

Article

Optimizing Ecological Zoning in Arid Oases Based on the Multivariate Ecological Security Index: A Case Study of the Kashgar Oasis, China

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Abstract

Global climate change and rapid urbanization have intensified ecological security risks in arid oasis regions, creating an urgent need for reliable ecological security assessment and spatial zoning to support regional sustainable development. Taking the Kashgar Oasis as the study area, this study combined the pressure-state-response (PSR) framework with the Mazziotta–Pareto Index (MPI) to construct a Multivariate Ecological Security Index (MESI), with the aim of reducing excessive compensation among different ecological dimensions and highlighting ecological weaknesses. Based on multisource spatial data from 2010 to 2025, we further examined the spatiotemporal evolution of ecological security, spatial relationships among ecological dimensions, and ecological security zoning. The main results were as follows: (1) Ecological security exhibited a pronounced spatial gradient, with higher levels in mountainous areas, intermediate levels in oasis areas, and lower levels in desert areas. High ecological security areas were concentrated mainly in mountainous regions, river corridors, and natural oasis areas, whereas low ecological security areas occurred primarily in urban expansion areas, agricultural development zones, and desert margins. (2) Ecological security changed substantially over the study period, following three successive stages: expansion of moderate-security areas, increasing spatial differentiation, and overall recovery, with the recovery trend becoming increasingly apparent after 2020. (3) The ecological dimensions exhibited marked spatial heterogeneity. Mountainous areas and river corridors were generally characterized by lower human disturbance, lower land desertification sensitivity, and higher ecosystem service capacity, whereas oasis margins and urban expansion fronts showed more complex spatial mismatches and potential trade-offs. (4) Six ecological security functional zones were delineated based on multidimensional ecological characteristics and the overall ecological security state, and differentiated management strategies were proposed for the respective zones. Overall, by jointly considering multiple ecological dimensions and their imbalances, this study links ecological security assessment, spatial relationship identification, and spatially continuous zoning, thereby providing an integrated analytical framework for identifying ecological weaknesses and supporting differentiated ecological management in arid oasis regions.



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1. Introduction

Oases are ecological and socioeconomic hubs in arid regions. They maintain ecological balance, provide essential ecosystem services, and support regional development [1,2].

Despite their importance, oasis ecosystems are highly vulnerable because of limited natural resources and fragile environmental conditions [3]. Climate warming has intensified water scarcity and land degradation [4], while urban expansion, agricultural development, and transportation infrastructure have increased human disturbance. Together, these pressures alter landscape patterns, degrade habitats, and weaken ecosystem functions [5]. As a result, ecological security has become a major challenge for oasis sustainability. Assessing ecological security and identifying ecological management zones are therefore essential for improving ecological resilience and supporting sustainable development [6,7].

Ecological security describes an ecosystem's ability to maintain its health, integrity, and long-term stability while continuously providing resources and ecosystem services for human well-being [8]. Growing environmental challenges have made ecological security a global concern and a major research topic in geography, ecology, and environmental science [9,10]. Existing assessment approaches include ecological footprint analysis [11], indicator-based assessment [12], and landscape ecological analysis [13]. Ecological footprint analysis focuses on the balance between resource supply and demand but provides limited information on ecosystem processes [14]. Landscape ecological analysis captures changes in landscape patterns but cannot fully represent the combined effects of environmental constraints and anthropogenic activities on ecosystem function [15]. Because ecological security in arid oases is driven by both natural and anthropogenic factors, no single method can adequately capture its complexity. The pressure–state–response (PSR) framework overcomes this limitation by integrating ecological pressure, ecosystem state, and ecological response into a unified assessment framework. Owing to its clear structure and broad applicability, it has become one of the most widely adopted frameworks for ecological security assessment [16,17].

Despite substantial progress, current studies still have several limitations. Most indicator systems are integrated using compensatory weighting methods, such as the analytic hierarchy process (AHP) and the entropy weighting method. These approaches rely partly on subjective weight assignment and assume that indicators are fully substitutable, which may introduce compensation effects [18,19]. This assumption is often unrealistic for arid oases, where ecological security is constrained by scarce water resources, severe desertification risk, and intense human–environment conflicts [20]. Under these conditions, the weakest ecological factor often determines the overall system performance, resulting in threshold effects and nonlinear responses [21]. Consequently, compensatory methods may conceal critical weaknesses, underestimate ecological vulnerability, and overestimate ecological security. The Mazziotta–Pareto Index (MPI) has recently emerged as an effective noncompensatory alternative. By introducing an imbalance penalty mechanism, the MPI reduces compensation among indicators and better identifies the factors limiting ecological security [22]. These advantages make it particularly suitable for ecological security assessment in environmentally constrained and ecologically fragile arid oases [23].

Ecological security zoning serves as an important bridge between ecological security assessment and ecological governance. It identifies spatial differences in ecological security and provides a scientific basis for resource allocation and differentiated governance [24]. Existing studies have widely applied quadrant analysis, K-means clustering, and self-organizing maps (SOM) to delineate ecological zones [25]. However, traditional clustering methods primarily group areas according to attribute similarity and pay limited attention to spatial adjacency. This often produces fragmented zoning results that are unsuitable for practical ecological management [26]. Moreover, ecological security depends on interactions among multiple ecological dimensions rather than on individual indicators. Synergistic and trade-off relationships among ecological dimensions cannot be captured through ecological security classification alone. Spatially Constrained Multivariate Clustering improves

zoning continuity by incorporating spatial adjacency constraints [27,28], whereas trade-off and synergy analyses reveal interactions among ecological dimensions [29]. Nevertheless, existing studies have generally applied these approaches independently, with limited integration between analyses of the spatial organization of ecological security and relationships among ecological dimensions. As a result, the linkage between ecological security zoning and ecological governance remains inadequate.

To address these research gaps, this study focuses on two interrelated scientific questions: (1) how ecological security can be comprehensively assessed while accounting for imbalances and limiting-factor effects among ecological pressure, land desertification sensitivity, and ecosystem service capacity in arid oases; and (2) how spatial trade-offs and synergies among different ecological security dimensions can be identified and the resulting ecological security assessment translated into spatially continuous, functionally differentiated, and management-relevant ecological units. To address these questions, this study applies the pressure–state–response (PSR) framework and employs the Mazziotta–Pareto Index (MPI) to construct the Multivariate Ecological Security Index (MESI) [23]. Ecological security patterns in the Kashgar Oasis are then examined from three complementary perspectives: ecological security dynamics, spatial trade-offs and synergies among ecological dimensions, and the spatial organization of ecological security.

The main contribution of this study lies in incorporating imbalances and limiting-factor effects among ecological security components into the analytical framework and integrating ecological security assessment, spatial relationship analysis, and Spatially Constrained Multivariate Clustering into an ecological security assessment and zoning framework for arid oases. The MPI-based MESI reduces excessive compensation among ecological dimensions and highlights ecological constraints arising from imbalances among them, thereby mitigating the tendency of conventional compensatory aggregation methods to obscure ecological weaknesses. Building on this assessment, the spatial relationship analysis identifies synergies, trade-offs, and spatial mismatches among the ecological security dimensions, while separately examining the spatial associations between each component dimension and the overall ecological security state represented by MESI. This distinction provides a more comprehensive characterization of the spatial organization of ecological security. Spatially Constrained Multivariate Clustering further incorporates both the component dimensions and MESI: the former characterize the specific features of different ecological security dimensions, whereas MESI represents the overall state reflecting their integrated level and degree of imbalance. The resulting zoning therefore accounts for both dimension-specific differences and the overall ecological security state. By maintaining spatial continuity, this approach translates multidimensional differences in ecological security into management units with distinct ecological characteristics, thereby improving the rationale, spatial interpretability, and management relevance of ecological security zoning.

2. Materials and Methods

2.1. Study Area

The Kashgar Oasis is located on the western margin of the Tarim Basin in southern Xinjiang, China (Figure 1). It covers approximately 12,355 km² and comprises the main oasis and several surrounding smaller oases [30]. To ensure the integrity of administrative units, this study defines the research area as the 11 counties and county-level cities associated with the oasis. The study area encompasses the oasis and its surrounding mountainous areas, Gobi landscapes, and desert ecosystems, including areas along the margins of the Taklimakan Desert. The region features a typical oasis landscape formed through long-term alluvial deposition by the Kashgar River. It has a temperate continental arid climate with

low precipitation and high evaporation [31,32]. Ecosystems are fragile and have long been subject to water scarcity and land desertification [33].

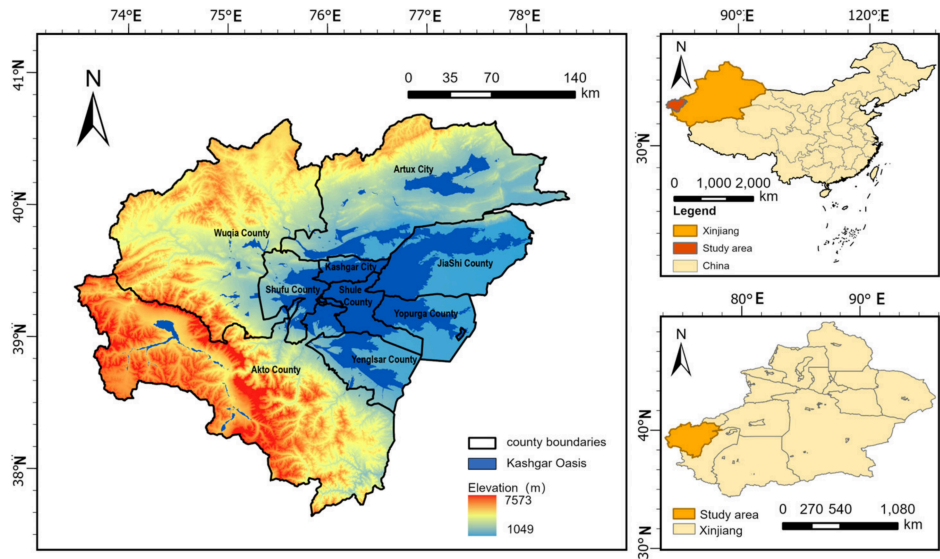


Figure 1. Location of the Kashgar Oasis.

2.2. Data Sources

In this study, multiple spatial datasets, including land use, topography, climate, vegetation, soil, population, nighttime light, and road network data, were integrated to evaluate ecological security. Table 1 summarizes the spatial resolution and sources of all the datasets. To ensure consistency across datasets, all spatial data were projected into the WGS 1984 UTM Zone 43 N coordinate system. Data preprocessing, including clipping and resampling, was performed using ArcGIS 10.8. This preprocessing ensured a consistent basis for the subsequent calculation of ecological security indicators and spatial analyses.

Table 1. Data sources and spatial resolutions.

Data	Spatial Resolution	Year	Source
Population	1 km	2010, 2015, 2020, 2025	WorldPop (https://www.worldpop.org/)
Nighttime Lighting Index	1 km	2010, 2015, 2020, 2025	Resource and Environment Science and Data Center (https://www.resdc.cn/)
Distance to road	—	—	OpenStreetMap (https://www.openstreetmap.org/)
Land use	30 m	2010, 2015, 2020, 2025	[34]
Grazing Intensity	250 m	2010, 2015, 2020, 2024	National Earth System Science Data Center (https://www.nesdc.org.cn/)
DEM	30 m	2025	Geospatial Data Cloud (https://www.gscloud.cn/)
Slope	30 m	2025	Derived from DEM
Normalized Difference Vegetation Index (NDVI)	30 m	2010, 2015, 2020, 2025	U.S. Geological Survey (USGS), via Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_COMPOSITES_C02_T1_L2_ANNUAL_NDVI) (accessed on 29 August 2026)
Fractional vegetation cover (FVC)	30 m	2010, 2015, 2020, 2025	Derived from NDVI

Table 1. Cont.

Data	Spatial Resolution	Year	Source
Aridity Index	1 km	2010, 2015, 2020, 2024	National Earth System Science Data Center (https://www.geodata.cn/)
Wind speed	1 km	2010, 2015, 2020, 2025	National Cryosphere Desert Data Center (https://www.ncdc.ac.cn/)
Precipitation	1 km	2010, 2015, 2020, 2025	National Earth System Science Data Center (https://www.geodata.cn/)
Evapotranspiration	1 km	2010, 2015, 2020, 2025	National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdc.ac.cn/)
Depth of root limiting layer	1 km	—	[35]
Plant available water content	—	—	ISRIC—World Soil Information (https://data.isric.org/)
Harmonized World Soil Database (HWSD) soil data	100 m	2025	Resource and Environment Science and Data Center (https://www.resdc.cn/)
Administrative boundary	—	2025	Tianditu (https://www.tianditu.gov.cn/)

2.3. Ecological Security Assessment

2.3.1. Construction of the Assessment Framework

The Kashgar region is located within a typical arid oasis–desert transition zone, where ecological security is jointly influenced by strong human disturbance, environmental sensitivity, and ecosystem service capacity. In accordance with the environmental characteristics of the study area, this study constructed the Multivariate Ecological Security Index (MESI) using the Mazziotta–Pareto Index (MPI) within the pressure–state–response (PSR) framework to provide an integrated representation of regional ecological security and establish the ecological security assessment framework (Figure 2). On this basis, the spatiotemporal evolution of ecological security was further examined, trade-offs and synergies among different ecological security dimensions were identified, and ecological security zoning was conducted.

Specifically, the pressure (P) component represents external human disturbance imposed on ecosystems and is characterized by the Human Footprint Index (HFI), which integrates population density, nighttime light intensity, transportation disturbance, land use disturbance, and grazing intensity [36]. The state (S) component reflects ecosystem conditions and susceptibility under prevailing environmental and land-use conditions [37]. In arid oasis systems, desertification is a major manifestation of ecological vulnerability and is strongly influenced by soil properties, topography, vegetation, climatic aridity, wind conditions, and land use. Accordingly, the Land Desertification Sensitivity Index (LDSI) was adopted to characterize state-related ecological sensitivity and susceptibility to land degradation in the Kashgar Oasis. In this study, the response (R) component reflects the capacity of ecosystems to respond to environmental pressures and maintain essential ecological functions. This interpretation represents an operational adaptation of the conventional PSR framework, in which the response dimension more commonly refers to societal or institutional responses; in this study, it is used to characterize ecosystem functional response capacity rather than direct human or institutional responses. It is represented by the Comprehensive Ecosystem Service Index (CESI), which integrates four ecosystem services—water retention, carbon storage, habitat quality, and soil conservation—to characterize

ecosystem functional performance in regulating ecological processes and buffering environmental disturbances [38,39]. Together, these three components provide a multidimensional representation of ecological security in arid oasis systems.

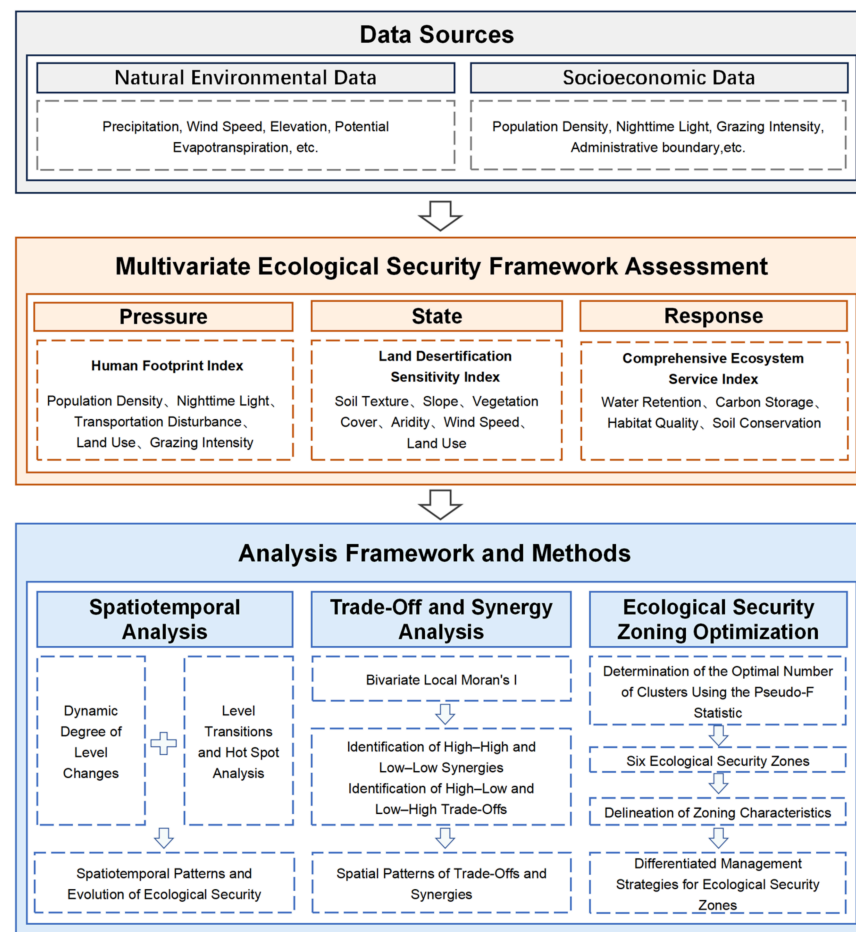


Figure 2. Research framework and methodological workflow.

Building on these three component dimensions, the MPI-based MESI provides an integrated representation of the overall ecological security state arising from their combined effects. MESI is neither a fourth ecological security dimension independent of pressure, state, and response nor a simple linear aggregation of its component indices; rather, it captures both the overall level of the component dimensions and the degree of imbalance among them. Accordingly, subsequent analyses distinguish relationships among the component dimensions as synergies, trade-offs, and spatial mismatches, while relationships between each component dimension and MESI are defined as spatial associations with the overall ecological security state. Ecological security zoning follows the approach adopted in previous studies for integrating multidimensional ecological characteristics [40], while simultaneously accounting for dimension-specific differences and the overall state represented by MESI.

2.3.2. Human Footprint Index

The human footprint index (HFI) was used to quantify the intensity of human disturbance to natural ecosystems. Five indicators were selected on the basis of the HFI proposed by Sanderson et al. [41], previous studies [42], and the major ecological issues in the study area: population density, nighttime light intensity, transportation disturbance, land use disturbance, and grazing intensity.

Transportation disturbance was evaluated using the road disturbance classification method proposed in previous studies [43], with modifications to reflect the road network of the study area. Disturbance scores were assigned to each road category according to its ecological impact (Table 2), with higher scores indicating greater disturbance. The overall transportation disturbance intensity was calculated as the sum of the scores across all road categories.

Table 2. Road disturbance scores.

Road Type	Road Buffer Distance (km)			
	0–1	1–5	5–10	10–15
Expressway	10	8	7	5
Railway	9	7	5	3
Arterial Road	10	8	4	2
Primary Road	8	6	3	0
Secondary Road	7	5	3	0
Tertiary Road	6	4	1	0
Minor and Other Roads	2	0	0	0

Land use disturbance was quantified by assigning disturbance scores to different land use types. Impervious surfaces were assigned the highest disturbance score, followed by cropland, water bodies and wetlands, forests, shrublands and grasslands, and bare land and permanent snow/ice, with scores of 9, 7, 5, 3, and 0, respectively. The land use interference score (LUIS) was calculated on the basis of previous studies [44] as follows:

$$LUIS = \sum_{i=1}^n P_i \times S_i \quad (1)$$

where P_i is the proportion of land use type i within a grid cell and S_i is the disturbance score assigned to land use type i .

2.3.3. Land Desertification Sensitivity

The land desertification sensitivity index was developed on the basis of the environmental characteristics of the study area and the availability of relevant datasets. Indicator selection followed the revised Mediterranean Desertification and Land Use (MEDALUS) model [45,46], the desertification sensitivity assessment method proposed in the Technical Specification for Ecological Function Regionalization [47], the assessment model described in the Guidelines for Delineating Ecological Conservation Redlines [48], and previous related studies [49]. Six indicators were ultimately selected to characterize land desertification sensitivity: soil texture, slope, vegetation cover, aridity, wind speed, and land use. Soil texture and land use were classified and scored according to the criteria reported in previous studies, while the remaining indicators were treated as continuous variables (Table 3).

Table 3. Classification criteria for the land desertification sensitivity index.

Category	Insensitive	Slightly Sensitive	Moderately Sensitive	Highly Sensitive	Extremely Sensitive
Soil Texture	Bedrock	Clayey	Gravelly	Loamy	Sandy
Land Use	Bare Land	Snow/Ice, Impervious Surface	Cropland, Water Bodies, Wetlands	Forest	Shrubland, Grassland
Score	1	3	5	7	9

2.3.4. Comprehensive Ecosystem Service Index

The comprehensive ecosystem service index (CESI) integrates multiple ecosystem services and reflects regional ecosystem service capacity. On the basis of the InVEST (version 3.20.0) modeling framework, four key ecosystem services—water retention, carbon storage, habitat quality, and soil conservation—were selected for assessment in consideration of previous studies and data availability in the study area. The evaluation methods are described below.

Water Retention

Water retention was estimated using the water balance approach, in which the difference between precipitation and evapotranspiration was used to characterize the capacity of vegetation and soil to intercept, infiltrate, and regulate precipitation. The water retention service was calculated by adjusting the water yield generated by the InVEST model using the topographic index:

$$WR_{xi} = \min\left(1, \frac{249}{V_i}\right) \times \min\left(1, \frac{0.9 \times TI_x}{3}\right) \times \min\left(1, \frac{K_x}{300}\right) \times Y_{xi} \quad (2)$$

$$TI_x = \log\left(\frac{\text{Drainage Area}}{\text{Soil Depth} \times \text{Percent Slope}}\right) \quad (3)$$

where WR_{xi} denotes the annual water retention (mm) of grid cell x for land use type i ; V is the flow velocity coefficient (dimensionless), which represents the influence of different land use types on surface runoff; TI_x denotes the topographic index, which is calculated from the contributing drainage area, soil depth, and slope percentage; and K_x is the saturated soil hydraulic conductivity; and Y_{xi} denotes the annual water yield (mm) of grid cell x for land use type i . The flow velocity coefficients were assigned following previous studies and local environmental conditions [50]. The parameter values are listed in Table A1 of Appendix A.

Carbon Storage

Carbon storage was estimated using land use data. Total ecosystem carbon storage was calculated as the sum of carbon stored in aboveground biomass, belowground biomass, soil organic matter, and dead organic matter:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (4)$$

where C_{total} denotes the total ecosystem carbon storage ($\text{t} \cdot \text{hm}^{-2}$) and C_{above} , C_{below} , C_{soil} , and C_{dead} denote the carbon densities of aboveground biomass, belowground biomass, soil organic matter, and dead organic matter, respectively. Carbon density values were adjusted following previous studies and local environmental conditions [51]. The corrected values are provided in Table A2 of Appendix A.

Habitat Quality

Habitat quality was estimated on the basis of habitat suitability, the intensity and weights of threat factors, and the sensitivity of different land use types to these threats. The habitat quality index reflects habitat integrity and ecological suitability and was calculated as follows:

$$Q_{xj} = H_j \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right) \quad (5)$$

where Q_{xj} denotes the habitat quality index of land use type j at grid cell x (0–1); H_j denotes habitat suitability; D_{xj}^z denotes the cumulative threat level affecting grid cell x ; k is the half-saturation constant; and z is the scaling constant. Model parameters were determined

following previous studies and local environmental conditions [52]. The detailed parameter values are listed in Tables A3 and A4 of Appendix A.

Soil Conservation

Soil conservation was estimated as the difference between potential soil loss and actual soil loss. This approach measures the capacity of vegetation and soil to reduce soil erosion.

$$SC = A_p - A_a \quad (6)$$

$$A_p = R \times K \times LS \quad (7)$$

$$A_a = R \times K \times LS \times C \times P \quad (8)$$

where SC denotes the soil conservation amount ($\text{t} \cdot \text{hm}^{-2} \cdot \text{a}^{-1}$), A_p denotes potential soil loss without vegetation cover, A_a denotes actual soil loss under existing land-cover conditions, R is the rainfall erosivity factor, K is the soil erodibility factor, LS is the slope length and steepness factor, C is the vegetation cover and management factor, and P is the conservation practice factor.

The rainfall erosivity factor (R) describes the potential of rainfall to cause soil erosion. It was calculated using the Wischmeier empirical equation [53] and monthly precipitation data interpolated with the ANUSPLIN method:

$$R = \sum_{i=1}^{12} 1.735 \times 10^{(1.51 \lg \frac{P_i^2}{P} - 0.8188)} \quad (9)$$

where R denotes the rainfall erosivity factor ($\text{MJ} \cdot \text{mm} \cdot \text{hm}^{-2} \cdot \text{h}^{-1} \cdot \text{a}$), P denotes the annual precipitation (mm), and P_i denotes the precipitation in month i (mm).

The soil erodibility factor (K) represents the susceptibility of soil to rainfall-induced detachment and transport. It was estimated using the EPIC model based on soil texture data:

$$K = \{0.2 + 0.3 \exp[-0.0256 SAN(1 - SIL/100)]\} \cdot \left(\frac{SIL}{CLA + SIL} \right)^{0.3} \times \left[1.0 - \frac{0.25C}{C + \exp(3.72 - 2.95C)} \right] \times \left[1.0 - \frac{0.7SN_1}{SN_1 + \exp(-5.51 + 22.9SN_1)} \right] \quad (10)$$

where K denotes the soil erodibility factor ($\text{t} \cdot \text{h} \cdot \text{MJ}^{-1} \cdot \text{mm}^{-1}$); SAN , SIL , and CLA denote the sand, silt, and clay contents (%), respectively; C denotes the soil organic carbon content (%); and SN_i denotes the fraction of soil particles other than sand.

$$SN_i = 1 - SAN/100.$$

The soil conservation effect is controlled mainly by vegetation cover and management (C) and conservation practices (P), which represent the effects of biological and engineering measures on soil erosion control, respectively [54]. The C factor is defined as the ratio of soil loss under vegetation cover to that under bare soil (0–1), reflecting the protective effect of vegetation against rainfall erosion. The P factor is defined as the ratio of soil loss after conservation practices to that under upslope cultivation (0–1). Parameter values for the C and P factors were assigned following the Chinese Soil Erosion Regionalization Scheme [55] and previous studies conducted in the Tarim River Basin. The corresponding parameter values are listed in Table A5 of Appendix A.

2.4. Indicator Calculation and Classification

All indicators were standardized using positive or negative normalization according to their relationship with the target index. Different integration methods were then

adopted according to the characteristics of each index and the relationships among its secondary indicators.

The secondary indicators of the CESI exhibit synergistic and complementary effects. Their combined performance reflects the overall ecosystem service capacity. Therefore, the index was calculated using an entropy weight-based weighted summation model:

$$C = \sum_{i=1}^n w_i \cdot x_i \quad (11)$$

where C is the composite index, n is the number of indicators, w_i is the entropy-derived weight of the i th indicator, and x_i is the standardized value of the i th indicator.

The secondary indicators of the LDSI and the HFI exhibit a limiting-factor effect, whereby a single unfavorable indicator can substantially increase the overall sensitivity or disturbance level. Therefore, these indices were integrated using a multiplicative model:

$$S = \prod_{i=1}^n x_i = x_1 \times x_2 \times x_3 \times \cdots \times x_n \quad (12)$$

where S is the target index, x_i is the standardized value of the i th secondary indicator (which ranges from (0, 1)), and n is the number of secondary indicators.

To evaluate ecosystem conditions under external pressures, the Mazziotta–Pareto index (MPI) was employed to integrate the PSR-based indices and construct the MESI. By introducing a nonlinear penalty coefficient, the MPI reduces the compensatory effect among indicators and increases the influence of limiting factors, thereby providing a more robust assessment of ecological security in the study area. The index was calculated as follows:

$$MESI_i = M_{zi} \left(1 - cv_i^2 \right) \quad (13)$$

$$M_{zi} = \frac{\sum_{j=1}^3 z_{ij}}{3} \quad (14)$$

$$S_{zi} = \sqrt{\frac{\sum_{j=1}^3 (z_{ij} - M_{zi})^2}{3}} \quad (15)$$

$$cv_i = \frac{S_{zi}}{M_{zi}} \quad (16)$$

where $MESI_i$ is the $MESI$ of the i th grid cell, M_{zi} is the mean value of all the indicators, S_{zi} is the standard deviation of all the indicators, and cv_i is the coefficient of variation. A lower cv_i yields a penalty coefficient closer to 1, resulting in an $MESI$ value close to the mean indicator value and indicating high consistency among indicators. Conversely, a higher cv_i produces a smaller penalty coefficient and a lower $MESI$ value, suggesting that one or more limiting indicators constrain the ecological security level.

On the basis of the characteristics of the desert–oasis ecosystem and previous ecological security assessment studies in arid regions, the standardized $MESI$ values were classified into five ecological security levels using the natural breaks (Jenks) method. The five classes were very low, low, moderate, high, and very high. To ensure comparability across years, a unified set of classification thresholds was established from the complete time series $MESI$ dataset and applied consistently to all the study years. This approach reduces classification bias caused by interannual differences in data distribution and improves the reliability of spatiotemporal ecological security analyses.

2.5. Dynamic Degree Analysis

Dynamic degree analysis was used to quantify temporal changes in transitions among index classes over different periods. The dynamic degree indicates the annual rate and intensity of class transitions, reflecting the speed and magnitude of changes over time. The dynamic degree was calculated as follows:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{n} \times 100\% \quad (17)$$

where K denotes the annual dynamic degree of area transition for a given index class; U_a and U_b denote the areas of the corresponding transition type at the beginning and the end of the study period, respectively; and n is the duration of the study period (years).

2.6. Spatial Autocorrelation Analysis

Spatial autocorrelation was assessed using Moran's I , which measures the spatial dependence of a variable on the basis of its attribute values and geographic locations. Spatial autocorrelation was examined at both the global and local levels.

Global Moran's I was used to evaluate the overall spatial autocorrelation of ecological variables and determine whether their distributions were clustered, dispersed, or random. Positive Moran's I values indicate that neighboring spatial units have similar attribute values, whereas negative values indicate dissimilar neighboring values. Moran's I ranges from -1 to 1 . Values close to ± 1 indicate strong spatial autocorrelation, whereas values close to 0 indicate a random spatial distribution. The index was calculated as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (18)$$

where w_{ij} is the spatial weight between spatial units i and j ; x_i and x_j are the variable values of spatial units i and j , respectively; and $\bar{x}$ is the mean value of the variable.

Hot spot analysis was performed using the Getis-Ord G_i^* statistic to identify statistically significant clusters of high and low values. For each spatial feature, G_i^* is expressed as a z score. Higher positive z scores indicate stronger clustering of high values (hot spots), whereas lower negative z scores indicate stronger clustering of low values (cold spots).

Bivariate local Moran's I was employed to identify potential spatial trade-offs and synergies among HFI, LDSI, and CESI, and to examine spatial associations between the individual ecological security dimensions and MESI. This method reveals local spatial associations between two variables and classifies them into four patterns: high-high (HH), low-low (LL), high-low (HL), and low-high (LH). The statistics were calculated in GeoDa 1.22 as follows:

$$I_i^{KI} = \frac{x_i^K - \bar{x}_K}{S_K^2} \sum_{j=1}^n \left(w_{ij} \frac{x_j^I - \bar{x}_I}{S_I^2} \right) \quad (19)$$

where I_i^{KI} is the bivariate local Moran's I value for grid cell i ; x_i^K is the value of the K ecological environmental factor in grid cell i ; x_j^I is the value of the I ecological environmental factor in neighboring grid cell j ; and $\bar{x}_K$ and $\bar{x}_I$ are the mean values of the K and I ecological security dimensions, respectively.

2.7. Spatially Constrained Multivariate Clustering Analysis

This study employed the Spatially Constrained Multivariate Clustering tool in ArcGIS Pro 3.4 to account for both attribute homogeneity and spatial continuity in ecological security zoning. The method applies a regionalization approach based on a minimum spanning tree

(MST) [27]. By incorporating spatial connectivity constraints into the clustering process, it maintains spatially contiguous zones while improving within-zone attribute homogeneity.

The standardized values of LDSI, CESI, HFI, and MESI were used as clustering variables to jointly characterize dimension-specific ecological conditions and the overall ecological security state. Although MESI is mathematically derived from HFI, LDSI, and CESI and is therefore not independent of its component indices, it was retained as a complementary clustering variable rather than as an independent fourth ecological dimension. HFI, LDSI, and CESI characterize dimension-specific conditions, whereas MESI summarizes their integrated level and the degree of imbalance captured by the MPI penalty mechanism. A similar zoning approach that incorporates both component sub-indices and a composite index has also been applied in ecological zoning studies [40]. Spatial connectivity was defined using the Contiguity Edges Corners criterion, i.e., Queen contiguity, whereby grid cells sharing either a common edge or a common vertex were considered spatially adjacent.

3. Results

3.1. Spatiotemporal Evolution of Ecological Security Components

3.1.1. Human Footprint Index

The HFI exhibited a distinct concentric spatial pattern (Figure 3). Very low- and low-disturbance areas were located primarily in high-altitude mountains and interior deserts. In contrast, high- and very high-disturbance areas were concentrated in urban built-up areas, transportation corridors, and intensively cultivated farmland. The moderate-disturbance areas were distributed mainly along the oasis margins and urban–rural transition zones. Overall, the disturbance intensity decreased from the oasis core toward the surrounding mountains and desert, highlighting the strong spatial concentration of anthropogenic activities within the oasis ecosystem.

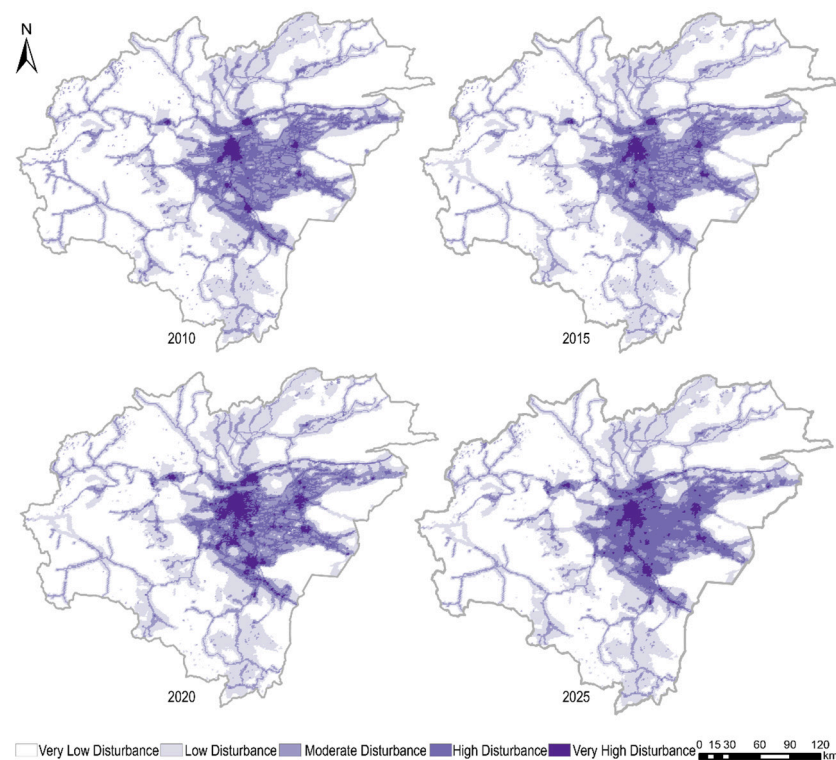


Figure 3. Spatial distribution of the human footprint index (HFI).

Temporal changes in the HFI exhibited clear stage-specific patterns (Table 4). Human disturbance remained relatively stable from 2010 to 2015. The most pronounced changes

occurred during 2015–2020, when the area under very high disturbance increased by 34.44%. From 2020 to 2025, the area under high disturbance expanded by a further 10.66%, whereas the area under very high disturbance decreased by 8.15%, indicating that human disturbance continued to expand while the spatial concentration of the highest-intensity disturbance declined.

Table 4. Dynamic degrees of the Human Footprint Index (HFI).

Period	Very Low	Low	Moderate	High	Very High	Overall Dynamic Degree
2010–2015	0.37%	0.78%	−0.78%	−3.55%	−0.47%	0.39%
2015–2020	−0.56%	0.45%	−1.33%	1.43%	34.44%	0.49%
2020–2025	−0.07%	−0.50%	−2.80%	10.66%	−8.15%	0.71%

Spatial transitions in the HFI were concentrated primarily within the oasis and along its margins (Figure 4), with the greatest changes occurring during 2015–2020. Hot spots of HFI change were located mainly in urban expansion areas, agricultural development zones, and along oasis margins, whereas mountainous areas and the interior desert remained relatively stable. Overall, the HFI followed a temporal sequence from relative stability to rapid expansion and, subsequently, to a slower pace of spatial adjustment.

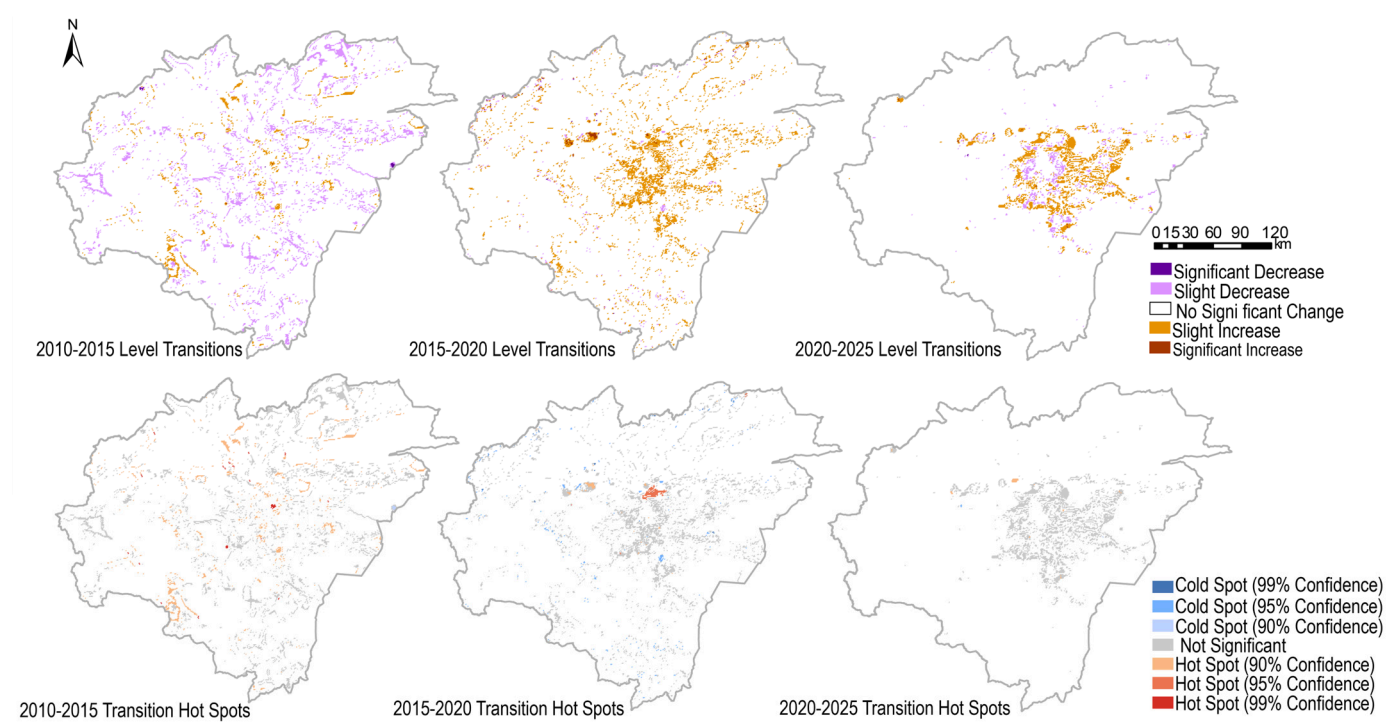


Figure 4. Spatial transitions of the human footprint index (HFI).

3.1.2. Land Desertification Sensitivity

The spatial pattern of land desertification sensitivity in the Kashgar Oasis displayed a concentric gradient during 2010–2025, which was consistent with the oasis–desert landscape pattern (Figure 5). Very low- and low-sensitivity areas were distributed mainly in the mountainous and piedmont regions. Areas with moderate sensitivity were concentrated in the mountain–oasis and oasis–desert transition zones, whereas areas with high and very high sensitivity were primarily located in the farmland–desert ecotone surrounding the oasis and along the desert margins.

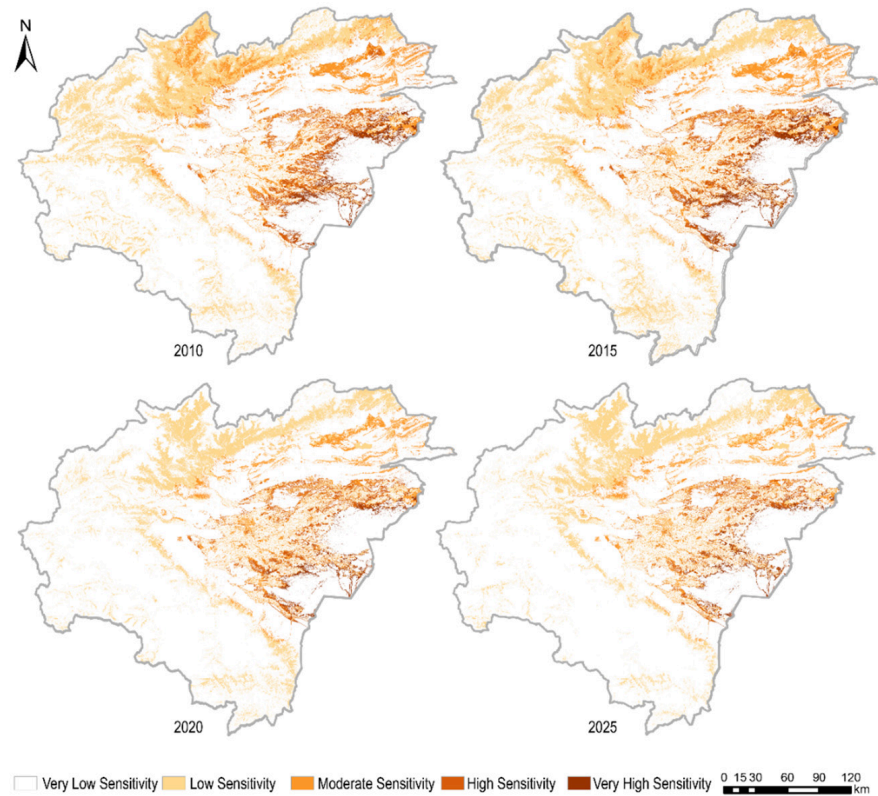


Figure 5. Spatial distribution of the land desertification sensitivity index (LDSI).

Land desertification sensitivity showed an overall declining trend from 2010 to 2025 (Table 5), although the magnitude of change varied among periods. Changes were relatively limited during 2010–2015. The most pronounced adjustment occurred during 2015–2020, when the areas classified as very highly and highly sensitive decreased by 9.96% and 2.15%, respectively. This downward trend continued during 2020–2025, with the highly and very highly sensitive areas declining by a further 5.19% and 1.44%, respectively.

Table 5. Dynamic degrees of the land desertification sensitivity index (LDSI).

Period	Very Low	Low	Moderate	High	Very High	Overall Dynamic Degree
2010–2015	−0.15%	1.18%	−1.35%	−1.98%	5.23%	0.25%
2015–2020	1.87%	−4.94%	−6.04%	−2.15%	−9.96%	1.38%
2020–2025	0.30%	−0.53%	−1.31%	−5.19%	−1.44%	0.25%

Spatial transitions in the LDSI were concentrated mainly along the oasis margins and within the oasis–desert ecotone (Figure 6), whereas mountainous areas and relatively stable ecological areas exhibited comparatively minor changes. Hot spots of LDSI change occurred primarily in the oasis–desert transition zone and the farmland–desert ecotone. Overall, the decline in land desertification sensitivity was characterized mainly by the contraction and spatial adjustment of highly sensitive areas along the oasis margins.

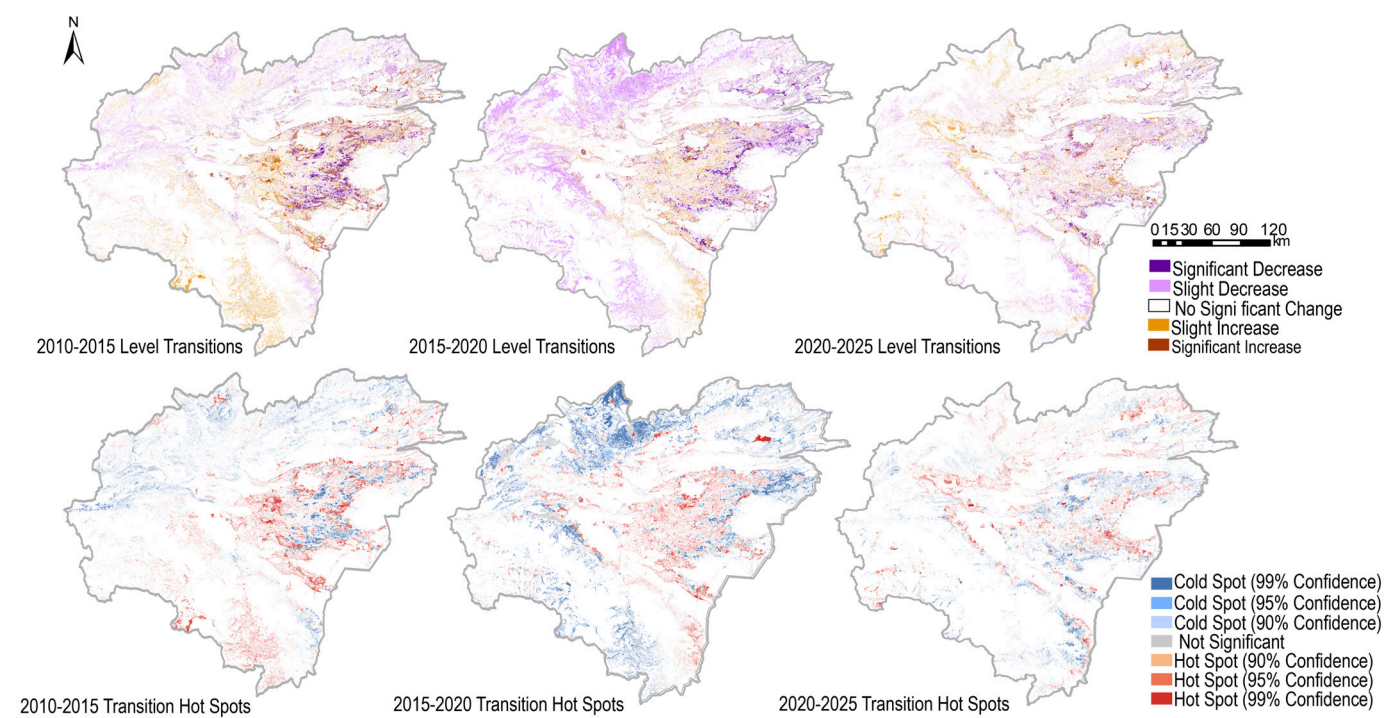


Figure 6. Spatial transitions of the land desertification sensitivity index (LDSI).

3.1.3. Comprehensive Ecosystem Service Index

The spatial pattern of ecosystem service levels was closely associated with topography, hydrology, vegetation, and human activity intensity. Very low levels were distributed mainly in ecologically fragile zones, including desert margins around the oasis, high-elevation bare rock areas, and snow- and ice-covered regions. Very high levels were concentrated in the mid- and high-elevation areas along the southern slopes of the Tianshan and Kunlun Mountains. Moderate levels occurred mainly along the rivers and hills, resulting in a gradual spatial transition that reflected clear differences in ecosystem service capacity across the Kashgar Oasis (Figure 7).

Compared with land desertification sensitivity, ecosystem service levels exhibited greater temporal variability (Table 6). During 2010–2015, the areas classified as low and very high ecosystem service levels both increased, whereas the moderate-level area decreased by 5.75%, reflecting a degree of spatial differentiation. From 2015 to 2020, the moderate-level ecosystem service area increased markedly by 18.88%, while the high- and very high-level areas decreased by 3.06% and 2.75%, respectively, indicating an overall shift toward the moderate level. During 2020–2025, the high-level area increased by 7.49%, whereas the moderate-level area decreased by 7.68%, indicating a degree of upward recovery in ecosystem service levels.

Table 6. Dynamic degrees of the comprehensive ecosystem service index (CESI).

Period	Very Low	Low	Moderate	High	Very High	Overall Dynamic Degree
2010–2015	−0.16%	4.51%	−5.75%	−1.23%	5.11%	0.79%
2015–2020	0.22%	0.80%	18.88%	−3.06%	−2.75%	1.08%
2020–2025	−1.59%	1.03%	−7.68%	7.49%	−2.46%	1.73%

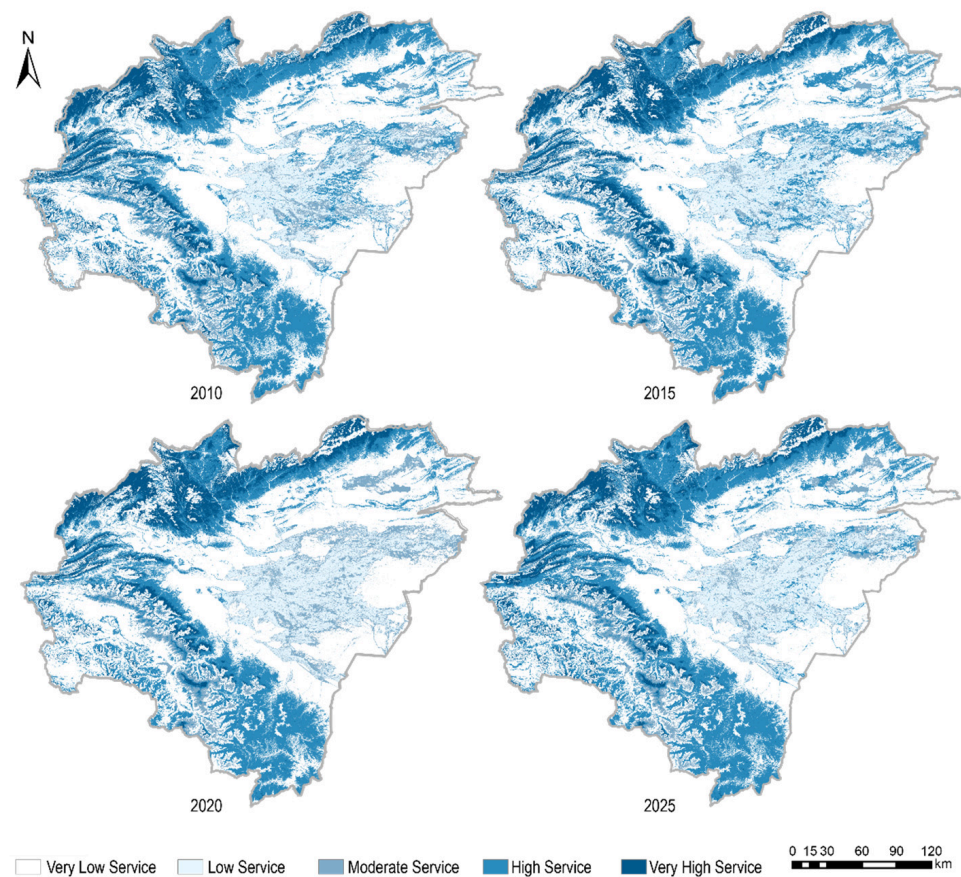


Figure 7. Spatial distribution of the comprehensive ecosystem service index (CESI).

Spatial transitions in ecosystem service levels also exhibited clear stage-specific differences (Figure 8). During 2015–2020, areas experiencing declines in ecosystem service levels expanded from the oasis interior toward the oasis–desert transition zone. After 2020, areas of improvement again became dominant and extended toward the western mountainous areas and oasis margins. Hot spots of CESI change were concentrated mainly in the oasis core and western mountainous areas. Overall, ecosystem service levels underwent a sequence of localized fluctuations, decline, and subsequent recovery, with the oasis core consistently remaining one of the most dynamically changing areas.

3.2. Evaluation and Evolution of the Multivariate Ecological Security Index

The spatial distribution of ecological security levels in the Kashgar Oasis was closely aligned with local geographic and ecological conditions (Figure 9). This reflected a dual structure driven by human activities and natural environmental constraints. Areas with very low and low ecological security were widely distributed across developed urban land, intensively cultivated areas, and ecologically fragile zones. This pattern highlights the spatial concentration of low-security areas within the oasis system. In contrast, high- and very high-security areas were concentrated in mountainous regions and river corridors, which served as key zones for maintaining regional ecological stability.

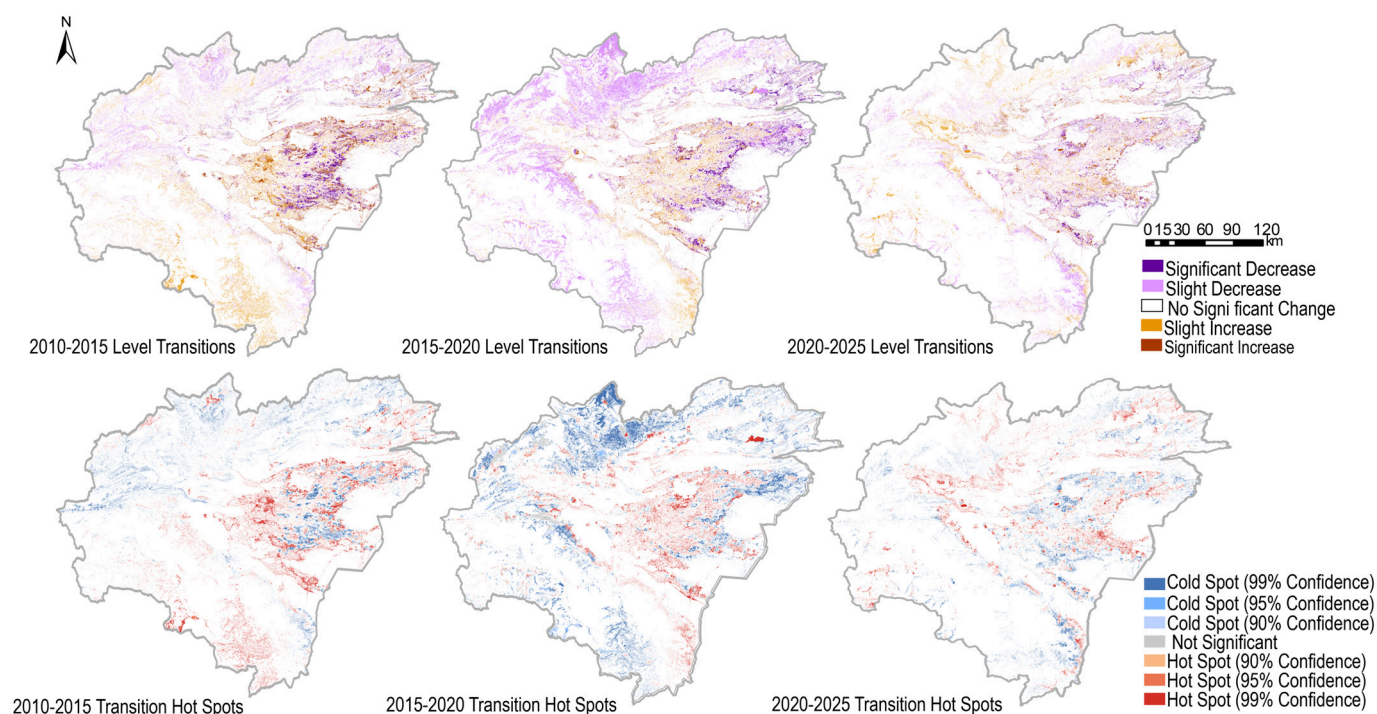


Figure 8. Spatial transitions of the comprehensive ecosystem service index (CESI).

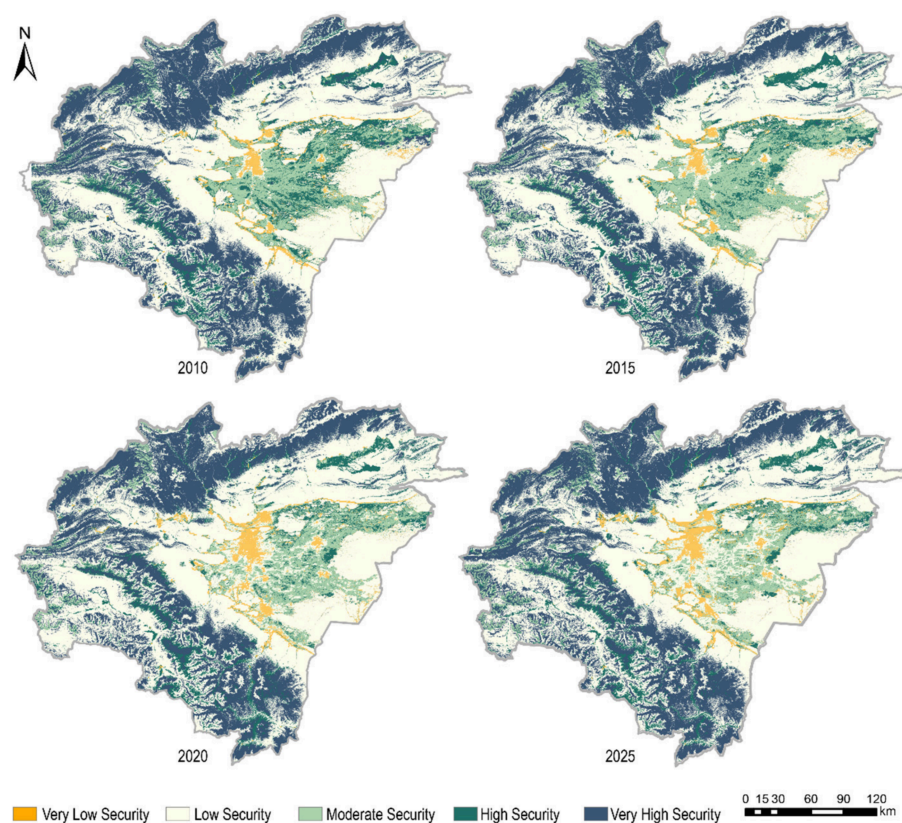


Figure 9. Spatial distribution of the multivariate ecological security index (MESI).

Temporal changes in MESI exhibited clear stage-specific characteristics (Table 7). During 2010–2015, the area classified as moderate ecological security increased by 5.29%, indicating an overall shift toward the moderate level. The most pronounced decline in ecological security occurred during 2015–2020, when the area classified as very low ecological security increased by 9.31%, representing the largest change among the five

ecological security levels. During 2020–2025, the area under very high ecological security increased by 2.55%, indicating that ecological security began to recover toward higher levels. Overall, the temporal evolution of MESI followed three successive stages: expansion of moderate-security areas, increasing spatial differentiation, and overall recovery.

Table 7. Dynamic degrees of the multivariate ecological security index (MESI).

Period	Very Low	Low	Moderate	High	Very High	Overall Dynamic Degree
2010–2015	−1.55%	0.08%	5.29%	−0.34%	−1.40%	0.52%
2015–2020	9.31%	1.07%	−2.98%	−0.01%	−1.17%	0.69%
2020–2025	0.92%	−1.12%	−1.02%	−0.95%	2.55%	0.75%

The temporal evolution of MESI was accompanied by both consistent and divergent changes among its component indices, with the greatest divergence occurring during 2015–2020. Over this period, human disturbance increased markedly, whereas land desertification sensitivity declined overall, and ecosystem service levels shifted from the high and very high classes toward the moderate class. At the same time, the area classified as very low ecological security increased substantially. Changes in the component indices were therefore not fully synchronized with the evolution of overall ecological security. After 2020, land desertification sensitivity continued to decline, ecosystem service levels showed an upward recovery, and the area under very high human disturbance decreased, while the area classified as very high ecological security increased. These patterns indicate clear stage-specific differences in the spatial and temporal correspondence between the component indices and overall ecological security.

Spatial transitions among ecological security levels exhibited marked heterogeneity (Figure 10). During 2010–2015, changes were concentrated mainly within the oasis and along its eastern and western margins. From 2015 to 2020, areas experiencing declines in ecological security expanded considerably and were distributed primarily across the oasis core and its surrounding margins, making this the period with the most pronounced decline in ecological security during the study period. During 2020–2025, ecological conditions improved in mountainous areas and parts of the oasis, accompanied by a gradual recovery of areas with high ecological security levels.

Hot spot analysis of MESI level transitions showed that hot spots of ecological security change were concentrated primarily within the oasis and in piedmont transition zones, whereas cold spots occurred mainly in mountainous areas and relatively stable desert regions. Here, hot and cold spots represent spatial clusters of relatively high and low MESI level-transition intensity, respectively, rather than clusters of high and low absolute MESI values. Consequently, although mountainous areas generally exhibited high ecological security levels, they could still appear as cold spots in the change analysis because of their relatively low intensity of ecological security level transitions.

Overall, ecological security evolved through three stages—expansion of moderate-security areas, increasing spatial differentiation, and overall recovery—with the most active changes concentrated primarily within the oasis system.

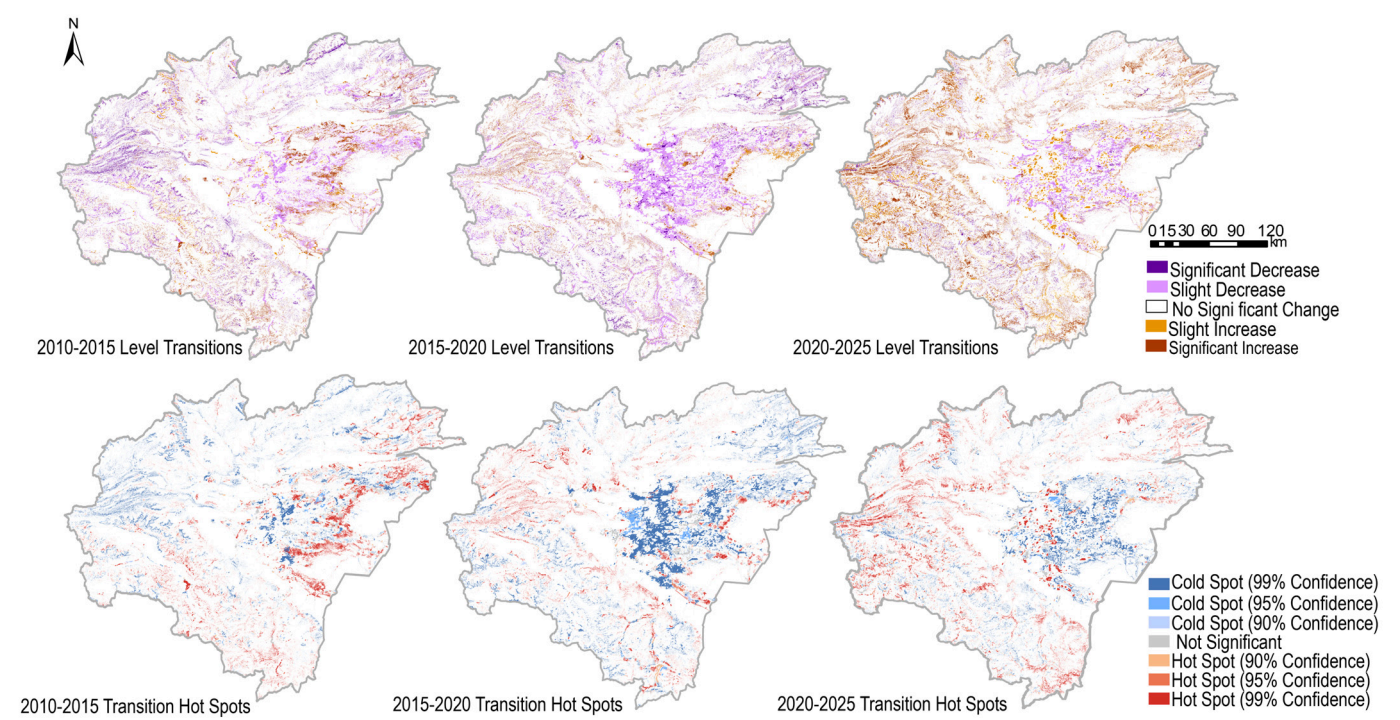


Figure 10. Spatial transitions of the multivariate ecological security index (MESI).

3.3. Trade-Off and Synergy Analysis
3.3.1. Bivariate Spatial Association Characteristics

Bivariate local spatial autocorrelation analysis identified four types of local spatial association patterns: high–high (H–H), low–low (L–L), high–low (H–L), and low–high (L–H). The H–H and L–L types represent same-direction spatial associations, whereas the H–L and L–H types represent opposite-direction spatial associations. These patterns were used to characterize the spatial relationships among the three ecological security dimensions—LDSI, HFI, and CESI—and, in conjunction with the ecological meanings of the respective indicators, to examine their potential trade-offs and synergies (Table 8).

Table 8. Spatial association types among ecological security dimensions based on bivariate local Moran’s I.

Type	Not Significant	High–High (HH)	Low–Low (LL)	High–Low (HL)	Low–High (LH)
LDSI-CESI	41.53%	8.19%	28.51%	18.98%	2.79%
LDSI-HFI	43.92%	10.44%	32.84%	6.42%	6.38%
CESI-LDSI	51.73%	7.38%	27.05%	4.21%	9.63%
HFI-LDSI	51.74%	8.41%	30.72%	3.17%	5.96%
CESI-HFI	43.92%	8.67%	21.96%	8.19%	17.27%
HFI-CESI	41.53%	5.13%	22.57%	22.04%	8.73%

Overall, the spatial associations among the ecological dimensions exhibited pronounced spatial heterogeneity and were concentrated mainly within the oasis, desert, and their transition zones. Local spatial association patterns also differed substantially among indicator pairs, indicating that human disturbance, land desertification sensitivity, and ecosystem service capacity were not fully synchronized in space.

Among the different indicator pairs, HFI and LDSI exhibited relatively pronounced same-direction spatial associations. Areas characterized by low land desertification sensitivity and low human disturbance accounted for 32.84%, whereas areas with high land desertification sensitivity and high human disturbance accounted for 10.44%, indicating con-

sistent spatial clustering of human disturbance and land desertification sensitivity in some areas. By contrast, both HFI–CESI and LDSI–CESI exhibited a mixture of same-direction and opposite-direction spatial associations, reflecting pronounced spatial heterogeneity and local mismatches among human disturbance, land desertification sensitivity, and ecosystem service capacity.

Because MESI is constructed by integrating HFI, LDSI, and CESI, the spatial associations between each component dimension and MESI are reported separately (Table 9). These relationships are interpreted as spatial associations between the component dimensions and the overall ecological security state rather than as trade-offs or synergies between independent ecological dimensions. The spatial association patterns differed markedly among the three component dimensions. CESI–MESI was dominated by same-direction spatial associations, with H–H and L–L types jointly accounting for 60.10%. In contrast, HFI–MESI was characterized primarily by opposite-direction spatial associations, with H–L and L–H types together accounting for 41.80%. LDSI–MESI exhibited substantial proportions of both same-direction and opposite-direction associations, accounting for 35.72% and 29.64%, respectively. These results indicate that the component dimensions exhibit distinct spatial correspondence patterns with the overall ecological security state.

Table 9. Spatial association types among individual ecological security dimensions and MESI based on bivariate local Moran’s I.

Type	Not Significant	High–High (HH)	Low–Low (LL)	High–Low (HL)	Low–High (LH)
LDSI–MESI	34.64%	8.27%	27.45%	21.59%	8.05%
MESI–LDSI	51.73%	3.44%	25.20%	8.15%	11.48%
CESI–MESI	34.64%	28.80%	31.30%	1.07%	4.20%
MESI–CESI	41.53%	26.79%	30.83%	0.39%	0.47%
MESI–HFI	43.92%	1.43%	19.48%	15.43%	19.75%
HFI–MESI	34.64%	4.69%	18.87%	25.17%	16.63%

3.3.2. Spatial Distribution Patterns

The spatial association patterns among the major ecological security dimensions in the Kashgar Oasis, derived from bivariate local spatial autocorrelation analysis, are shown in Figure 11. Overall, the spatial relationships among HFI, LDSI, and CESI exhibited pronounced spatial heterogeneity. Mountainous areas, major river corridors, and parts of the oasis core were characterized mainly by the spatial co-occurrence of different ecological dimensions, with lower human disturbance, lower land desertification sensitivity, and higher ecosystem service capacity forming relatively consistent spatial combinations in some areas. The interior desert also exhibited some same-direction spatial associations, although these were expressed primarily as the co-occurrence of low values of different ecological attributes under natural environmental constraints. By contrast, oasis margins, ecological transition zones, urban expansion fronts, and desert–mountain transition areas displayed more complex opposite-direction spatial associations, reflecting pronounced local spatial mismatches among human disturbance, land desertification sensitivity, and ecosystem service capacity.

Taken together, the spatial relationships among the ecological security dimensions varied distinctly along the mountain–oasis–desert gradient. Ecological dimension combinations were relatively coordinated in mountainous areas, river corridors, and parts of the oasis core, whereas spatial mismatches were more pronounced along oasis margins, ecological transition zones, and development fronts. These opposite-direction spatial associations indicate that the ecological dimensions did not vary synchronously in some local areas and may reflect potential trade-offs among them.

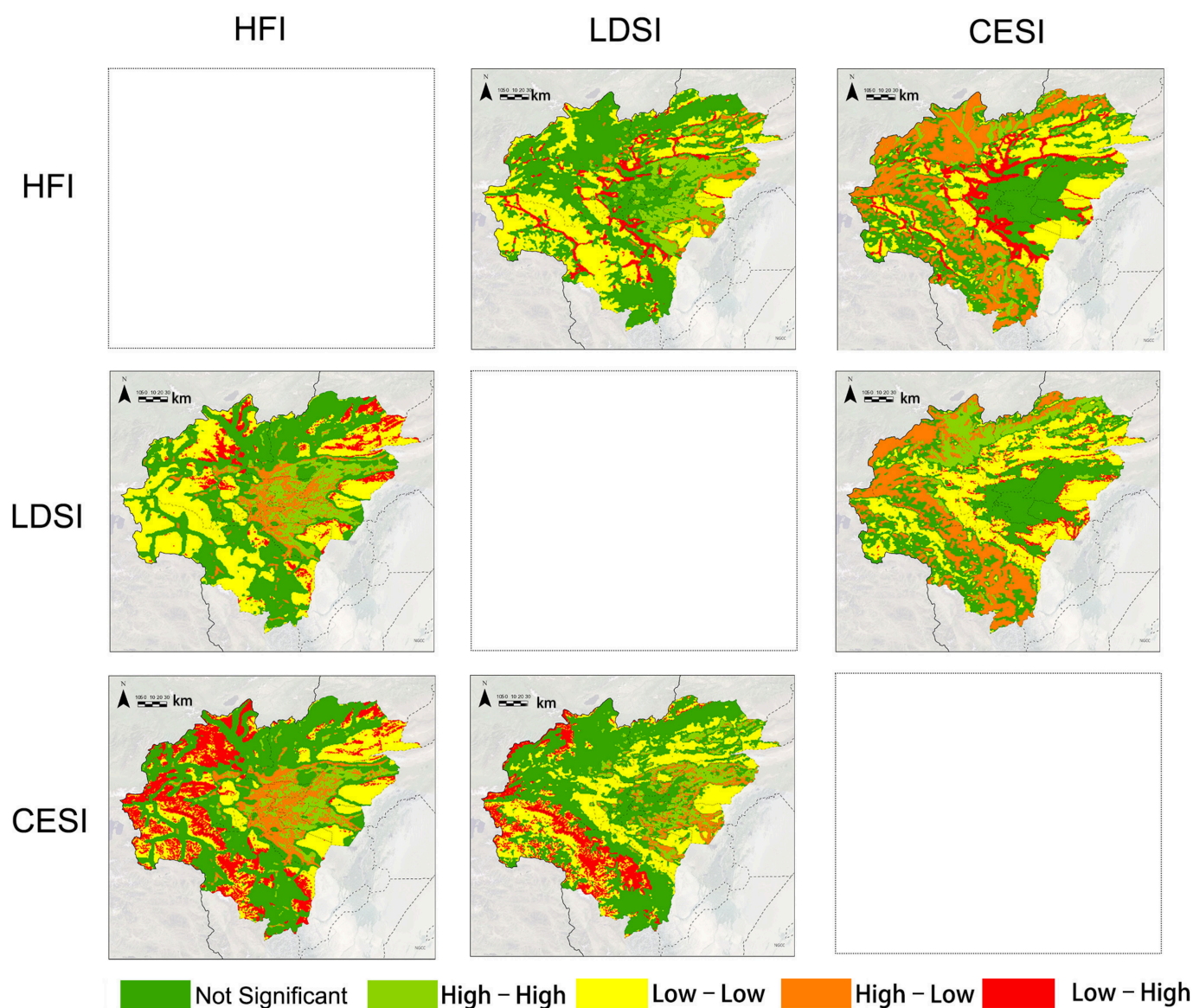


Figure 11. Spatial distribution of trade-offs and synergies among ecological security dimensions.

The spatial association patterns between the component dimensions and MESI are presented in Figure 12. Same-direction spatial associations between CESI and MESI were particularly evident and occurred mainly in mountainous areas, river corridors, and parts of the oasis. Opposite-direction spatial associations between HFI and MESI were more prominent and were concentrated primarily within the oasis and along its margins. LDSI and MESI exhibited both same-direction and opposite-direction spatial associations, mainly along oasis margins and in desert transition areas. These patterns primarily characterize the spatial correspondence between individual component dimensions and the overall ecological security state and are not further interpreted as trade-offs or synergies between independent ecological dimensions.

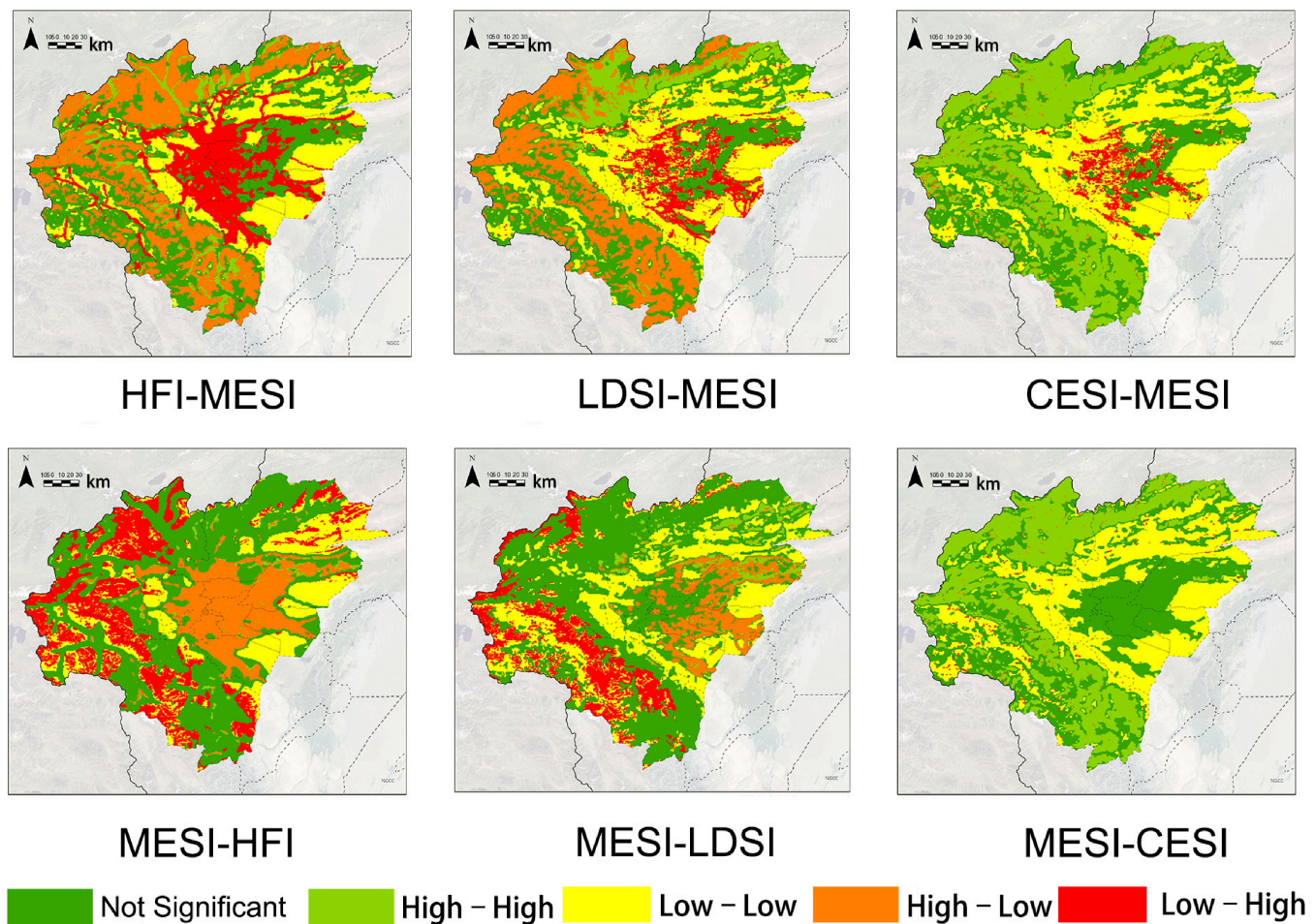


Figure 12. Spatial distribution of associations between individual ecological security dimensions and MESI.

3.4. Spatially Constrained Multivariate Clustering Analysis

3.4.1. Selection of the Optimal Cluster Number and Cluster Characteristics

The optimal number of clusters was determined using the pseudo-F statistic to evaluate clustering solutions ranging from 2 to 30 (Figure A1 in Appendix A). A clear elbow point was identified at six clusters, where the decline in the pseudo-F value became much slower. The six-cluster solution maintained clear separation among clusters while preserving a complete ecological security gradient. It therefore provided a reasonable basis for subsequent ecological zoning and management.

The six clusters exhibited distinct ecological characteristics (Figure A2 in Appendix A). Clusters with high ecological security were characterized by high values of both the CESI and the MESI. In contrast, clusters with low ecological security showed consistently low values across all the indicators. Transitional clusters had indicator values close to the overall median, highlighting their buffering role between high- and low-security areas. Overall, the clustering results demonstrated high within-cluster consistency and clear between-cluster separation. The ecological characteristics of the six clusters closely reflected the “mountain–oasis–desert” landscape pattern of the study area, supporting the ecological relevance and interpretability of the clustering results.

3.4.2. Cluster-Based Ecological Zoning

The ecological characteristics and spatial distribution of the six clusters are summarized in Figure 13 on the basis of the standardized mean values of the four core indicators, namely, the LDSI, CESI, HFI, and MESI.

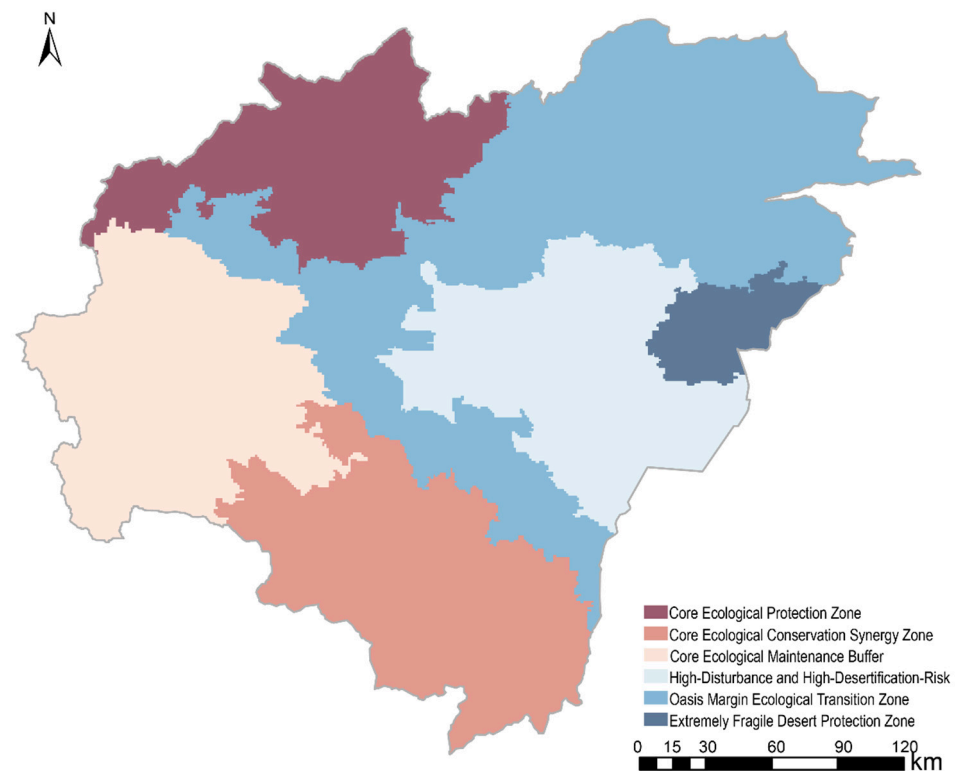


Figure 13. Ecological security zoning based on Spatially Constrained Multivariate Clustering using HFI, LDSI, CESI, and MESI.

Cluster 1 was characterized by a low LDSI (-0.38), moderate CESI (0.18), relatively high MESI (0.34), and low HFI (-0.46). It was distributed mainly across piedmont alluvial fans, low-mountain grasslands, semifixed sandy lands, and extensive alpine bare land. These areas provide important ecological functions and conservation values, including ecological buffering, water conservation, and natural heritage protection.

Cluster 2 had the highest HFI (1.31) and LDSI (0.77), whereas the CESI (-0.31) and MESI (-0.79) remained relatively low. This cluster was primarily distributed across developed areas, intensively cultivated farmland, and the expanding frontiers of oasis development, indicating strong anthropogenic disturbance associated with urbanization and agricultural expansion.

Cluster 3 had the highest CESI (1.02) and MESI (1.02), while the LDSI (-0.01) and HFI (-0.30) remained relatively low. It was distributed mainly across middle- to high-elevation mountainous areas, major river corridors, and well-preserved natural oases with dense vegetation, representing the core ecological security areas of the study region.

Cluster 4 had relatively high CESI (0.48) and MESI (0.60), together with low LDSI (-0.34) and HFI (-0.31). This cluster was located mainly in the eastern part of Akto County, where mountainous terrain and relatively high vegetation cover support important ecosystem functions, including water retention and soil conservation. Human activities were dominated by ecotourism and low-intensity grazing.

Cluster 5 exhibited relatively low CESI (-0.50) and MESI (-0.45), whereas the LDSI (0.03) and HFI (-0.02) were close to the overall average. It was distributed mainly across

desert regions and the farmland–desert ecotone along the oasis margins, representing a transitional landscape between oasis and desert ecosystems.

Among all the clusters, cluster 6 had the lowest CESI (−1.08) and MESI (−0.86). The HFI remained low (−0.60), while the LDSI was slightly above the overall average (0.04). This cluster was distributed mainly along the margins of the Taklimakan Desert, across extensive Gobi and barren areas, and in other extremely arid regions, representing areas with the lowest ecological security under strong natural environmental constraints.

To assess the sensitivity of ecological zoning to the choice of clustering variables, this study compared the four-variable scheme with a three-variable scheme containing only HFI, LDSI, and CESI, while keeping all other settings unchanged. After MESI was removed, the spatial extent and boundaries of some zones changed. Examination of representative areas showing pronounced differences against remote sensing imagery revealed that, under the three-variable scheme, some areas with distinct land-cover characteristics were assigned to the same cluster. When MESI was included, these areas were further differentiated, yielding spatial patterns that corresponded more closely to the observed differences in land cover.

This comparison suggests that MESI provides complementary information on the overall ecological security state and the degree of imbalance among component dimensions, thereby improving the spatial differentiation of ecologically heterogeneous areas and the interpretability of the resulting zoning. Accordingly, the four-variable scheme was retained as the primary zoning result, while the three-variable scheme is presented in Appendix A (Figure A3) as a sensitivity analysis.

4. Discussion

4.1. Declining Desertification Sensitivity but Lagging Ecological Security Recovery

The results reveal a temporal pattern in the Kashgar Oasis from 2010 to 2025 characterized by a continuous decline in land desertification sensitivity but a lagged improvement in ecological security. Although land desertification sensitivity decreased overall throughout the study period, MESI still declined during 2015–2020, suggesting that reduced land desertification sensitivity does not necessarily translate immediately into a corresponding improvement in overall ecological security. This pattern suggests that changes in ecological security in arid oases may reflect the combined influences of ecological restoration, the expansion of human activities, and changes in ecosystem services.

This temporal asynchrony may, to some extent, reflect competition between ecological restoration and regional development in water-limited oasis systems. On the one hand, vegetation restoration, desertification control, and related ecological conservation measures can increase surface cover, stabilize the soil surface, and reduce susceptibility to wind erosion, thereby helping to lower land desertification sensitivity. On the other hand, agricultural intensification, urban expansion, and infrastructure development continue to increase the intensity of human activities and resource demand. In arid oasis regions in particular, both irrigated agriculture and natural ecosystems depend heavily on limited water resources, creating substantial potential for competition between agricultural production and ecological maintenance. Agricultural development may reduce land desertification sensitivity in some areas by increasing local vegetation cover and reducing bare land; however, high irrigation demand and intensive land use may also reduce water availability for natural ecosystems and place additional pressure on habitat integrity and ecosystem service provision. Improvements in basic ecological conditions therefore do not necessarily imply a synchronous recovery of ecosystem functions and overall ecological security.

These processes may help explain the ecological mismatch observed during 2015–2020. Over this period, areas with high and very high land desertification sensitivity decreased

substantially, while human disturbance increased rapidly and the areas with high and very high ecosystem service levels also declined. This pattern suggests that, although desertification control and vegetation restoration may have contributed to improvements in some basic ecological conditions, the pressures associated with agricultural, urban, and infrastructure expansion, together with adverse effects associated with shifts in ecosystem service provision, may have offset some of these ecological improvements, contributing to the temporary decline in overall ecological security. Similar studies have also reported that rapid land development and urbanization may reduce regional ecological security by increasing ecological pressure and altering the structure of ecosystem service provision [56].

After 2020, the spatial pattern of human disturbance underwent further adjustment: the area under very high disturbance decreased by 8.15%, whereas the area under high disturbance increased by 10.66%. This pattern indicates a contraction of the most intensive disturbance while relatively high levels of human activity continued to expand toward the surrounding oasis areas. During the same period, areas with high and very high land desertification sensitivity continued to decline, the area with high ecosystem service levels increased by 7.49%, and MESI showed an overall recovery trend. These concurrent changes suggest that, as the effects of ecological restoration, land-use optimization, and resource management gradually accumulated, the positive effects of ecological improvement may have begun to offset some of the pressures associated with regional development, thereby supporting the recovery of ecological security. Nevertheless, the continued expansion of high-disturbance areas suggests that anthropogenic pressure remains an important constraint on the long-term ecological security of the Kashgar Oasis.

Future ecological governance in the Kashgar Oasis should therefore extend beyond improvements in basic ecological conditions, such as reductions in desertified land and increases in vegetation cover, and place greater emphasis on the sustained enhancement of ecosystem service functions and ecological resilience. Given the severe constraints on water resources, particular attention should be directed toward optimizing agricultural water allocation, improving irrigation efficiency, limiting high-intensity land development, and strengthening the protection of ecological barriers in mountainous areas and along river corridors. Such measures may help translate localized environmental improvements associated with ecological restoration into more stable, long-term gains in ecological security [57,58].

4.2. Spatial Trade-Offs and Synergies Reveal Heterogeneous Ecological Processes

The spatial relationships among the ecological dimensions identified in this study correspond closely to the natural geographic gradient of the Kashgar Oasis from mountains through piedmont areas and oases to deserts. This pattern suggests that spatial differences in regional ecological security are influenced not only by human activities but also by natural processes associated with hydrothermal conditions, topography, and water availability. Because different landscape units differ in resource conditions and ecological functions, they exhibit distinct combinations of ecological dimensions. In mountainous areas and major river corridors, lower human disturbance, lower land desertification sensitivity, and higher ecosystem service capacity show relatively clear spatial co-occurrence. The comparatively favorable hydrothermal conditions and vegetation cover in these areas support ecological functions such as water retention, soil conservation, and habitat maintenance. By contrast, in extremely arid desert areas, multiple ecological functions are simultaneously constrained by limited water availability and sparse vegetation, resulting in lower ecosystem service levels and stronger natural environmental constraints.

More complex spatial associations and trade-offs occur along oasis margins, in farmland–desert ecotones, and across mountain–oasis–desert transition zones. These

areas are characterized both by relatively active agricultural development and urban expansion and by natural ecosystems that are highly sensitive to changes in water availability. Unlike ecological trade-offs in more urbanized regions, which are often driven primarily by the expansion of built-up land [59], relationships among ecological dimensions in the Kashgar Oasis may also be associated with water-resource allocation and the natural geographic gradient.

Within the mountain–oasis–desert system, mountain precipitation and glacier- and snowmelt-derived runoff are important water sources for both oasis agriculture and natural ecosystems. Irrigated agriculture, riparian vegetation, wetlands, and desert ecological barriers all depend on these limited water resources. Agricultural expansion or increased irrigation demand may therefore intensify competition between water use for agricultural production and ecological maintenance. Greater allocation of water to cropland may help sustain agricultural vegetation and reduce surface exposure in some areas, while potentially reducing water availability for riparian vegetation, natural oases, and ecosystems along desert margins. Such ecological processes associated with the allocation of limited water resources may help explain why spatial relationships among ecological dimensions are more complex along oasis margins and agricultural expansion fronts. Studies of arid inland river basins have similarly identified water availability as an important factor regulating ecosystem structure, ecosystem services, and their interrelationships [60–62].

Climate change may further intensify these water-mediated ecological interactions. In arid oasis systems, rising temperatures can increase evapotranspiration demand and may also alter the magnitude and seasonal distribution of mountain runoff through changes in glaciers and snow cover, thereby affecting the seasonality and stability of water supply to oases [63,64]. Although increased meltwater may temporarily enhance water availability in some upstream areas, fluctuations in water supply combined with agricultural irrigation demand may further intensify competition between agricultural and ecological water use [63,65]. Climate change may therefore exacerbate existing spatial mismatches and potential trade-offs among ecological dimensions, particularly along oasis margins and in downstream areas where ecosystem functions are more sensitive to variations in water supply. At the same time, continued warming may further increase climatic and hydrological risks in the arid regions of Xinjiang [66]. Future ecological security zoning and management should therefore incorporate climate change and uncertainty in water-resource availability to strengthen the adaptive capacity of oasis ecosystems.

From a regional management perspective, these spatial relationships indicate that different landscape units are closely connected through water flows and ecological processes. Mountain water retention, oasis agricultural production, and the maintenance of downstream desert ecosystems are not independent processes but components of an interconnected mountain–oasis–desert system. Ecological management based solely on administrative boundaries may therefore be insufficient to coordinate cross-regional ecological processes. Greater emphasis should be placed on integrated water-resource management at the watershed scale, balancing reasonable agricultural water use with the ecological water requirements of rivers, natural oases, and desert ecological barriers. Cross-regional collaborative management could further contribute to maintaining the ecological integrity and long-term resilience of the oasis system [67]. These mechanisms are proposed as plausible interpretations of the observed spatial and temporal patterns rather than as directly tested causal relationships.

4.3. Ecological Security Zoning Supports Differentiated Management Strategies

Building on the preceding analyses of the spatiotemporal evolution of ecological security and the spatial relationships among ecological dimensions, Spatially Constrained

Multivariate Clustering further divided the study area into six functional zones with distinct ecological characteristics and management requirements [68]. Based on the combined characteristics and spatial distributions of HFI, LDSI, CESI, and MESI, Clusters 1–6 were identified as the Piedmont Ecological Buffer Maintenance Zone, High Human Disturbance–High Desertification Sensitivity Control Zone, Core Ecological Conservation Zone, Ecological Conservation and Low-Intensity Utilization Zone, Oasis-Margin Ecological Transition Regulation Zone, and Desert Ecological Vulnerability Protection Zone, respectively. These zones differed markedly along the mountain–oasis–desert gradient, suggesting that ecological security governance should move beyond generalized management based solely on high, moderate, and low security levels toward differentiated management tailored to specific sources of ecological pressure and ecological functions.

More specifically, the Piedmont Ecological Buffer Maintenance Zone (Cluster 1) is characterized by relatively low ecological pressure. New high-intensity development should therefore be restricted, while the ecological buffering and connectivity functions of piedmont areas should be maintained. The High Human Disturbance–High Desertification Sensitivity Control Zone (Cluster 2) is subject to relatively strong human disturbance and high land desertification sensitivity; management should focus on controlling disorderly oasis expansion, optimizing the spatial arrangement of agricultural and construction land, and improving water-use efficiency. The Core Ecological Conservation Zone (Cluster 3) has the highest levels of ecosystem services and ecological security and should prioritize the protection of water-retention areas, river corridors, and natural vegetation. The Ecological Conservation and Low-Intensity Utilization Zone (Cluster 4) maintains relatively favorable ecological functions; human use intensity should be controlled while conserving ecological functions, particularly water retention and soil conservation.

The Oasis-Margin Ecological Transition Regulation Zone (Cluster 5) is located primarily within the farmland–desert ecotone and faces multiple pressures associated with agricultural expansion, land desertification sensitivity, and competition for water resources. Management should therefore emphasize stabilizing oasis boundaries, restricting inappropriate land reclamation, and strengthening windbreak and sand-fixation measures together with ecological buffer construction. Although the Desert Ecological Vulnerability Protection Zone (Cluster 6) experiences relatively low human disturbance, it has the lowest CESI and MESI values. Its low ecological security is strongly constrained by extreme natural conditions and limited water resources; accordingly, management should prioritize natural recovery, low-intervention conservation, and the protection of key wind–sand corridors while avoiding water-intensive artificial restoration approaches [69].

From an applied perspective, this zoning scheme can provide a supplementary basis for territorial spatial planning, ecological conservation and restoration, desertification prevention and control, and water-resource management. It is broadly consistent with the current territorial spatial planning priorities of Xinjiang and the Kashgar region, including the regulation of ecological conservation redlines, permanent basic farmland, and urban development boundaries, as well as the arid-region governance principle of aligning development and greening with water availability. The Core Ecological Conservation Zone can support the identification of priority conservation areas; zones characterized by high human disturbance and oasis-margin transition conditions can serve as focal areas for development-boundary management and land-use optimization; and the Desert Ecological Vulnerability Protection Zone can inform the selection of desertification-control and ecological restoration approaches. These applications are consistent with current policy directions in the Kashgar region concerning ecological-space conservation, management of oasis–desert transition zones, and desertification prevention and control [70].

Given the cross-regional hydrological connections among mountain water retention, oasis agriculture, and downstream desert ecosystems, greater emphasis should also be placed on integrated water-resource management at the watershed scale and coordinated governance across administrative boundaries [71]. Similar approaches involving watershed-scale water allocation and cross-jurisdictional coordination have been applied in Australia's Murray-Darling Basin, where coordination across jurisdictions supports integrated and sustainable basin-wide water-resource management. This experience may provide a useful reference for collaborative watershed governance in other water-limited regions [72].

4.4. Limitations and Uncertainties

Although this study developed an ecological security assessment and zoning framework for the Kashgar Oasis by integrating multisource spatial data, ecosystem service models, and spatial analytical methods, several limitations and uncertainties remain. First, inconsistencies in the spatial and temporal characteristics of multisource datasets may affect the assessment results. Spatial compatibility among datasets was achieved through unified projection, clipping, and resampling. In addition, owing to data availability, grazing intensity and the aridity index for 2025 were represented by data from 2024, the nearest available year, which may to some extent affect the characterization of short-term interannual variations. Future studies should prioritize datasets with consistent spatial resolutions and continuous time series and incorporate high-temporal-resolution remote sensing data and field observations for validation.

Second, indicator selection and model parameterization may introduce uncertainty into the ecological security assessment. Although the indicators and parameters used in this study were determined primarily on the basis of previous research and the specific conditions of the study area, alternative settings may produce some variation in the assessment results. Future research could therefore further evaluate the stability of the results under different parameter configurations.

Third, ecological zoning may be influenced by the combination of clustering variables, the number of clusters, and the specification of spatial contiguity constraints. This study compared a four-variable scheme comprising HFI, LDSI, CESI, and MESI with a three-variable scheme comprising HFI, LDSI, and CESI, and the comparison revealed a certain degree of sensitivity to the choice of variables. The resulting zoning should therefore be interpreted as a regionalization scheme with ecological and management relevance rather than as a unique spatial classification. Future studies could further compare alternative variable combinations, cluster numbers, and spatial constraint settings to assess the stability of the zoning results.

Finally, the Kashgar Oasis represents a single case study, and its physical geography, water-resource structure, and patterns of human activity have distinct regional characteristics. Nevertheless, the proposed framework of multidimensional ecological security assessment–spatial relationship identification–spatially constrained zoning may be extended to other arid oases with similar water-resource constraints and ecological gradients after regional adaptation of the indicator system and model parameters. Cross-regional comparisons under different climatic, water-resource, and land-use contexts could further evaluate the transferability and robustness of the framework. Future research could also integrate ecohydrological models, land-use scenario simulations, and socioeconomic data to enhance the comprehensive interpretation of ecological security assessment and zoning.

5. Conclusions

This study developed a multivariate ecological security assessment framework for the Kashgar Oasis by integrating the HFI, the LDSI, and the CESI. The Mazziotta–Pareto Index

(MPI) was used to construct the MESI. By combining bivariate spatial autocorrelation with Spatially Constrained Multivariate Clustering, the framework was used to characterize the spatiotemporal evolution of ecological security, identify the spatial relationships among key ecological components, and delineate ecological security zones over the period 2010–2025. The main conclusions are as follows.

- (1) Ecological security in the Kashgar Oasis clearly exhibited a spatial gradient, with high levels in mountainous areas, moderate levels in oasis regions, and low levels in desert areas. This pattern closely reflected regional environmental gradients and the intensity of anthropogenic activities. Ecological security evolved through three distinct stages: expansion of moderate-security areas, increasing spatial differentiation, and overall recovery. Although land desertification sensitivity declined continuously during the study period, improvements in ecological security occurred more gradually. These results indicate that ecological security in arid regions is shaped by the combined effects of ecosystem services, land desertification sensitivity, and human activities rather than by changes in any single ecological dimension.
- (2) HFI, LDSI, and CESI exhibited pronounced spatial heterogeneity and distinct local spatial association patterns. The spatial relationships among these ecological dimensions varied markedly along the mountain–oasis–desert gradient. Mountainous areas, river corridors, and some natural oases were generally characterized by lower human disturbance, lower land desertification sensitivity, and higher ecosystem service capacity, whereas oasis margins, farmland–desert ecotones, and urban expansion fronts exhibited more complex combinations of ecological dimensions, reflecting localized differences among human disturbance, land desertification sensitivity, and ecosystem services.
- (3) Spatially Constrained Multivariate Clustering identified six ecological security zones with distinct ecological characteristics. The resulting zoning pattern closely corresponded to the mountain–oasis–desert composite ecosystem. By integrating ecological security assessment, spatial association analysis, and ecological zoning, this study provides a basis for ecological security governance and differentiated ecological management in arid oasis regions. The proposed analytical framework may also inform ecological security assessment and zoning in other arid regions, including areas outside China with similar water-resource constraints and ecological gradients. Future research could incorporate ecological and hydrological data with higher temporal resolution, evaluate the robustness of zoning results under different methodological settings, and further assess the applicability and transferability of the framework across different arid regions.

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Abbreviations

The following abbreviations are used in this manuscript:

PSR	Pressure–State–Response
MPI	Mazziotta–Pareto Index
MESI	Multivariate Ecological Security Index
HFI	Human Footprint Index
LDSI	Land Desertification Sensitivity Index
CESI	Comprehensive Ecosystem Service Index

Appendix A

Appendix A.1

Table A1. Flow velocity coefficients for different land use types.

Land-Use Type	Flow Velocity Coefficient (V_i)
Cropland	800
Forestland	180
Grassland	500
Water bodies	2012
Built-up land	2012
Unused land	1500

Table A2. Carbon density of different land use types (t hm^{-2}).

Land-Use Type	Aboveground Carbon Density	Belowground Carbon Density	Soil Organic Carbon Density	Dead Organic Carbon Density
Cropland	3.78	7.83	91.83	1.33
Forestland	13.25	12.95	125.82	3.27
Grassland	1.45	12.32	98.54	0.39
Water bodies	0.41	0	80.16	1.32
Built-up land	0.75	1.09	72.16	0
Unused land	0.06	1.49	73.73	0

Table A3. Habitat suitability and sensitivity of different land use types to selected threat factors.

Land-Use Type	Habitat Suitability	Cropland	Built-Up Land	Unused Land
Cropland	0.4	0.2	0.8	0.4
Forestland	1	0.5	0.8	0.2
Grassland	0.9	0.2	0.5	0.3
Water bodies	1	0.4	0.6	0.5
Built-up land	0	0	0	0.1
Unused land	0.1	0.1	0.3	0.2

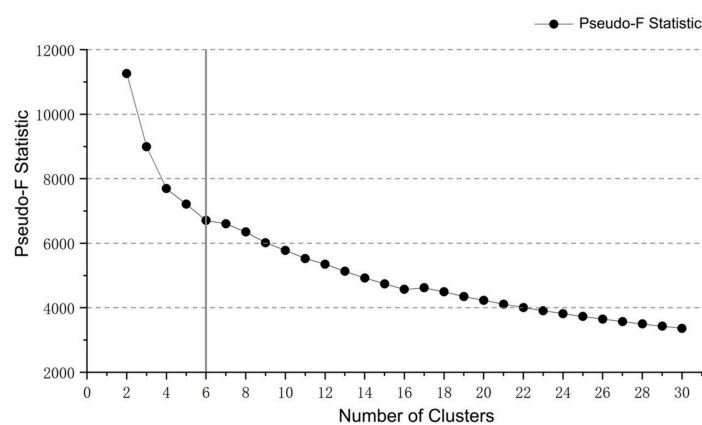
Table A4. Threat factors and their characteristics.

Threat Factor	Maximum Effective Distance (km)	Weight	Decay Type
Cropland	2	0.2	Linear
Built-up Land	8	1	Exponential
Unused Land	3	0.4	Exponential

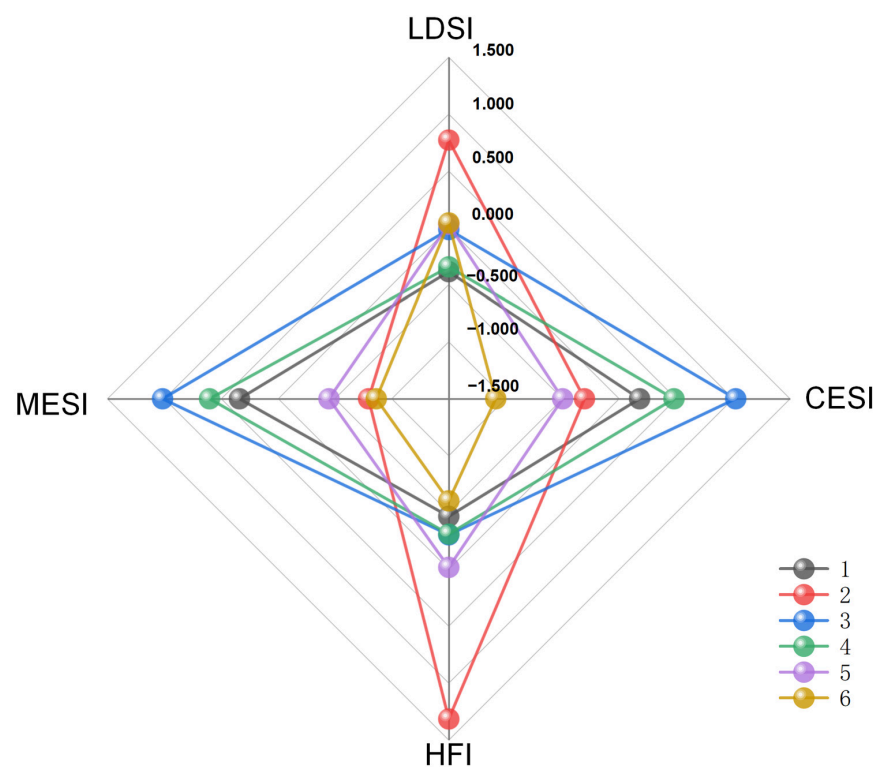
Table A5. C and P factor values for different land use types.

Land-Use Type	C Factor	P Factor
Cropland	0.22	0.35
Forestland	0.06	1
Grassland	0.07	1
Water bodies	1	0
Built-up land	0.2	0
Unused land	1	1

Appendix A.2

**Figure A1.** Variation in the pseudo-F statistic with the number of clusters. The vertical line indicates the selected optimal number of clusters ($k = 6$).

Appendix A.3

**Figure A2.** Standardized indicator profiles of the six ecological clusters.

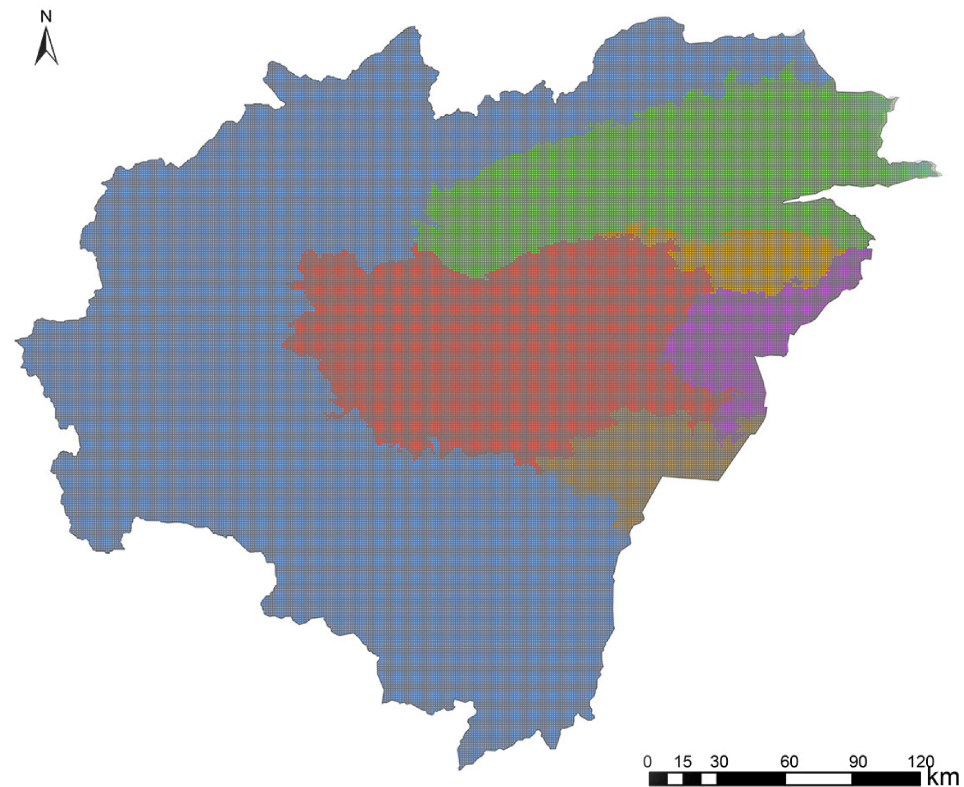


Figure A3. Ecological security zoning based on Spatially Constrained Multivariate Clustering using HFI, LDSI, and CESI. The different colors represent the six clusters (Clusters 1–6).

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