
3. Potential restoration zone (III). It is located in the northwest, northeast, and southwest of Fuping County, accounting for 14% of the total area. Except for soil conservation service, the ecosystem services are of low levels. A single ecosystem service is provided. This zone is mainly distributed in the topographic positions of Classes IV and V, with generally low vegetation coverage and exhibiting the need for improving the regional ecological stability.
4. Critical restoration zone (IV). It is located in the central and eastern part of Fuping County, accounting for 41.5% of the total area, with all ecosystem services at a low level. This zone is mainly distributed in the topographic positions of Classes II–IV, with a concentration of unused land. The vegetation coverage is low, and the ecological environment is severely damaged.

DISCUSSION AND CONCLUSION

In this study, we analyzed the ecological function zones in Fuping County using the PSO-SVM model based on the ecosystem services in the study area. First, the five ecosystem services of habitat quality, soil conservation, water yield, carbon sequestration, and food production were assessed using the InVEST model to clarify their spatial distribution patterns. Then, the topographic gradient effect of each ecosystem service was determined, and the K-means clustering algorithm was applied to identify the four types of ecosystem services bundles. Finally, the PSO-SVM model was applied to obtain the various ecological function zones, including the food production zone, ecological conservation zone, potential restoration zone, and critical restoration zone, in Fuping County.

Although this study has the advantages of simple operation and high repeatability, several limitations still remain. When evaluating the soil conservation service, the coefficient of rooting depth, plant available water capacity, and soil carbon density were obtained with reference to relevant literature or calculated from the available empirical equations. We did not conduct field sampling and measurements, which would have certainly affected the accuracy of the assessment results. We only assessed the ecosystem services and delineated the ecological function zones in Fuping County in 2018 and did not thoroughly investigate the dynamic changes in the ecosystem services. Moreover, we automated the ecological function zoning by determining the ecological function zone boundaries using the SVM model. However, small patches were still observed in the zoning results owing to the number of sample points, and the results need to be further processed using ArcGIS tools. Therefore, revealing the spatiotemporal variation patterns of ecosystem services and further modifying the zoning method shall be the focus points of future studies.

Regardless of the limitations in this study, we have provided a new research idea for ecological function zoning. This study can help promote further application and exploration of the PSO-SVM model in ecological zoning studies. It can also facilitate the local government to improve the ecological environment and formulate relevant policies, in addition to providing a scientific basis for national territory spatial planning and the implementation of rural revitalisation strategy.

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REFERENCES

Balzan, M.V., Caruana, J. and Zammit, A. 2018. Assessing the capacity and flow of ecosystem services in multifunctional landscapes: Evidence of a rural-urban gradient in a Mediterranean small island state. Land Use Policy, 146(75): 711-725.

Bommarco, R., Kleijn, D. and Potts, S.G. 2013. Ecological intensification: Harnessing ecosystem services for food security. Trends Ecol. Evol., 28(04): 230-238.

Boser, B. (ed.) 1992. A Training Algorithm for Optimal Margin Classifiers. ACM Press, (0):144-152.

Chen, J.Y., Wang, H.M., Liu, G. and Bai, Y. 2019. Evaluation of ecosystem services and its adaptive policies in the Hangjiahu region from the water-energy-food perspective. J. Resources and Environment in the Yangtze Basin, 28(3): 542-553.

Crouzat, E., Mouchet, M., Urkelboom, F., Byczek, C., Meersmans, J., Berger, F., Verkerk, P.J. and Lavorel, S. 2015. Assessing bundles of ecosystem services from regional to landscape scale: Insights from the French Alps. J. Appl. Ecol., 52(5): 1145-1155.

Ding, S.F., Qi, B.J. and Tan, H.Y. 2011. A review of research on the support vector machine theory and algorithm. Univ. Electron. Sci. Technol. China, 40(1): 2-10.

Du, K.L., Guan, Y.L., Pei, D.D., Xue, J. and Xu, L.L. 2018. Remote sensing classification of wetlands based on PSO parameter optimised support vector machine: A case study of some areas of Poyang Lake. J. Jiangxi Sci., 36(1): 66-72+129.

Guo, R., Wang, X.K., Lu, F., Duan, X.N. and OUYang, Z.Y. 2008. Soil carbon sequestration and its potential by grassland ecosystems in China. J. Acta Ecol. Sin., 28(2): 862-867.

Han, B., Wang, X.K., Lu, F., Duan, X.N. and Ouyang, Z.Y. 2008. Soil carbon sequestration and its potential by cropland ecosystems in China. Acta Ecol. Sin., 28(2): 612-619.

Hong, B.T., Ren, P., Yuan, Q.Z. and Wang, L. 2019. Ecological Function Regionalization in the Upper Yangtze River. J. Ecol. Rural Environ., 35(8): 1009-1019.

Kareiva, P., Watts, S., Mcdonald, R. and Boucher, T. 2007. Domesticated nature: Shaping landscapes and ecosystems for human welfare. Science, 316(5833): 1866-1869.

Liu, H.Y., Xiao, W.F., Li, Q., Tian, Y., Zhang, Q.R. and Zhu, J.H. 2021. Spatiotemporal variations and trade-offs of ecosystem services in Beijing. Chin. J. Ecol., 40(1): 209-219.

Liu, J., Fu, B., Zhang, C.H., Hu, Z.P. and Wang, Y.K. 2019. Assessment of ecosystem water retention and its value in the upper reaches of Minjiang River Based on the InVEST model. Resources and Environment in the Yangtze Basin, 28(3): 577-585.

Liu, J.H., Xu, H., Wang, Y., Li, H. and Shen, W.D. 2018. Evaluation of ecological risk and carbon fixation from land use change: A case study of Huanghua City, Hebei Province. Chin. J. Eco-Agric., 26(8): 1217-1226.

Mao, Q., Peng, J., Liu, Y.X., Wu, W., Zhao, M. and Wang, Y. 2019. An ecological function zoning method coupling SOFM and SVM: A case study in Ordos. J. Acta Geogr. Sin., 74(3): 460-474.

Niu, Z.P., Wang, X.F., Luo, G.X. and Yi, L.C. 2020. Ecological function zoning of Tibet Autonomous Region based on SOFM network at watershed scale. J. Bull. Soil Water Conserv., 40(4): 116-123.

Pan, Y., Zheng, H., Yi, Q.T. and Li, R.N. 2021. The change and driving factors of ecosystem service bundles: A case study of Daqing River Basin. J. Acta Ecol. Sin., 41(13): 5204-5213.

Peng, L., Deng, W., Huang, P. and Liu, Y. 2021. Evaluation of multiple ecosystem services landscape index and identification of ecosystem service bundles in Sichuan Basin. Acta Ecol. Sin., 41(23): 1-13.

Raudsepp-Hearne, C., Peterson, G.D. and Bennett, E.M. 2010. Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. Proc. Nat. Acad. Sci. U. S. A., 96(107): 5242-5247.

Riechers, M., Barkmann, J. and Tscharntke, T. 2018. Diverging perceptions by social groups on cultural ecosystem services provided by urban green. Landsc. Urban Plan., 33(175): 161-168.

Sharp, R., Douglass, J., Wolny, S. 2020. InVEST 3.9.0 User's Guide [M/OL]. https://storage.googleapis.com/releases.naturalcapitalproject.org/invest-userguide/latest/index.html

Turner, K.G., Odgaard, M.V., Bøcher, P.K., Dalgaard T. and Svenning, J. C. 2014. Bundling ecosystem services in Denmark: Trade-offs and synergies in a cultural landscape. Landsc. Urban Plan., 29(125): 89-104.

Wu, Q.B., Wang, X.K., Duan, X.N., Deng, L.B., Lu, F., Ouyang, Z.Y. and Feng, Z.W. 2008. Vegetation carbon sequestration and its potential by forest ecosystems in China. Acta Ecol. Sin., 28(2): 517-524.

Xu, C.X., Gong, J., Li, Y., Yan, L.L. and Gao, B.L. 2020. Spatial distribution characteristics of typical ecosystem services based on terrain gradients of the Bailongjiang Watershed in Gansu. Acta Ecol. Sin., 40(13): 4291-4301.

Xu, X.M. 2014. SVM parameter optimisation and its application in classification. Dalian: Dalian Maritime University.

Yan, X., Huang, F.R., Li, Q., Zhou, H.F. and Li, L.H. 2021. Regionalisation of the matching degree of water, soil, and heat resources in Central Asia based on ecosystem services using PSO-SOFM neural network. Chin. J. Eco-Agric., 29(2): 241-255.

Zhang, L.P. 2005. Theory and practices of the particle swarm optimisation algorithm. Hangzhou: Zhejiang University.

Zhao, N. 2020. Evaluation of carbon storage and habitat quality of the land system of Bohai Bay coast based on the InVEST model. Baoding: Hebei Agricultural University.

Zhu, W.B., Zhang, J.J., Cui, Y.P., Zheng, H. and Zhu, L.Q. 2019. Assessment of the territorial ecosystem carbon storage based on land use change scenarios: A case study of the Qihe River Basin. Acta. Geog. Sinica., 74(3): 446-459.