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Spatiotemporal evolution and driving forces of ecosystem service value and ecological risk in the Ulan Buh Desert

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A clear understanding of the spatiotemporal evolution and driving factors of ecosystem service value (ESV) and the landscape ecological risk index (ERI) can effectively link human well-being and ecosystem security, which is essential for sustainable ecosystem management. Based on multitemporal land use data (1990, 2000, 2010, and 2018), the spatiotemporal evolution of ESV and the ERI in the Ulan Buh Desert was evaluated. The driving forces of ESV and the ERI were quantitatively evaluated by the Geodetector model. The results show that 1) from 1990 to 2018, total ESV in the Ulan Buh Desert increased from 7.00×10^8 yuan to 11.09×10^8 yuan. Low-ESV areas accounted for approximately 72.28% of the study area. High-ESV and moderate-high-ESV areas were mainly distributed along the Yellow River and the northeastern region. 2) During the study period, the ecological risk of the Ulan Buh Desert generally decreased; only the ecological risk of the northeastern region improved significantly, and high-risk areas were mainly distributed across sand dunes located in the middle of the desert. 3) There was a negative correlation between ESV and the ERI in the study area, and the main relationship was low value-high risk. 4) Driving force analysis results show that natural and human impact factors jointly affected the spatiotemporal differentiation of ESV and the ERI in the Ulan Buh Desert. Among the influencing factors, the interaction between the distance to a highway and annual precipitation had the strongest impact. The implementation of relevant policies in the study area should be guided by ESV and the ERI, and the protection and restoration of various ecosystems in the study area must be strengthened.

KEYWORDS

Ulan Buh Desert, ecosystem service value, ecological risk, spatiotemporal evolution, driving forces

1 Introduction

Ecosystem services represent the benefits that human populations derive from ecosystems (Costanza et al., 1997; Daily, 1997; Millennium Ecosystem Assessment, 2005). While providing services, ecosystems also face various ecological risks themselves (Xie et al., 2015; Cao et al., 2019). Ecological risk refers to the likelihood of adverse effects of disturbances on ecosystems (Mann et al., 2021). However, with the development of the social economy, landscape patterns and ecological processes have changed profoundly, which has impacted ecosystem services and ecological risks to different degrees, seriously threatening human well-being (Li et al., 2016). Ecosystem service value (ESV) and the ecological risk index (ERI) quantify the capacity of an ecosystem to provide services and the extent to which a region is exposed to ecological risks, respectively. Therefore, comprehensive consideration of ESV and the ERI provides a basis for the prevention of regional ecological risk and the improvement of ecosystem functions and plays an important role in the construction of regional ecological security patterns (Zhu and Chen., 2022).

In recent years, there has been increasing interest in introducing ESV and the ERI into environmental policies and governance (Gong et al., 2021). Scholars have conducted a series of scientific studies on the quantitative assessment, spatiotemporal evolution and influencing factors of ESV and ecological risk. At present, research on ESV has mainly concentrated on river basins (Woldeyohannes et al., 2020; Pan et al., 2021), cities (Wang et al., 2019; Hou et al., 2020; Rahman and Szabo, 2021), natural reserves (Sannigrahi et al., 2019; Yan et al., 2022) and so on. The main research methods used include the equivalent factor method (Xie et al., 2003; Jia et al., 2021; Liu et al., 2021) and material conversion method (Goldstein et al., 2012; Fadaei et al., 2020; Wang J et al., 2020). The obtained results contribute to the construction of regional ecological civilizations. Studies on landscape ecological risk have mostly focused on cities (Wang D et al., 2021; Al-Hameedi et al., 2022), river basins (Tian et al., 2019; Zhang et al., 2021), mining areas (Wu et al., 2021; Xu et al., 2021) and so on. The spatiotemporal distribution of regional ecological risk is explored by constructing a relative ecological risk assessment model (Bartolo et al., 2012; Heenkenda and Bartolo, 2016) to provide a basis for landscape ecological risk management. However, the abovementioned studies fail to consider the link between ESV and ecological risk. Most studies on ESV consider the benefits brought only by ecosystems while neglecting the potential risks faced by ecosystems under the disturbances of human activities. In contrast, special assessments of ecological risk have considered only the loss degree of an ecosystem when it is disturbed and have neglected the benefits ecosystems provide for human beings. At the same time, there is currently a lack of comprehensive consideration of ESV and the ERI together (Jr et al., 2009; Forbes and Calow, 2013; Xu et al., 2016; Wang, 2021; Karimian et al., 2022), especially for

desert ecosystems. Due to the natural conditions of drought and a lack of rain, desert ecosystems are extremely fragile and face ecological risks such as sandstorms and landslides. The comprehensive evaluation of the ESV and ERI of desert ecosystems and the exploration of their driving forces can provide a theoretical basis for the protection and restoration of desert ecosystems.

The Ulan Buh Desert is among the eight largest deserts in China. It is located in the core area of the northern wind-sand belt of the national ecological restoration security pattern (Jin, 2022). The ecological security of this desert is related to people's well-being, to the socioeconomic development of the Yellow River Basin and even to that of the Beijing-Tianjin region. This paper aims to solve the following scientific problems through analysis and research: 1) to evaluate the spatial and temporal evolution of ESV and ERI values in the Ulan Buh Desert and 2) analyze the driving factors affecting the spatiotemporal distribution of ESV and ERI values. This study provides a scientific basis for formulating scientific risk prevention and ecological remediation countermeasures for the Ulan Buh Desert.

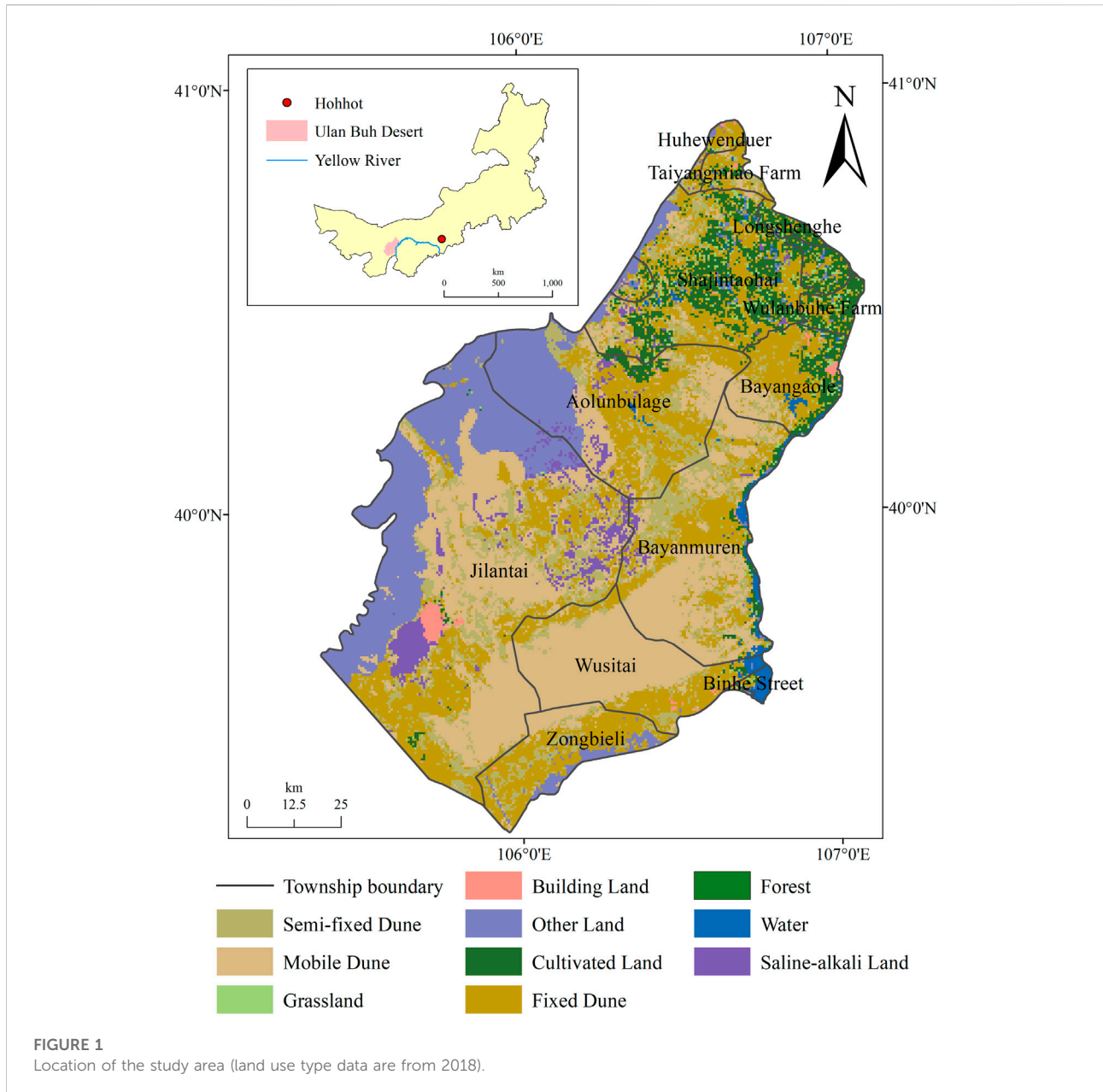
2 Study area and methods

2.1 Study area

The Ulan Buh Desert (39° 17'-40° 46'N, 105° 24'-107° 01'E) straddles the Alxa League and the Bayan Nur of Inner Mongolia, covering a total area of 1.3×10^8 hm². It is bounded by Langshan Mountain in the northwest, the Hetao Plain in the northeast, the Yellow River in the east and Helan Mountain in the south (Wang X et al., 2020). The region has a temperate arid climate with an annual precipitation level of 151 mm, an annual average temperature of 7.8°C and a large difference in temperature between the daytime and nighttime (Cao et al., 2022). The plant community is dominated by xerophytes. The topography of the study area is low in the middle and high in the surrounding regions. Soil types mainly include gray desert soil, cumulated irrigated soil, aeolian sand soil, solonchak and light brown calcic soil (Ji and Guo., 1995). The main land use types are sand dunes (Figure 1).

2.2 Data sources and preprocessing

Land use data collected from July to September in 1990, 2000, 2010 and 2018 were taken from Landsat five Thermal Mapper (TM) and Landsat eight Operational Land Imager (OLI) images of the United States Geological Survey (USGS; <https://www.usgs.gov/>). With the support of ENVI 5.3, radiometric calibration, atmospheric correction and mosaic processing were carried out successively. Land use maps of the study area from 1990 to 2018 were obtained using the object-oriented classification



method and visual interpretation. The overall classification accuracy level was 85.13% (Song et al., 2021). According to the interpretation results, land use types were divided into grasslands, cultivated land, water bodies, building land, forests, mobile dunes, fixed dunes, semifixed dunes, saline-alkali land and other land. Mobile, fixed and semifixed dunes were merged into dunes during the ESV calculation process. Socioeconomic data were selected from the 1990–2018 statistical yearbooks of Inner Mongolia and the China grain yearbook (Inner Mongolia Bureau of Statistics, 2022).

Annual precipitation, digital elevation model (DEM), soil type and distance to highway data were provided by the Data

Center for Resources and Environmental Sciences, Chinese Academy of Sciences (<https://www.resdc.cn/>) with spatial resolutions of 1 km, 30 m, 1 km and 1 km, respectively. The median normalized difference vegetation index (NDVI) with masked clouds and cloud shadows based on the red and near infrared bands of the surface reflectance collections for Landsat five and 8 (USGS Landsat Surface Reflectance Tier 1) for July to September in 1990, 2000, 2010 and 2018 were derived from the Google Earth Engine (GEE; <https://code.earthengine.google.com/>), a cloud-based computing platform. Slope and aspect data were calculated from DEM data with a spatial resolution of 30 m.

2.3 Calculation of ESV and ecological risk

The study area was divided into 1716 3-km × 3-km square grids with the support of ArcMap 10.2. First, ESV and the ERI were calculated based on the grid units and assigned to the central points of each grid cell. Then, ordinary kriging interpolation was performed based on the central points to obtain the spatial distributions of ESV and the ERI in the study area.

2.3.1 Evaluation of ESV

Based on the value equivalent factor method proposed by Xie (Xie et al., 2015) and the actual willingness to pay of Inner Mongolia, the equivalent factor of the ESV of the Ulan Buh Desert was found to be 253.31 yuan-hm⁻² (Song et al., 2021) after adjusting the coefficient and removing the effect of inflation. The ESV per unit area of the Ulan Buh Desert is shown in Supplementary Table S1.

Based on the geometric interval classification method of ArcGIS, the ecosystem value of the study area was divided into five grades: low (0, .0026], moderate-low (.0026, .0055], moderate (.0055, .0085], moderate-high (.0085, .0180] and high (.0180, ∞) (× 10⁸ yuan).

2.3.2 Calculation of the ERI

Based on the research of Zeng (Zeng and Liu., 1999), the ERI model was constructed by using the landscape disturbance index and landscape fragility index:

$$ERI_k = \sum_{i=1}^n \frac{A_{ik}}{A_k} \times R_i$$

$$R_i = E_i \times F_i$$

$$E_i = aC_i + bD_i + cN_i$$

where ERI_k is the ERI value in the k^{th} area of the study area, A_{ik} is the area of the i^{th} landscape type in the k^{th} area, and A_k is the area of the k^{th} area. N is the total number of grid units in the study area, R_k is the landscape loss index in the k^{th} area, E_k is the landscape disturbance index in the k^{th} area, and F_k is the landscape fragility index. C_i , D_i and N_i represent the landscape fragmentation index, landscape isolation index and fractal dimension index of the k^{th} area, respectively, while a , b and c are the weights of the above indices, which are set to .5, .3 and .2, respectively, in this work according to previous research (Li et al., 2020; Zhang et al., 2020; Ran et al., 2022). The landscape fragility index, which indicates the degree to which different landscape types are affected by external disturbance, is set as follows (Zhang et al., 2018): other land types are set to 8, dunes are set to 7, saline-alkali land are set to 6, water bodies are set to 5, cultivated land are set to 4, grasslands are set to 3, forests are set to 2, and building land is set to 1; after normalization, these landscape fragility index values are found to be .222, .194, .167, .139, .111, .083,

.056, and .028, respectively. The calculation formulas of these indices are provided in Table 1.

Based on the geometric interval classification method of ArcGIS and the actual conditions of the Ulan Buh Desert, the ERI values of the study area were divided into five grades: low (0, .0650), moderate-low (.0650, .0710), moderate (.0710, .0760), moderate-high (.0760, .0840) and high (.0840, ∞).

2.4 Bivariate spatial autocorrelation model

In this paper, a bivariate local autocorrelation model is used to reflect the degree of correlation between local ESV and the ERI by using Moran's I index. The formula for calculating Moran's I index is as follows (Qiao et al., 2020; Jin et al., 2021; Li C et al., 2022):

$$I_{sr} = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} \left(\frac{y_{is} - \bar{y}_s}{\sigma_s} \right) \left(\frac{y_{ir} - \bar{y}_r}{\sigma_r} \right)}{(n-1) \sum_{i=1}^n \sum_{j=1}^n W_{ij}}$$

where I_{sr} is the bivariate local autocorrelation coefficient of ESV and ERI; n is the total number of grid units in the study area; $y_{i,s}$ and $y_{i,r}$ are the ESV and ERI in the i^{th} area, respectively; both σ_s and σ_r are variances; and W_{ij} is the weight matrix.

2.5 Geodetector

Geodetector is a set of statistical methods that test the spatial heterogeneity of variables and reveal the driving force behind variations (Wang and Xu., 2017).

The factor detector uses the q value to express the explanation degree of an independent variable to the spatial heterogeneity of the dependent variable. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST}$$

$$SSW = \sum_{h=1}^L N_h \sigma_h^2, \quad SST = N \sigma^2$$

where h is the number of layers of variables x or y , N_h and N indicate the number of samples in the h^{th} layer and the whole area, respectively, and σ_h^2 and σ^2 indicate the variance of variable y in the h^{th} layer and the whole area. SSW and SST represent the sum of variance in the h^{th} layer and whole area, respectively. The range of the q value is [0,1], and the higher the q value is, the stronger the explanation degree of independent variable x to dependent variable y is.

The interaction detector is applied to analyze interactions between the independent variables X_1 and X_2 . The detection is performed as follows: first, the q values of independent variables X_1 and X_2 are calculated; then, the interaction

TABLE 1 Calculation formulas of each subindex in the landscape disturbance matrix.

Name	Computing method	Parameter meaning	Ecological meaning
Landscape fragmentation index C_i	$C_i = n_i/A_i$	Where n_i is the number of patches of the i^{th} landscape type and A_i is the total area of the i^{th} landscape type.	Reflects the degree of landscape fragmentation; the higher the value is, the greater the degree of human disturbance to the landscape is and the lower the internal stability of the landscape is Wang H et al. (2021).
Landscape isolation index D_i	$D_i = \frac{A}{2A_i} \sqrt{\frac{n_i}{A}}$	Where A is the total area of landscape, A_i is the total area of the i^{th} landscape type and n_i is the number of patches of the i^{th} landscape type.	Reflects the separation degree of patch spatial distribution in landscape types; the higher the value is, the more complex the landscape distribution is and the lower the internal stability of the landscape is.
Landscape fractal dimension index N_i	$\frac{2 \ln(TE_i/4)}{\ln A_i}$	Where TE_i is the perimeter of the i^{th} landscape type and A_i is the total area of the i^{th} landscape.	Reflects the complexity and stability of the landscape shape. The values usually range from [1, 2]. The higher the value is, the more complex the landscape distribution is and the higher the internal stability of the landscape is Peng et al. (2010).

TABLE 2 Interaction detection types.

Criterion	Interaction type
$q(X_1 \cap X_2) < \min [q(X_1), q(X_2)]$	Non-linear weakening
$\min [q(X_1), q(X_2)] < q(X_1 \cap X_2) < \max [q(X_1), q(X_2)]$	Single-factor non-linear weakening
$q(X_1 \cap X_2) > \max [q(X_1), q(X_2)]$	Two-factor enhancement
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independence from each other
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Non-linear enhancement

between X_1 and X_2 is calculated as $q(X_1 \cap X_2)$, and $q(X_1)$, $q(X_2)$ and $q(X_1 \cap X_2)$ are compared to analyze their interactive behaviors (Table 2).

In this study, human influence factors, such as the distance to a highway, and natural factors, such as the NDVI, precipitation, slope, aspect and soil type, are selected as independent variables, while ESV and the ERI are selected as dependent variables. According to the data distribution characteristics, precipitation, slope, aspect and soil type data were classified into 6, 6, 6 and 7 categories, respectively, using the natural breaks method, and the NDVI and distance to a highway data were divided into 6 and 9 categories, respectively, using the geometric interval classification method. Based on the 3 km × 3 km grid, the variables were extracted to represent the center of each grid cell and were input into the Geodetector for the driving force analyses of ESV and the ERI.

3 Results

3.1 Land use dynamics

From 1990 to 2018, dunes were the main land use type in the Ulan Buh Desert, accounting for more than 70% of the area

(Figure 2). The area of mobile dunes decreased significantly over this period, while the areas of fixed dunes, semifixed dunes and cultivated land increased gradually during the study period. The shifting areas of mobile dunes to semifixed dunes were $11.70 \times 10^4 \text{ hm}^2$, $13.99 \times 10^4 \text{ hm}^2$ and $19.63 \times 10^4 \text{ hm}^2$ from 1990–2000, 2000–2010 and 2010–2018, respectively. The shifting areas of grasslands to cultivated land were $1.57 \times 10^4 \text{ hm}^2$ and $.63 \times 10^4 \text{ hm}^2$ from 1990–2000 and 2000–2010, respectively. The change rates of building land, water bodies and forest areas were small during the study period. In general, the main form of land use type transfer in the study area was flow between dune types.

3.2 Spatiotemporal dynamic analysis of ESV

The total ESV in the Ulan Buh Desert showed a fluctuating and increasing trend from 7.00×10^8 yuan in 1990 to 6.17×10^8 yuan in 2000 and then continued to increase to 11.09×10^8 yuan by 2018, exhibiting a change rate of 58.41%, indicating that the ESV of the study area improved from 1990–2018 (Table 3). According to the results obtained for the four periods, the ESVs provided

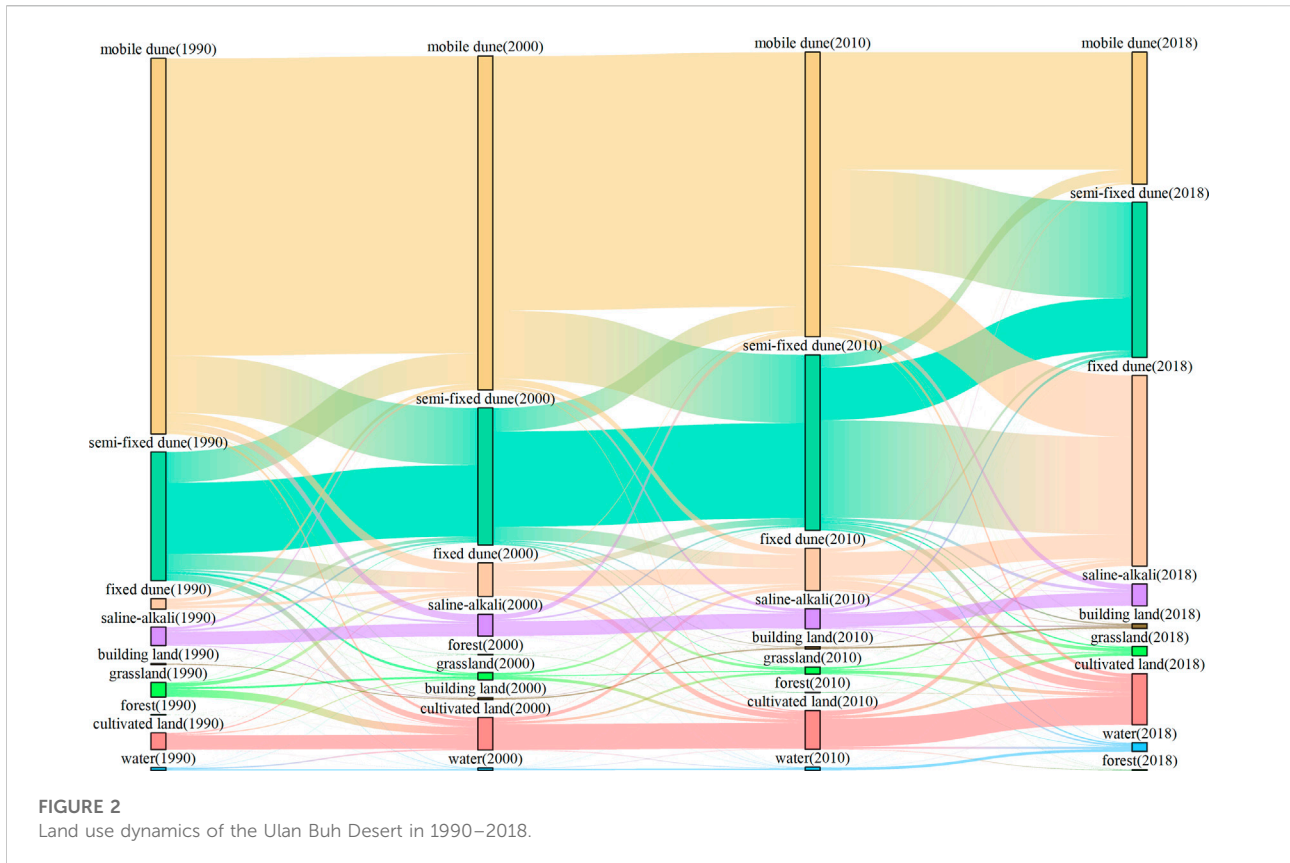
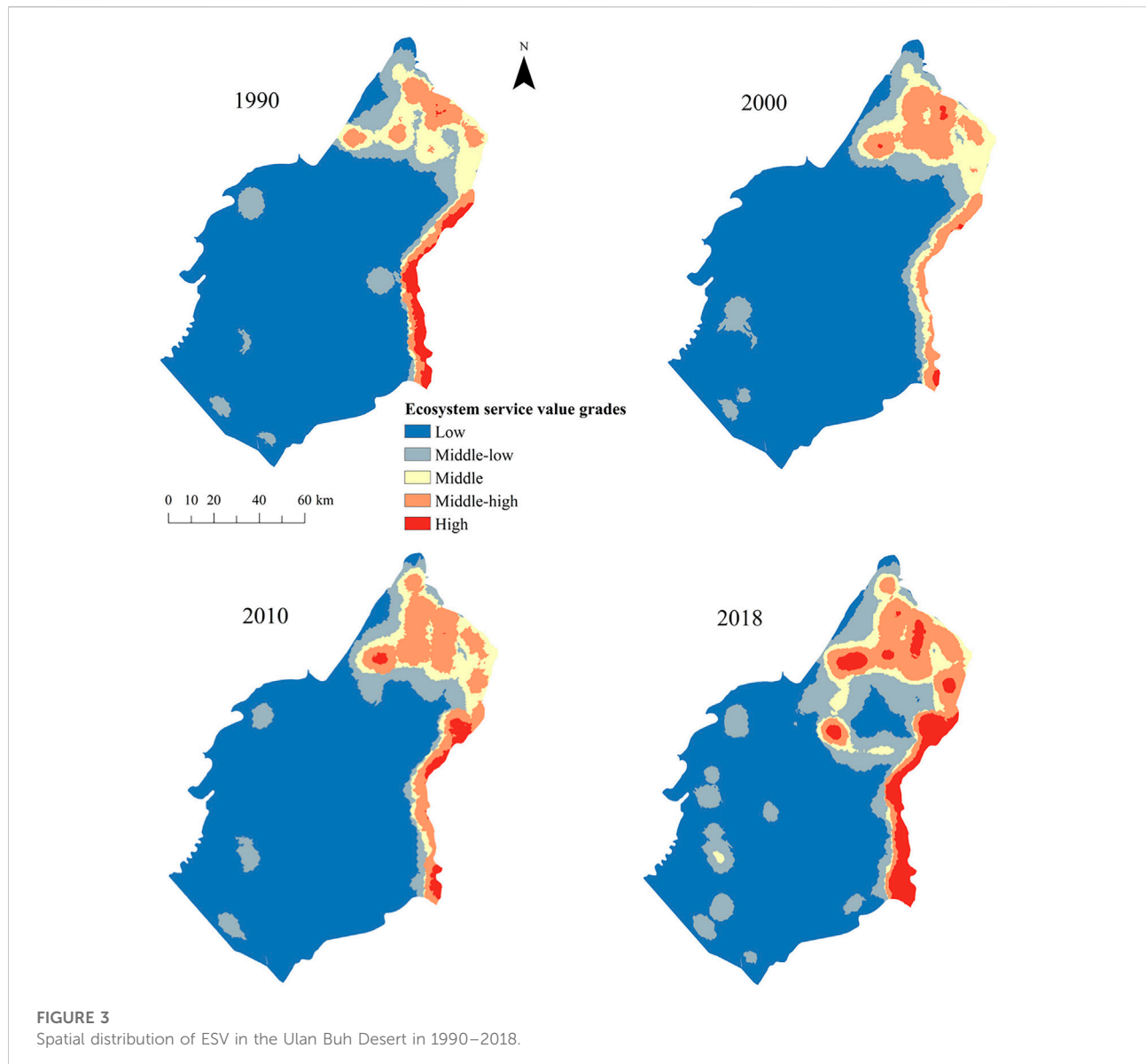


TABLE 3 ESVs of different land-use types in the Ulan Buh Desert from 1990–2018.

Land use type	ESV ($\times 10^6$ yuan)				Δ ESV ($\times 10^6$ yuan)/change ratio (%)		
	1990	2000	2010	2018	1990–2000	2000–2010	2010–2018
Cultivated land	35.20	67.86	81.81	107.57	32.66/92.78	13.95/20.56	25.76/31.49
Water body	257.60	163.60	230.12	625.26	-94.00/-36.49	66.52/40.66	395.14/171.71
Building land	.11	.20	.24	.43	.09/81.82	.04/20	.19/79.17
Grassland	39.40	19.38	19.74	24.66	-20.02/-50.81	.36/1.86	4.92/24.92
Forest	1.40	6.19	7.39	8.73	4.79/342.14	1.20/19.39	1.34/18.13
Other land	64.30	66.95	63.03	61.51	2.65/4.12	-3.92/-5.86	-1.52/-2.41
Saline-alkali land	2.00	2.38	2.10	2.43	.38/19.00	-.28/-11.76	.33/15.71
Dune	300.09	290.76	291.44	278.44	-9.33/-3.11	.68/0.23	-13.00/-4.46
Total	700.10	617.32	695.87	1109.03	-82.78/-11.82	78.55/12.72	413.16/59.37

by different land use types could be ranked as follows: dunes > water bodies > cultivated land > other land > grasslands > forests > saline-alkali land > building land. Among them, the ESV of dunes first decreased and then

increased with a change rate of -2.88% before further decreasing with a change rate of -4.46% between 2010 and 2018, while the values of water bodies and grassland first decreased and then increased. The change rate of water



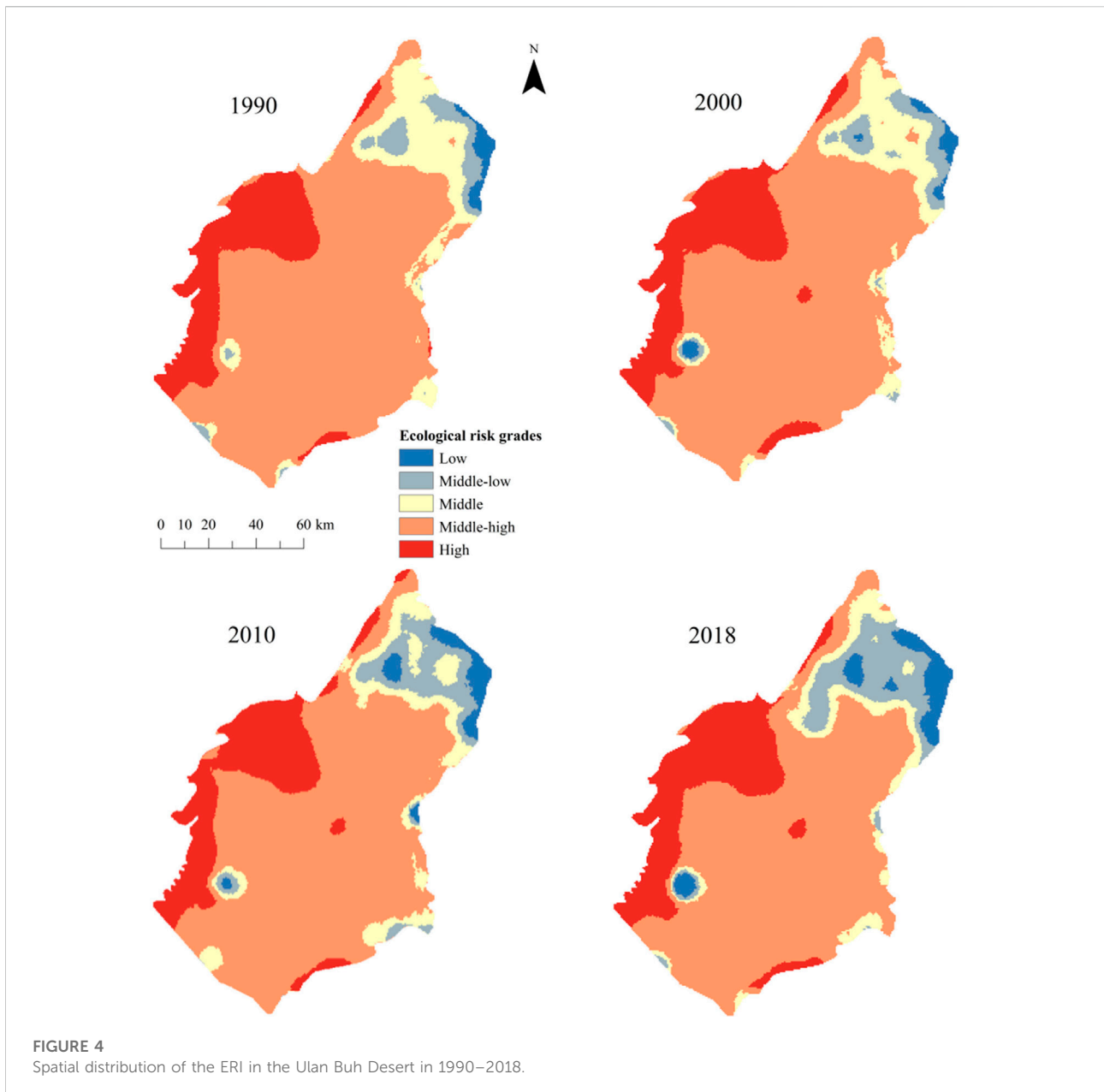
bodies was 142.73% from 1990 to 2018. In addition, the ESVs of cultivated land, forests and building land increased gradually.

In terms of its spatial distribution, the ESV of the Ulan Buh Desert was high in the northeast and low in the southwest (Figure 3). The study area mainly consisted of moderate-low-value areas and low-value areas. Portions of the moderate-high and high-value areas were intensively distributed in clusters in the northeastern part of the study area, while the other portions were located along the Yellow River in the eastern region. The area of moderate-high and high-value areas first decreased and then increased from 1990–2018. The areas of cultivated land and water bodies were relatively large, so the ESVs they provided were high. Low-value and moderate-low-value areas were mainly

distributed in dune regions in the middle of the study area. The moderate-value area was distributed in the shape of a circle around the moderate-high-value area, and this area decreased gradually, potentially because the transfer of grasslands to cultivated land led to a continuous change from the moderate-value area to the moderate-high-value area.

3.3 Spatiotemporal dynamic analysis of the ERI

In general, the ERI of the study area was low in the northeast and high in the southwest (Figure 4). The study area was dominated by a moderate-high-risk area, which was mainly

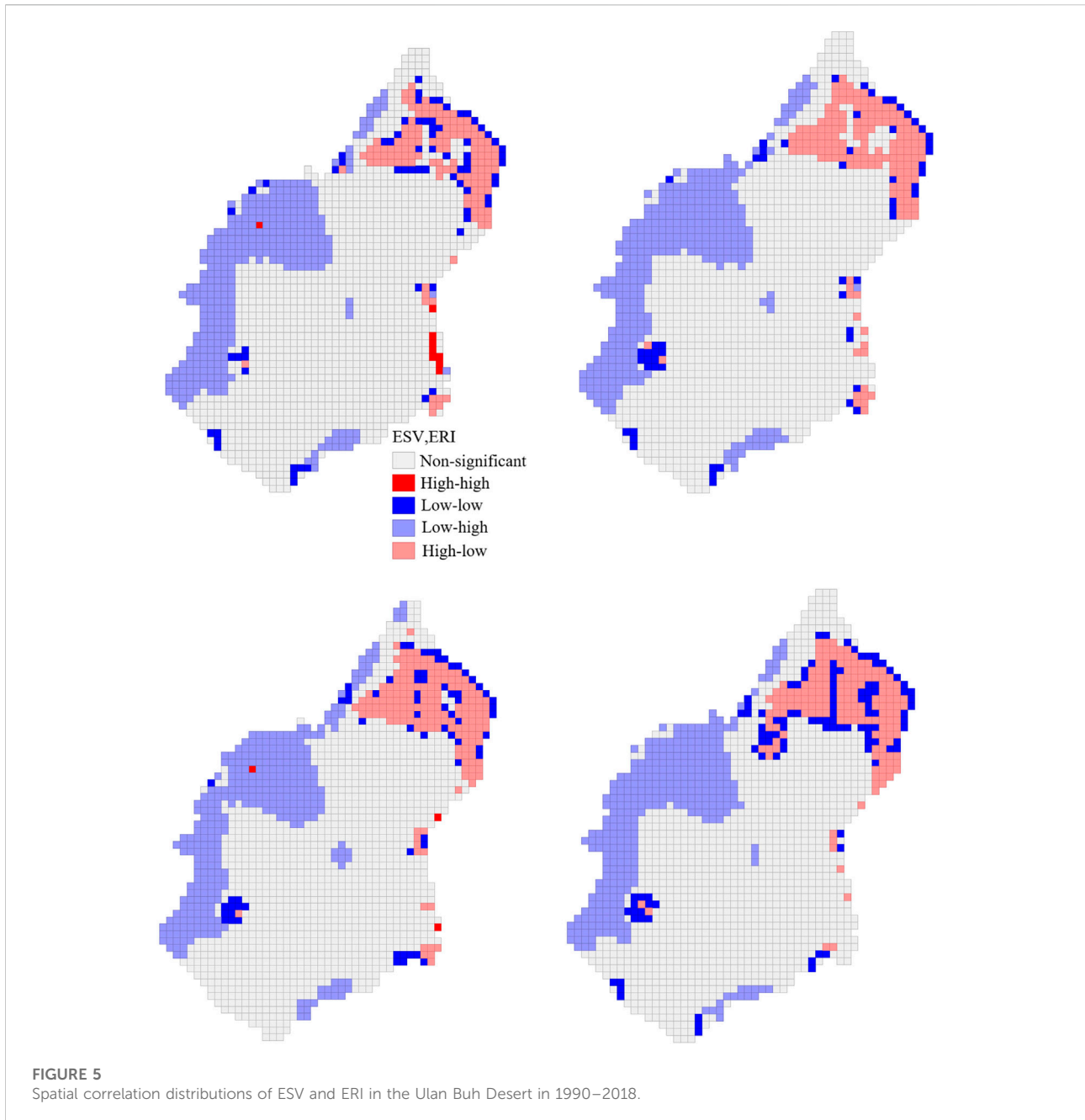


distributed in the dune area. However, the area of moderate-high risk decreased from $99.83 \times 10^4 \text{ hm}^2$ to $90.88 \times 10^4 \text{ hm}^2$ from 1990 to 2018. The ecological risk status of the northeast plain region gradually improved, and moderate-risk and moderate-high-risk areas gradually changed to low-risk and moderate-low-risk areas.

3.4 Spatial correlations of ESV and the ERI

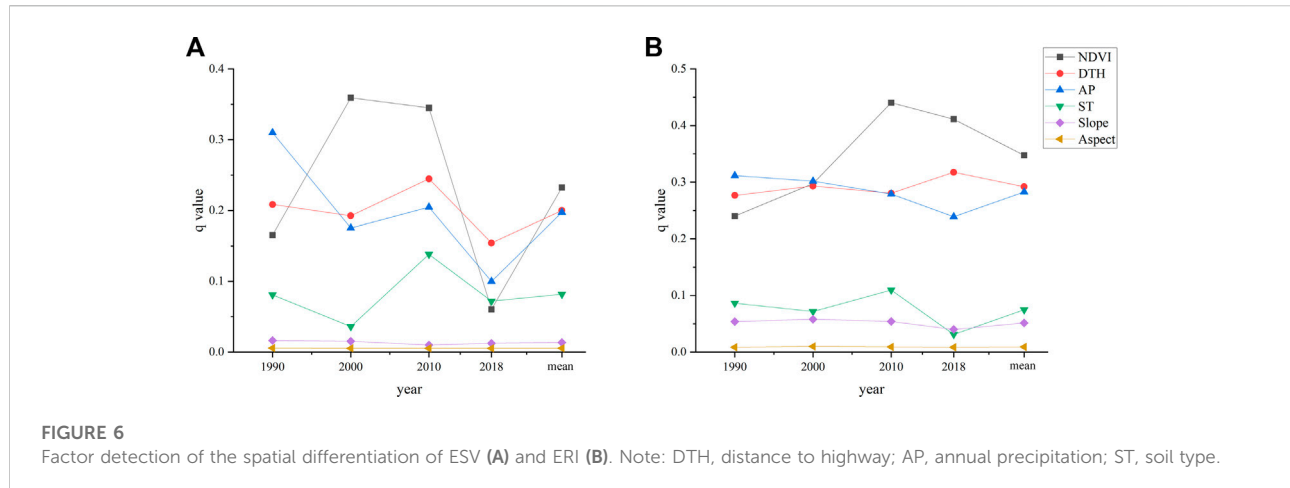
Based on the bivariate local spatial autocorrelation method of GeoDa software, the correlation between the

ESV and ERI of the Ulan Buh Desert was analyzed. The results show that the Moran's I index values for 1990–2018 ranged from -0.103 , -0.209 , and -0.217 to -0.136 , indicating that there was a certain negative correlation between ESV and the ERI in the Ulan Buh Desert. As shown in Figure 5, the areas where ESV and the ERI were significantly correlated were mainly distributed in other land areas in the western Ulan Buh Desert and along the northeastern border with the Hetao Plain. The areas were divided into five patterns with regard to correlation behavior: high value-high risk, low value-low risk, low value-high risk, high value-low risk and non-significant correlation (Figure 5).



Low value-high risk areas refer to areas with low ESVs per unit area but high ERIs; these areas were mainly distributed in the town of Jilantai and the eastern area of the town of Aolunbulage and accounted for 19.64%, 20.22%, 19.99%, and 19.35% of the overall area in 1990, 2000, 2010 and 2018, respectively. High value-low risk areas refer to areas with high ESVs per unit area but low ERIs; these regions were mainly distributed in the northeastern part of the study area. Their areal proportion showed a fluctuating growth trend, increasing from 8.10% in

1990 to 9.97% in 2018. High value-high risk areas refer to areas with high ESVs and ERIs. These regions were distributed along the Yellow River in the eastern part of the study area, accounting for approximately .52% of the study area in 1990. There was no clustered distribution of high value-high risk areas from 2000–2018. Low value-low risk areas refer to areas with low ESVs and ERIs. These regions were scattered in the northeastern part of the study area but concentrated in the building land area. The non-significant correlation area accounted for 64.39–67.54%



of the total study area and was dominated by various types of sand dunes that were continuously distributed over a large area.

3.5 Analysis of driving forces of ESV and the ERI

A factor detector can detect the explanatory degree of different driving factors to dependent variables, and the higher the q value is, the greater the explanatory degree is. Figures 6A, B show the contributions of different factors to the spatial differentiation of ESV and the ERI. In terms of the q mean, the explanatory power of each ESV driver could be ranked in descending order as follows: the NDVI (.233) > distance to a highway (.200) > soil type (.197) > precipitation (.082) > slope (.014) > aspect (.005). The NDVI, distance to a highway and soil type were the main driving factors of ESV spatial differentiation, while precipitation, slope and aspect were secondary factors. The explanatory powers of the ERI drivers, in descending order, were as follows: the NDVI (.347) > distance to a highway (.292) > soil type (.283) > precipitation (.075). The NDVI, distance to a highway and soil type were the main driving factors of the spatial distribution of ERI, while precipitation, slope and aspect were secondary factors. On the whole, the influence of natural factors on the spatial differentiation of ESV and the ERI was greater than that of human impact factors.

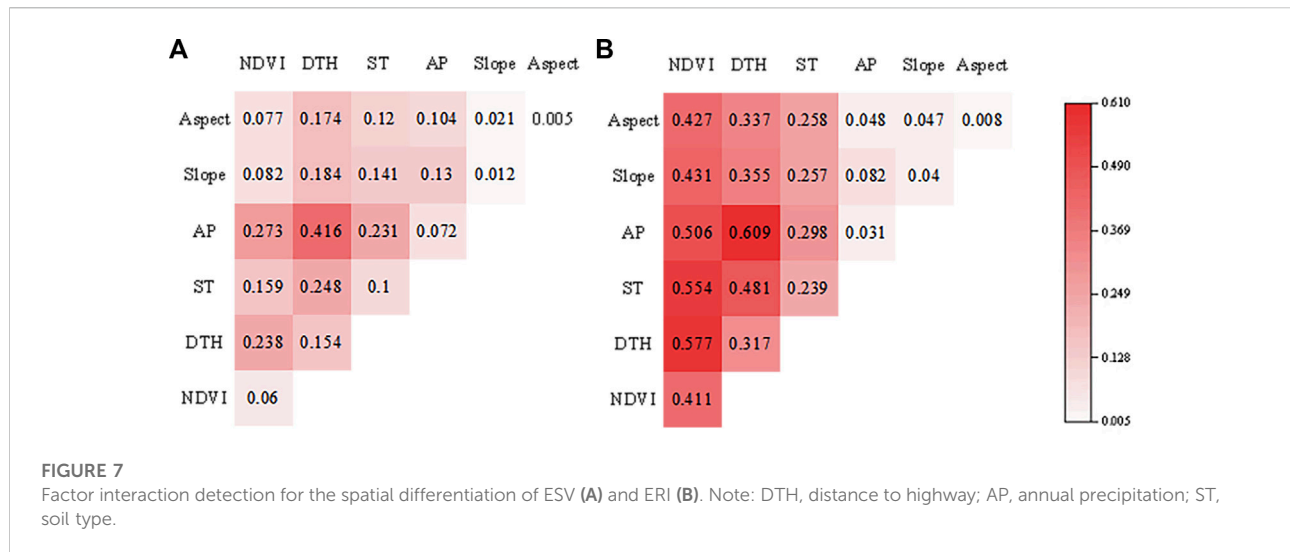
The interaction results of various ESV-influencing factors show that the interaction between any two factors was stronger than that of any single factor, indicating that ESV in the study area was affected by the interactions among multiple factors (Figure 7A). The interaction between the distance to a highway and precipitation was the strongest (41.6%). The interactions between the distance to a highway and other factors were significantly stronger than the interactions among other factors, further proving the important effect of the distance to

a highway on the spatial differentiation of ESV. This result also shows that natural and human impact factors affected spatial patterns of ESV in the study area. Among the ERI-influencing factors, the interaction of any two factors had a greater influence on ERI than any single factor itself (Figure 7B). Among them, the interactive interpretation of the distance to a highway and precipitation was the strongest, reaching 60.9%. The interaction of any two factors significantly enhanced the influence of each factor on the ERI, indicating that the spatial differentiation of the ERI in the study area was jointly affected by multiple factors.

4 Discussion

4.1 Influencing factors and strategies based on spatial correlation

ESV showed a trend of first decreasing and then increasing, while the ERI decreased year by year from 1990 to 2018. The driving force results show that the distance to a highway and NDVI are the main factors affecting the spatiotemporal differentiation of ESV and the ERI in the study area, while the interaction of distance to a highway and annual precipitation has the strongest effect on these variables in the study area (Yu et al., 2020; Sun, et al., 2021). ESV showed a trend of first decreasing and then increasing from 1990–2018. Coincidentally, the annual change in precipitation in the Ulan Buh Desert is similar to that of ESV, which also indirectly indicates the strong influence of precipitation on ESV (Sánchez-Canales et al., 2012). ESV in the study area reached its peak in 2018. This may be attributed to the increase in precipitation, which provided sufficient water for the growth of vegetation and crops (Long et al., 2022). At the same time, the construction of new roads also enabled the transmission of



human and material resources, which was also conducive to the growth of vegetation (Klarenberg et al., 2018; Carvalho and Szlafsztein, 2019). This will further lead to the improvement of ecological functions such as food production and raw material supply. The ERI decreased year by year from 1990 to 2018. As the main factor affecting the distribution of the ERI, the NDVI showed an increasing trend during the study period. The increase in vegetation coverage plays an important role in suppressing sand dust storms and soil wind erosion (Yu, 2018), reducing ecological risks faced in the study area. After 2010, the construction of highways increased ecological risk in the study area to a certain extent. However, in general, the increase in precipitation and NDVI has offset the negative impact of highway construction on ecological risk, so ecological risk in the study area is decreasing year by year.

Spatially, previous studies (Wang, 2019) and this study found that higher ESV was mainly distributed across the northeast plain and Yellow River shore with lower risk levels. The areas of lower ESV were mainly concentrated in dunes in middle and other land areas in the west with higher risk. Forests, grassland and cultivated land are widely distributed in the northeast plain and along the Yellow River with relatively high vegetation coverage. The types of ecosystem services provided are complex and diverse, and ecosystem functions are relatively stable. Meanwhile, the transportation of human and material resources is very convenient due to the short distance to a highway, which is conducive to expanding the planting range of crops and the degree of water use. This will lead to the improvement of food production, raw material supply and other functions. The high vegetation coverage in the northeast plain helps suppress sand dust storms, thus reducing the possibility of ecological risks. Various sand dunes are widely distributed in the middle of the study area with relatively low vegetation coverage. The ESV provided is low due to the presence of relatively simple ecosystem functions. At the same time, the bare surface is also vulnerable to natural disasters such as

sandstorms and landslides. The interaction of distance to a highway and precipitation had the strongest effect on the ERI, meaning that the closer an area is to a highway, the higher the degree of ecological risk faced by the arid region is. The northwestern part of the town of Jilantai and the town Aolunbulage are located close to a highway and experience relatively little annual precipitation, so they face high levels of ecological risk (Li L et al., 2022). In addition, the distributions of ESV and the ERI were related to annual precipitation. However, the overall difference in precipitation in this study area was not significant, so it had a limited influence.

In general, the total ESV in the Ulan Buh Desert increased from 1990 to 2018 but still presented high landscape ecological risk. To prevent the spread and transfer of high-ecological-risk areas, corresponding governance measures should be taken based on the zoning results of the spatial correlation between ESV and the ERI: the study area was dominated by low value-high risk areas, accounting for approximately 19.8% of the entire study area. Landscape types in these regions mainly include the Gobi Desert, mountainous regions and other land types. While the ESVs were low in these regions, they faced high levels of ecological risk. The protection and restoration of such land use types should be strengthened, and attention should be given to reducing damage to the ecological environments in these areas. Landscape types in the high value-low risk areas mainly included grasslands and cultivated land, and the ecosystem services provided by these land types were relatively significant. It is necessary to strengthen the protection and restoration of cultivated land ecosystems in this area and at the same time reduce human disturbances to the grassland ecosystems. Resources should be rationally used to maintain normal ecosystem functions; in addition, the Yellow River shore was identified as the main center of high value-high risk areas. While serving as the main supply area for ecosystem services in the study area, it also faced risks of drying up and

being converted by other land types. Therefore, supplemental ecological water projects should be reasonably carried out to improve the utilization efficiency of water resources, optimize the use of Yellow River water resources and alleviate the discrepancy between the supply and demand of local water resources. Low value-low risk areas were scattered in the northeastern plain region, and landscape types in these areas mainly included dunes and cultivated land. All kinds of dunes present are very likely to expand to surrounding areas, resulting in enlarged land desertification areas. The “Three North Shelter Forest” project should be continued to prevent the transfer and expansion of these dunes. Meanwhile, ecological agriculture and deserticulture should be carried out in a concentrated manner to increase vegetation coverage and achieve the effects of windbreaks and sand fixation, thereby reducing ecological risk and improving ecosystem functions.

4.2 Limitations and further research

The purpose of this study was to explore the spatiotemporal variation characteristics of ESV and the ERI, along with their driving mechanisms, in the Ulan Buh Desert to provide a theoretical basis for the scientific management and optimization of land use patterns. However, this work has some limitations. First, the basic data used are insufficient. Only four-phase remote sensing image data for 1990, 2000, 2010 and 2018 are used, and these data cannot accurately express specific spatiotemporal changes in ESV and the ERI from 1990–2018. Second, there is an obvious scale effect in the spatiotemporal distribution characteristics of the ESV and landscape ERI results (Yang et al., 2021). This paper analyzes driving factors only for the entire study area and cannot fully explain differences or influencing factors in local areas. Therefore, further identifications should be made in the future, priority areas for ecological security should be further identified in the future, and the influencing factors of these priority areas should be explored in a more targeted way to provide more detailed scientific guidance for local ecological security governance.

5 Conclusion

Based on four-phase land use data of the Ulan Buh Desert for 1990 to 2018 and with the technical support of ArcGIS 10.2 and Geodetector, in this paper, we evaluated spatiotemporal differences in ESV and the ERI for the Ulan Buh Desert. The driving mechanism behinds these variations were revealed using the Geodetector model, and the following results were obtained:

- 1) The ESV of the Ulan Buh Desert showed a fluctuating growth trend, ranging from 7.00×10^8 yuan in 1990 to 6.17×10^8 yuan in 2000 and then increasing to 11.09×10^8 yuan in 2018; the change rate was approximately 58.41%. The study area was dominated by high-risk areas, which were mainly distributed in dune regions. The high-risk area decreased year by year from 1990–2018.
- 2) There was a certain negative correlation between the ESV and ERI of the Ulan Buh Desert from 1990–2018.
- 3) The Geodetector results show that the interaction between the distance to a highway and precipitation was the main factor affecting the spatiotemporal differentiation of ESV and the ERI in the Ulan Buh Desert.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

HL and RW wrote the manuscript. HS and WC helped design the structure of the manuscript and discussed the methods. JS collected the data. LWe, YZ, XZ, and LWa were involved in the study design and critically revised the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The handling editor JW is currently organizing a Research Topic with the author LW.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenvs.2022.1053797/full#supplementary-material>

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