

Article

Spatio-Temporal Evolution of Habitat Quality and Its Response to Land Use Change in the Kaidu–Kongque River Basin, Northwest China

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Highlights

What are the main findings?

- An improved InVEST model with localized parameters quantitatively evaluated the spatiotemporal evolution of habitat quality in the Kaidu–Kongque River Basin (2000–2023).
- Habitat quality is linearly constrained by meteorological water deficit but exhibits a non-linear trade-off with surface soil moisture, revealing complex hydrological controls.

What are the implications of the main findings?

- The ecological protection scenario effectively reverses degradation, increasing average habitat quality by 21.3% by 2035 compared to the natural development scenario.
- Cultivated land expansion (36.2%) and construction land sprawl (10.3 times) caused severe habitat degradation, with human activities identified as the dominant driver.

Abstract

Arid inland river basins are ecologically fragile zones where habitat status is jointly shaped by anthropogenic land use interference and water-resource constraints; however, the combined effects of land use change and multi-scale hydrological conditions on habitat quality remain insufficiently understood. Taking the Kaidu–Kongque River Basin (KKRB) in northwest China as the study area, this study adopted 30 m CLCD land-cover datasets and a localized-parameter improved InVEST model to investigate habitat-quality dynamics from 2000 to 2023, combined with the PLUS model for multi-scenario simulation. Results revealed prominent “productive-land expansion and ecological-land contraction”: cultivated land increased by 36.2% and construction land expanded 10.3-fold, mainly encroaching on grassland, forming a typical “upstream improvement-downstream degradation” spatial pattern of habitat quality. Based on correlation analysis, we identified cross-scale ecohydrological coupling characteristics: meteorological water deficit exhibited a strong linear correlation with habitat quality at the basin scale, while surface soil moisture displayed an inverted-U-shaped non-linear trade-off relationship with

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habitat quality at local scales, jointly mediating spatial heterogeneity of habitat quality in this arid basin. Future scenario simulations indicated that only the Ecological Protection Scenario could substantially reverse degradation, with mean habitat quality projected to increase by 21.3% by 2035 relative to the natural-development scenario. This study clarifies how land use alteration and multi-scale water constraints jointly shape habitat-quality patterns, providing scientific support for land use optimization and ecological restoration in arid inland watersheds.

Keywords: Kaidu–Kongque River Basin; land use change; InVEST model; habitat quality; spatiotemporal evolution; arid inland river basin

1. Introduction

Amid the dual challenges posed by intensifying global climate change and increasing anthropogenic interference, watershed ecosystems are facing severe threats, including ecosystem service degradation and biodiversity loss. Land use transformation and hydrological regime alteration substantially reshape vegetation coverage, landscape connectivity, and habitat suitability, thereby triggering widespread spatial and temporal variations in habitat quality [1]. These ecological degradation issues further pose serious risks to regional ecological security and sustainable development. As key ecological units connecting terrestrial and aquatic systems, watersheds not only act as critical carriers for material transport and energy exchange but also form the foundation for sustaining socio-economic operations and ecological balance. However, over-exploitation of water resources and drastic land use changes under traditional development models have resulted in habitat fragmentation, wetland shrinkage, and desertification aggravation, which directly deteriorate ecological habitat conditions [2,3]. Consequently, scientifically assessing watershed habitat quality and revealing its response mechanisms to coupled human–water disturbances have become critical issues in ecological environmental research.

Against this backdrop, arid inland river basins serve as ideal regions for studying ecosystem response mechanisms. Their unique “mountain-oasis-desert” composite structure and extremely fragile ecological balance make ecological patterns highly dependent on limited water resources and extremely sensitive to human-induced and climatic disturbances. The Kaidu–Kongque River (KKR) Basin, located in the northeastern Tarim Basin, is a typical representative arid inland watershed. Supported by Tianshan snowmelt recharge and Bosten Lake regulation, the basin maintains large-scale wetland and oasis ecosystems and provides core habitats for rare wild species [4,5]. Nevertheless, intensified agricultural expansion and rapid urbanization in recent decades have caused intensive water exploitation and land use restructuring. The continuous decline of groundwater levels and downstream river drying have broken the original water-heat balance, resulting in vegetation degradation and severe habitat deterioration [6–9]. Although ecological water conveyance projects have been implemented to alleviate ecological pressure, the complex trade-offs between agricultural water consumption and ecological water demand continue to induce unstable and spatially heterogeneous habitat changes across the basin [10,11]. Therefore, clarifying the long-term evolutionary characteristics and driving mechanisms of habitat quality in the KKR Basin is essential for regional biodiversity conservation and ecological security maintenance, and can provide scientific references for ecological governance in global arid inland basins.

For the scientific quantification of habitat quality and its responses to anthropogenic activities, Habitat Quality Modeling represented by the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model has become a mainstream approach. Developed

by Stanford University and its partners, the InVEST Habitat Quality module simulates habitat degradation risk and habitat suitability by integrating Land Use/Land Cover (LULC) data, species sensitivity, and threat source distributions [12]. Owing to its flexible parameter settings and spatially explicit framework, this model has been widely applied and validated across global regions.

Numerous studies have adopted the InVEST model to explore ecological patterns in arid and semi-arid watersheds, highlighting the necessity of regional parameter localization for reliable simulation results. Relevant international practices show that calibrating threat weights or spatial decay distances can improve the capacity to capture habitat–threat overlaps. For instance, assessments in the Colorado River Basin demonstrated the impacts of agricultural water diversion on riparian habitat quality through calibrated threat weights for cropland and built-up land [13]. For the Amu Darya Basin, adjusting the decay distance for unused-land threats improved simulation accuracy by 15% compared with default settings [14]. Within China’s arid inland basins, similar localization efforts have yielded meaningful findings. Research in the Heihe River Basin adjusted construction-land threat weights and reproduced the typical “upstream improvement–downstream degradation” spatial pattern [15]. Further improvements have been achieved in the Tarim River Basin by coupling InVEST with the CA-Markov model and replacing linear threat decay with an exponential decay function to better reflect the gradual impacts of agricultural expansion [16].

Despite these valuable advances, several common limitations can be generalized from existing arid-region habitat-quality assessments. Most existing studies focus on relatively short time periods, which constrains our understanding of long-term cumulative effects of land use change on habitat quality. Parameter localization practices frequently focus merely on threat-weight tuning, while optimization of threat spatial-decay patterns for local conditions remains insufficient. Moreover, few studies have systematically linked InVEST outputs with ecological-engineering practices, limiting our ability to quantify the real effectiveness of human-oriented ecological interventions [17]. Most critically, habitat-quality evaluations are predominantly driven by land use information alone; physical coupling pathways describing multi-scale hydrological constraints (including water deficit and soil-moisture dynamics) are rarely incorporated into analytical frameworks [18,19].

To address the aforementioned research gaps, this study takes the Kaidu–Kongque River Basin as the study area and adopts model optimization and long-term time series analysis to systematically clarify the spatiotemporal evolution and driving mechanisms of habitat quality in typical arid inland basins. The core innovations are highlighted as follows: (1) Based on continuous long-term dataset spanning 2000–2023, this study systematically reveals the cumulative spatiotemporal variations in land use and habitat quality under long-term human–water interactions; (2) Comprehensive localization optimization of the InVEST model, including threat weight calibration and spatial attenuation pattern modification, is performed to improve the regional simulation accuracy of habitat quality assessment; (3) Three typical development scenarios (natural development, ecological conservation, and economic development) are adopted to predict future habitat evolutionary trends and identify optimal ecological restoration pathways; (4) Most importantly, this study further reveals the cross-scale hydrological regulatory mechanisms of habitat quality. By integrating meteorological water deficit and surface soil moisture datasets, this study quantitatively clarifies that basin-scale water balance exerts strong linear regulation on habitat quality, while local soil moisture constrains habitat evolution through an inverted-U nonlinear trade-off effect. This physical coupling mechanism complements traditional land use-based correlation analysis and provides new scientific insights for understanding habitat heterogeneity in arid inland basins.

Overall, this study systematically quantifies habitat quality dynamics and their multi-scale driving mechanisms, providing targeted quantitative support for ecological protection and sustainable land management in arid watersheds. The overall research framework of this study is shown in Figure 1.

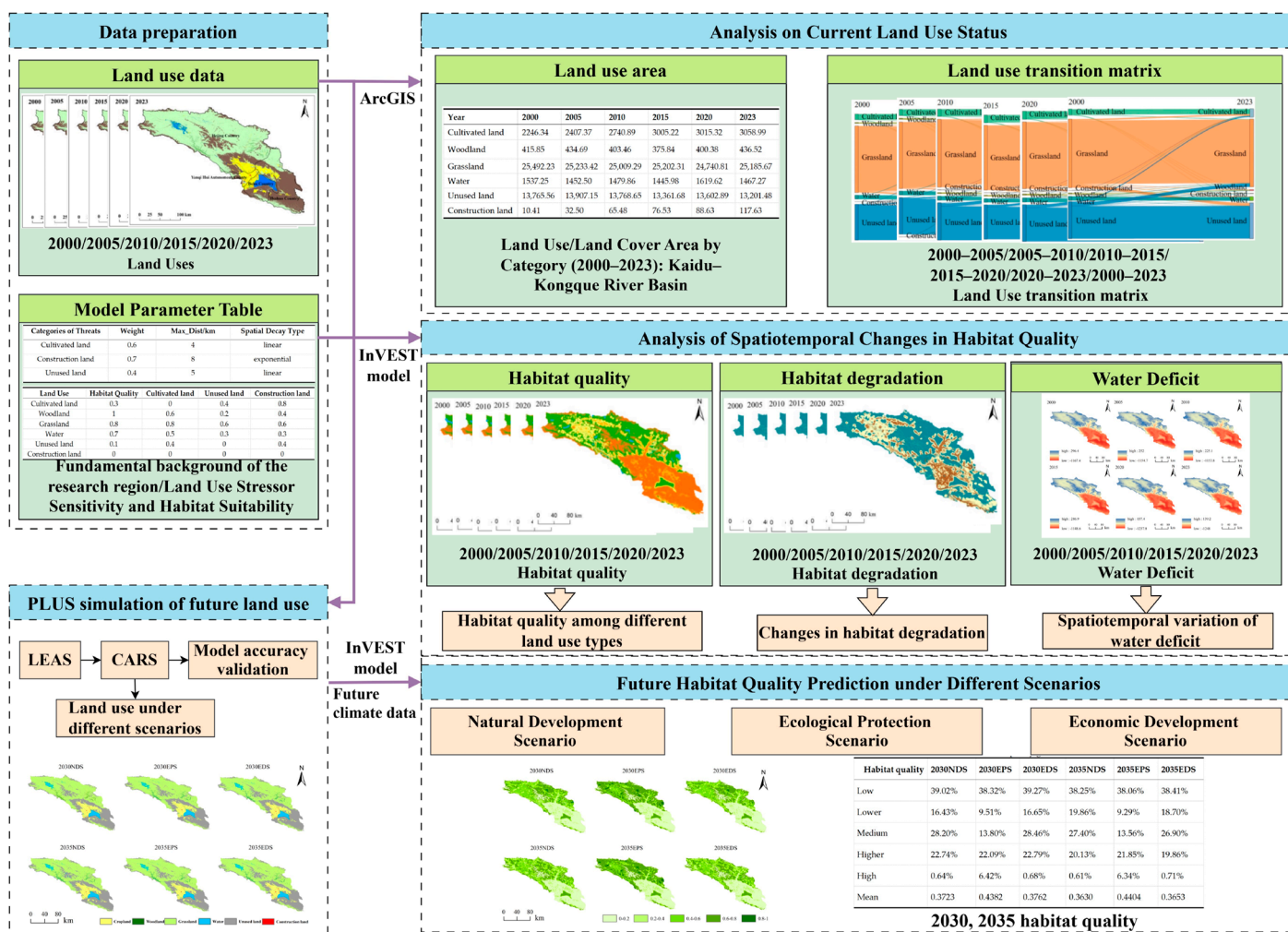


Figure 1. Research Methodology Flowchart.

2. Materials and Methods

2.1. Study Areas

Situated in the central-southern region of Xinjiang, the Kaidu–Kongque River (KKR) system lies in the northeastern Tarim Basin, with geographical coordinates ranging from 83°02' to 92°33'E and 40°09' to 43°43'N (Figure 2). As a typical inland river basin, it serves as a crucial ecological corridor connecting the Tianshan Mountains and the Tarim Basin [7]. Characterized by a significant topographic gradient descending from the northwest to the southeast, the basin elevation ranges from 700 m at the basin edge to 4800 m in the alpine zone. This elevation variation has formed a distinct vertical zoning pattern that encompasses four major landscape types: mountainous areas, oases, deserts, and eco-tones, providing an ideal natural laboratory for studying complex arid region ecosystems [6].

The basin features an extreme continental climate with an annual temperature range exceeding 40 °C. Spatially, the mean annual precipitation ranges from 50.15 to 287.28 mm, while potential evaporation is extremely high, resulting in a significant water deficit. This typical temperate arid climate pattern fundamentally constrains regional hydrological

processes and ecosystem resilience [9,20,21]. The hydrological system comprises the Kaidu River (main water source), Bosten Lake (the largest freshwater lake in Xinjiang), and the Peacock River (terminal drainage system), which collectively maintain the balance between ecological and socio-economic functions.

Soil and vegetation types exhibit distinct vertical and horizontal differentiation. In foothill zones, soils are primarily brown desert soil; alpine meadow soil dominates high-altitude areas, and aeolian sandy soil is distributed in transitional desert regions. Vegetation presents a spatial mosaic pattern characterized by the coexistence of arid desert shrubs and irrigated oasis ecosystems, forming a typical arid landscape complex.

From a socioeconomic perspective, the population is primarily concentrated in Korla City and surrounding oasis towns. The regional economy exhibits a distinctive “agriculture-industry-service” composite structure: agriculture, dominated by cotton, fruit cultivation, and irrigated crops, contributes approximately 35% of the regional GDP, while energy extraction, manufacturing, and logistics serve as other key pillars. The mutual interaction between this complex natural environment and intensive human activities designates the KKR system as a pivotal research area for exploring water resource governance and ecological security in arid areas.

In this study, hydrological sub-basin boundaries derived from DEM-based watershed delineation in ArcGIS 10.8.2 are adopted as the primary criterion for the upstream-downstream zoning of the Kaidu–Kongque River Basin.

The upstream zone corresponds to the entire Kaidu River sub-basin, which covers the mountainous source area of the Kaidu River and the Yanqi Basin before inflow into Bosten Lake; its elevation ranges from approximately 1048 m in the basin plain to above 4800 m in alpine areas.

The downstream zone refers to the Kongque River sub-basin, starting from the outflow of Bosten Lake and covering the oasis-desert reaches of the Kongque River, with elevations mostly below 1050 m. The spatial extents of these two sub-zones are illustrated in Figure 2.

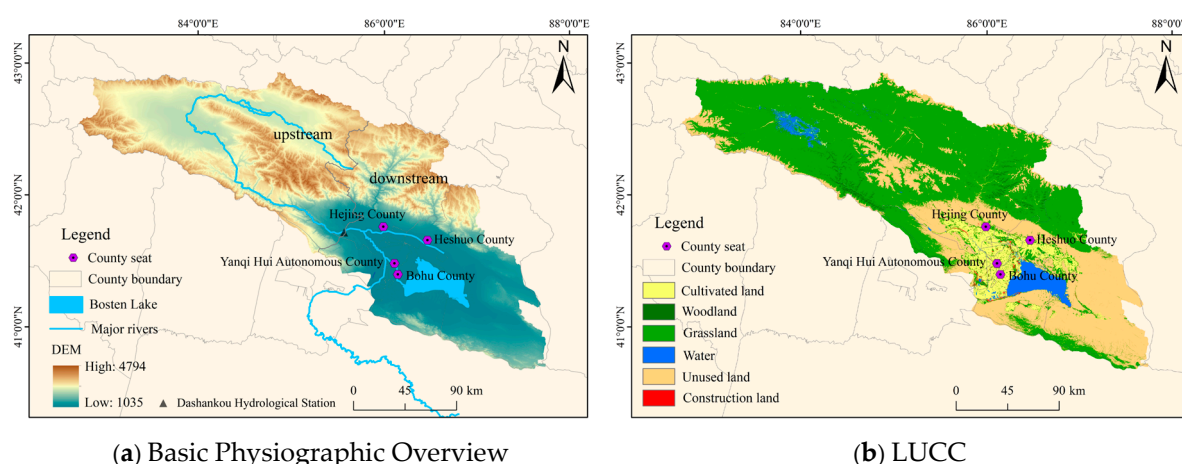


Figure 2. Study area location.

2.2. Data Origins and Processing Procedures

To ensure the scientific rigor and reproducibility of habitat quality assessment, this study followed the technical workflow of data collection, preprocessing, parameter configuration, and model calculation, and systematically integrated multi-source spatial data and attribute parameters. The specific implementation is as follows:

2.2.1. Data Sources

The core data for this study comprises land use/cover data spanning from 2000 to 2023 within the study area, which is sourced from the China Annual Land Cover Dataset (CLCD) [22]. This dataset was developed by the research team led by Yang and Huang at Wuhan University. It has a spatial resolution of 30 m, is constructed on the Google Earth Engine platform, and integrates 335,709 Landsat series images. After validation using 5131 independent samples, the overall classification accuracy reached 79.31%. Compared with global datasets such as MCD12Q1 and GlobeLand30, the CLCD demonstrates superior performance in arid regions, providing reliable data support for research on regional-scale land use dynamics.

2.2.2. Preprocessing Workflow

For raw CLCD data, this study performed standardized preprocessing in ArcGIS 10.8 to meet the input requirements of the InVEST model and the objectives of this regional research. The preprocessing workflow began with land use type recategorization: the original 10 land cover categories were consolidated into six core types, namely grassland, arable land, forest, water bodies, unused land, and construction land [23,24]. To ensure spatiotemporal consistency, topological verification and edge matching were performed on the recategorized raster data, and the total area error of all land features was strictly controlled within 0.5%. This process effectively eliminated redundant landscape information, reduced analytical complexity, and retained key data on ecological landscape patterns, laying a solid foundation for subsequent model calculation.

2.2.3. Parameter Selection

Based on the InVEST model framework requirements, regional ecological characteristics, and existing research findings, this study conducted localized calibration and screening of core parameters for the habitat quality module, with particular emphasis on identifying parameters related to threat factors and habitat sensitivity.

Considering the anthropogenic disturbance characteristics of arid inland river basins in the region, construction land, cultivated land and unused land were selected as primary threat factors [25,26]. Through the systematic literature review and integration of expert knowledge, referencing the InVEST model manual and similar regional studies, the relative impact weights of these three threat factors were set at 0.6, 0.7, and 0.4, respectively, to accurately reflect their differentiated impacts on habitat degradation [27–29].

According to InVEST reference guidelines and empirical environmental data, the maximum effective impact distances for cultivated land, construction land, and unused land were calibrated to 4 km, 8 km, and 5 km, respectively. For attenuation modeling, an exponential decay function was adopted to simulate nonlinear impact characteristics of construction land, while linear decay functions were used for cultivated land and unused land. Additionally, habitat suitability classification and stress factor sensitivity assessments for various land use types were completed by integrating land use data with regional ecological research [30,31]. Specific parameter configurations are detailed in Tables 1 and 2.

Table 1. Fundamental background of the research region.

Categories of Threats	Weight	Max_Dist/km	Spatial Decay Type
Cultivated land	0.6	4	linear
Construction land	0.7	8	exponential
Unused land	0.4	5	linear

Table 2. Stressor and habitat suitability.

Land Use	Habitat Quality	Cultivated Land	Unused Land	Construction Land
Cultivated land	0.3	0	0.4	0.8
Woodland	1	0.6	0.2	0.4
Grassland	0.8	0.8	0.6	0.6
Water	0.7	0.5	0.3	0.3
Unused land	0.1	0.4	0	0.4
Construction land	0	0	0	0

To verify the rationality of the parameter settings, the habitat quality outputs simulated by the InVEST model for 2000, 2005, 2010, 2015, and 2020 were compared with the corresponding data from the same years in China's High-resolution Ecological Environment Quality dataset (CHEQ, 2001–2021).

Because the CHEQ dataset does not provide data for 2000, the 2001 CHEQ dataset was used as a proxy for the 2000 InVEST-derived HQ for validation. For each corresponding year, the correlation coefficient between the InVEST-derived HQ and CHEQ data was calculated to evaluate their spatial consistency and provide external validation for the simulated habitat quality [32]. The CHEQ dataset was constructed by scholars such as Xu Dong and Yang Feng from Beijing Normal University based on multi-source remote sensing data. It exhibits high consistency with the environmental indicators released by China's environmental authority and is capable of objectively reflecting the regional ecological environment quality status. Validation results showed that the Pearson correlation coefficient varied between 0.658 and 0.781, and the Spearman correlation coefficient varied between 0.659 and 0.886, indicating that the local parameter settings are reasonable.

2.2.4. Meteorological and Soil Moisture Data

To further investigate the water-driven mechanisms underlying habitat quality in arid regions, this study incorporates additional meteorological and soil moisture datasets [33] to quantify both macroclimatic water budgets and local soil moisture conditions.

Meteorological data: Monthly precipitation (P) and potential evaporation (PET) records from 2000 to 2023 were obtained from the Qinghai–Tibet Plateau Data Center (<http://data.tpdc.ac.cn>, accessed on 18 June 2026). Meteorological water deficit (Water Deficit, WD) is defined as the difference between annual precipitation and annual potential evaporation ($WD = P - PET$), with negative values indicating greater climatic drought severity.

Soil moisture data: Surface soil volume moisture content (Soil Moisture Content, SMC, 0–10 cm) for the same period were sourced from the Global Land Data Assimilation System (GLDAS) (<https://ldas.gsfc.nasa.gov/gldas>, accessed on 18 June 2026). To ensure consistency with habitat quality spatial analysis, all meteorological and soil moisture raster datasets were resampled to a spatial resolution of 1000 m using ArcGIS and cropped/masked according to vector boundaries of the study area. Annual averages of WD and SMC were used for spatial correlation analysis with corresponding years' habitat quality indices.

2.3. Habitat-Quality Simulation Using the InVEST Model

This study applied the habitat quality module of InVEST version 3.14.0 [34,35] to conduct a systematic quantitative assessment of ecosystem health status in the KKRB. As a widely used tool in international ecological assessment, this model integrates spatial analysis and process simulation technologies, with its core logic focusing on establishing dynamic response relationships between habitat quality and threat sources. The imple-

mentation was carried out in three steps: First, digital characterization was performed using GIS technology to capture the spatial patterns, impact intensity, and attenuation gradients of threat factors—including farmland expansion, urban construction, and idle land development—thereby quantifying habitat stress levels. Second, ecological functional attributes of different land use types were integrated to evaluate regional habitat suitability. Finally, based on the threat-suitability coupling mechanism, a hierarchical calculation framework was employed to complete comprehensive regional suitability assessment, thereby revealing habitat degradation risks and quality levels within the watershed.

The habitat quality index is measured on a continuous 0–1 scale: values approaching zero indicate significant human disturbance, severe habitat fragmentation, and substantial degradation of ecosystem services. Higher values near 1 reflect greater habitat integrity and enhanced ecological carrying capacity, which not only provide wildlife with optimal habitats for reproduction but also maintain high biodiversity and ecosystem stability. This quantitative approach standardizes the presentation of watershed ecological conditions, offering a scientific foundation for developing conservation strategies.

In this study, we did not directly use the default parameter configuration of the InVEST-Habitat Quality module. Instead, we implemented targeted improvements tailored to the characteristics of arid inland river basins.

By synthesizing existing published regional studies on arid inland basins, we recalibrated the threat source weights for cropland, construction land, and unused land, rather than directly adopting the default global values. We further verified the rationality of this localized parameter scheme by comparing it with published ecohydrological observations and regional habitat records for the KKRb.

2.3.1. PLUS Model Simulation

The Patch-generating Land Use Simulation (PLUS) model uses multiple integrated sub-models to simulate land use dynamics. Based on the Land Expansion Analysis Strategy (LEAS) and the Random Forest algorithm, it establishes a rule mining framework that can effectively characterize the driving mechanisms underlying land use changes, providing a novel perspective for simulating regional land use dynamics [36]. The Land Expansion Analysis Strategy (LEAS) simplifies the analysis process while retaining the ability to represent complex transitions across multiple land use types. Using the land use expansion probabilities derived from LEAS, the model further develops a cellular automaton (CA) framework with multi-type stochastic patch seeds, enabling the simulation of growth processes for different land use types at fine spatial resolution [37].

This study employs the PLUS v1.4.2 software platform for land use change simulation. To characterize the evolutionary patterns of land use, the Monte Carlo method is applied to calculate the development probabilities of different land use types, which is expressed as follows:

$$D_{i,k}^t = \begin{cases} D_{i,k} \times (h \times \sigma_k) \times P_{i,k}^t, & \text{if } \mu_{i,k}^t = 0 \text{ and } h < D_{i,k} \\ D_{i,k} \times \mu_{i,k}^t \times P_{i,k}^t, & \text{otherwise} \end{cases} \quad (1)$$

Several parameters appear in the equation. For a given grid cell i and land use type k : $D_{i,k}$ is the growth probability; $P_{i,k}^t$ is an adaptive driving coefficient that responds to the difference between the current land quantity (iteration t) and the future demand for type k ; $\mu_{i,k}^t$ is the neighborhood effect, defined as the proportion of type k in neighboring cells; h is a stochastic term uniformly distributed between 0 and 1; and σ_k is a user-specified threshold that controls the emergence of new patches of type k .

Regarding the selection of driving factors, this study comprehensively considered both natural environmental conditions and human activity characteristics within the research area, and ultimately identified 14 variables as model inputs (Figure 3). These included annual average temperature, annual precipitation, population distribution, soil type, DEM, slope gradient, nighttime light intensity, distance to residential areas, distance to rivers, distance to railways, distance to major roads, distance to secondary roads, distance to tertiary roads, and distance to highways. Additionally, the study incorporated practical regional conditions and the model user manual, while referencing previous research findings [38].

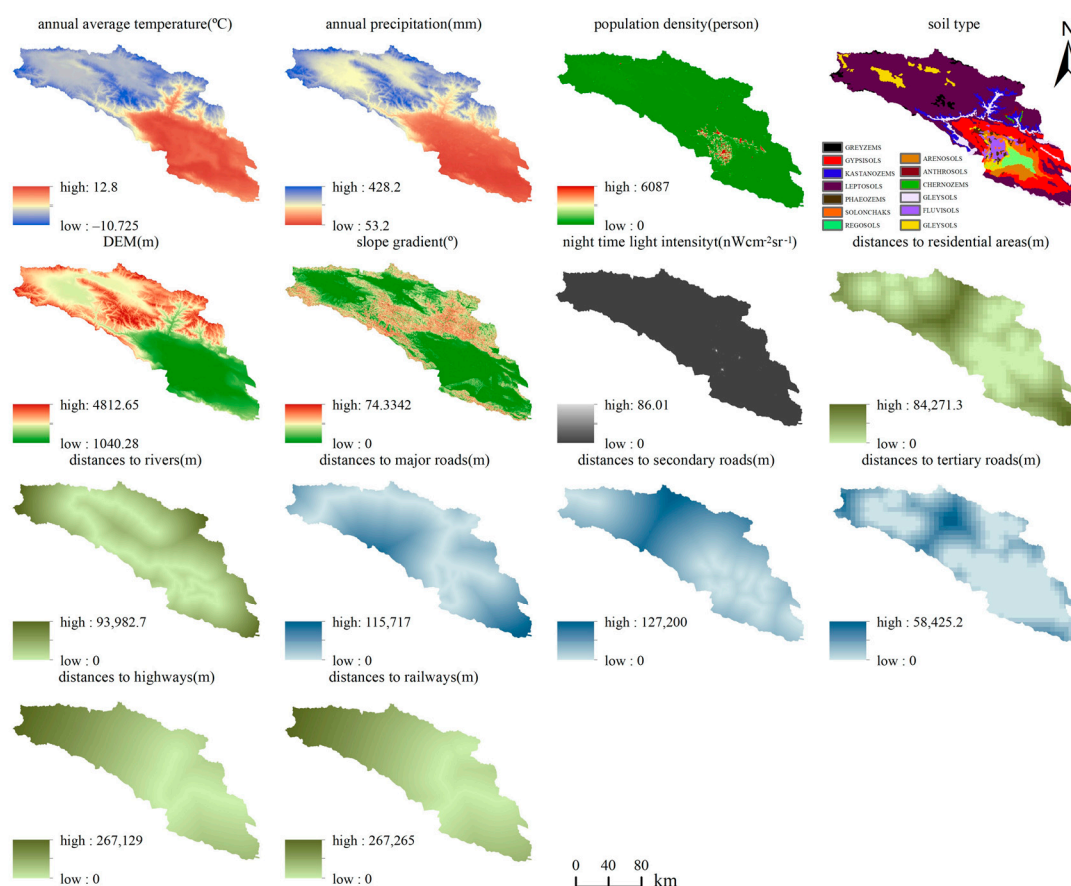


Figure 3. Selected driving factors for model input.

Neighborhood weights were determined based on the proportion of expanded land use types relative to the total expanded area from 2010 to 2023 [39]. The calculated neighborhood weight parameters for each land use type are presented in Table 3. In the transition matrix, 1 indicates that conversion from the row land use type to the column land use type is permitted, whereas 0 indicates that the conversion is restricted. The NDS represents a relatively unconstrained development pathway, while the EPS and EDS impose different transition constraints to emphasize ecological protection and economic development, respectively.

Table 3. Neighborhood Weight Parameters for Different Land Use Types.

Cultivated Land	Woodland	Grassland	Water	Unused Land	Construction Land
0.432	0.011	0.163	0.037	0.300	0.057

Based on the land use conversion matrix (Table 4), three future land use scenarios were constructed: Natural Development Scenario (NDS), Ecological Protection Scenario (EPS), and Economic Development Scenario (EDS), to simulate the evolution trends of land use patterns under different development pathways.

Table 4. land use conversion matrix.

Scenario		Cultivated Land	Woodland	Grassland	Water	Unused Land	Construction Land
NDS	Cultivated land	1	1	1	1	1	1
	Woodland	1	1	1	1	1	1
	Grassland	1	1	1	1	1	1
	Water	1	1	1	1	1	1
	Unused land	1	1	1	1	1	1
	Construction land	1	1	1	1	1	1
EPS	Cultivated land	1	1	1	0	0	0
	Woodland	0	1	0	0	0	0
	Grassland	0	1	1	0	0	0
	Water	0	0	0	1	0	0
	Unused land	1	1	1	1	1	1
	Construction land	1	1	1	1	1	1
EDS	Cultivated land	1	1	1	1	1	1
	Woodland	1	1	1	1	1	1
	Grassland	1	1	1	1	1	1
	Water	0	0	0	1	0	1
	Unused land	1	1	1	1	1	1
	Construction land	0	0	0	0	1	1

Model accuracy was validated by projecting the 2023 land use pattern from 2020 data and comparing the simulated results against the observed 2023 land use conditions (Figure 4). A total of 2,416,566 pixels covering six land use categories were evaluated, and the corresponding confusion matrix is presented in Table 5. The overall accuracy (OA) was 0.928, and the Kappa coefficient was 0.873, indicating a high level of agreement between the simulated and observed land use patterns. The confusion matrix further details the category-specific distribution and classification accuracy, confirming that the PLUS model is reliable for subsequent land use simulation.

Table 5. Land use confusion matrix.

Land Use Types	Cultivated Land	Woodland	Grassland	Water	Unused Land	Construction Land	Total
Cultivated land	151,316	526	15,042	1782	972	2125	171,763
Woodland	492	15,264	5280	427	7	54	21,524
Grassland	12,502	7754	1,302,333	2853	35,537	1359	1,362,338
Water	2664	630	10,648	75,976	1564	567	92,049
Unused land	2211	21	66,096	587	694,486	163	763,564
Construction land	528	2	1028	86	1364	2320	5328

Construction land	169,713	24,197	1,400,427	81,711	733,930	6588	2,416,566
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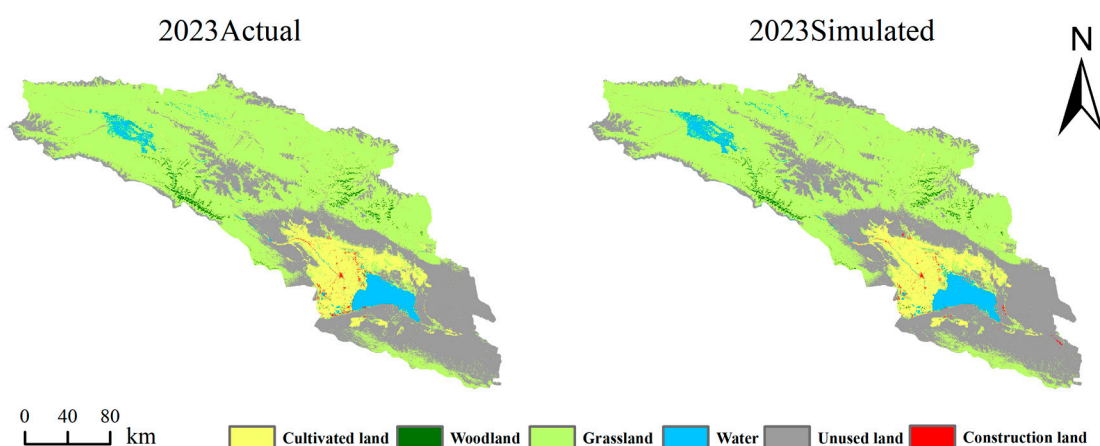


Figure 4. Comparison of Actual Land Use Distribution and Simulation Results in 2023.

2.3.2. Calculation of Habitat Degradation Degree (D_{xj})

The D_{xj} is employed to assess how much habitat degradation exists in grid cell x for land use type j , which directly reflects the severity of regional ecological pressure. The core calculation formula and parameter definitions are as follows:

$$D_{xj} = 1 - \exp\left(-\frac{\sum_{r=1}^R W_r \cdot r_y \cdot \beta_x \cdot S_{jr} \cdot i_{rxy}}{A}\right) \quad (2)$$

Among them, the variable r represents various threat factors. Let y be the count of grid cells that contain threat factor r , and Y_r is the total number of grid cells corresponding to the threat factor; the two together define the spatial distribution range of the threat source. The weight parameter W_r is determined by expert knowledge and historical research, and a larger value indicates a stronger potential destructive effect of the corresponding threat factor on habitat quality. r_y is the actual threat intensity of the threat factor r in grid cell y , which reflects the degree of interference from human activity. β_x is the threat accessibility of habitat grid cell x , which reflects the hindering or promoting effect of geographical factors such as topography and water systems on threat diffusion. S_{jr} is the sensitivity of land use type j to the threat factor r ; due to differences in ecological functions, different land use types have significant differences in their responses to the same threat. i_{rxy} is a distance decay function that quantifies the actual impact attenuation of threat factor r between grid cells y and x . The decay model (exponential or linear) can be selected according to the conditions of the local study area. A is a standardization constant used to balance magnitude differences among the calculation results of each parameter.

2.3.3. Calculation of Habitat Quality Index (Q_{xj})

Q_{xj} represents the habitat quality level of grid cell x as determined by its land use type j . The core calculation formula and parameter definitions are as follows:

$$Q_{xj} = H_j \cdot \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right) \quad (3)$$

Among them, H_j is based on the ecological function attributes of different land use types, reflecting the suitability of habitat type j , that is, the ability of the habitat to provide

resources and living conditions for organisms. The parameter k is a half-saturation constant with a value of 0.332, defined as half of the maximum relative habitat degradation value. It improves the goodness of fit of evaluation results by balancing the nonlinear relationship between habitat degradation and the habitat quality index. z is the model's default normalization constant with a value of 2.5, which is used to standardize unify the calculation results of habitat quality, ensuring that all final Q_{xj} values fall within the range of [0,1], to facilitate comparative analysis of habitat quality across different regions and periods.

3. Results

3.1. Analysis on Current Land Use Status in Kaidu–Kongque River Basin

3.1.1. Land Use Dynamics in the Kaidu–Kongque River Basin (2000–2023)

Spanning a total area of 43,467.6 km², the Kaidu–Kongque River Basin has experienced substantial land use restructuring from 2000 to 2023 (Table 6). Grassland and unused land constitute the dominant land-cover types across the whole basin. The most prominent feature is the continuous expansion of cultivated and construction land at the expense of natural ecological land.

Cultivated land increased steadily from 2246.34 km² in 2000 to 3058.99 km² in 2023, representing a cumulative increase of 36.2%. Large-scale agricultural reclamation has persistently encroached on natural ecological space and simplified native landscape structures, potentially undermining the integrity and stability of regional habitats. Benefiting from successive ecological restoration measures, forestland increased moderately from 415.85 km² to 436.52 km², with a cumulative growth of 5.0%, which reflects partial achievements of regional ecological conservation. Nevertheless, grassland exhibited complex changing trajectories and experienced a net area loss of 1.2%. This pattern of local degradation interspersed with partial recovery indicates long-term pressures from grazing and reclamation. Although targeted ecological management has mitigated degradation in some locations, grassland ecosystems remain overall unstable, constraining sustained improvements in regional habitat quality.

From a land-hydrology coupling perspective, the total area of water bodies gradually decreased from 1537.25 km² to 1467.27 km², corresponding to a cumulative reduction of 4.5%. The shrinkage of surface water exacerbates water scarcity in this arid basin, weakens the ecological carrying capacity of riparian zones, and poses persistent threats to aquatic and wetland-dependent habitats.

Unused land displayed an overall declining trend with obvious inter-period fluctuations. It peaked at 13,907.15 km² in 2005 and then decreased to 13,202.48 km² by 2023, yielding a cumulative reduction of 4.1%. Despite the reduction in bare-land area driven by ecological governance and land development, marked fluctuations imply that desertification risks have not been fundamentally eliminated, which remains a key constraint on the stability of downstream desert habitats.

Driven by rapid urbanization, construction land expanded by 10.3-fold over the study period and greatly intensified anthropogenic disturbance across the basin. Although glacial meltwater provides temporary hydrological support for agricultural development, unregulated expansion of cropland and built-up areas consumes regional water resources and may trigger groundwater decline and soil salinization. Such human-driven land use disturbances represent the primary underlying factor shaping spatial differentiation and overall degradation of habitat quality in the basin.

In summary, temporal land use changes reflect growing human-land conflicts within the study area. These long-term structural shifts in land cover establish a fundamental

terrestrial background for interpreting spatiotemporal variations in habitat quality of the Kaidu–Kongque River Basin.

Table 6. Land Use/Land Cover Area by Category (2000–2023): Kaidu–Kongque River Basin (km²).

Year	2000	2005	2010	2015	2020	2023
Cultivated land	2246.34	2407.37	2740.89	3005.22	3015.32	3058.99
Woodland	415.85	434.69	403.46	375.84	400.38	436.52
Grassland	25,492.23	25,233.42	25,009.29	25,202.31	24,740.81	25,185.67
Water	1537.25	1452.50	1479.86	1445.98	1619.62	1467.27
Unused land	13,765.56	13,907.15	13,768.65	13,361.68	13,602.89	13,201.48
Construction land	10.41	32.50	65.48	76.53	88.63	117.63

3.1.2. Analysis of Spatial Changes in Land Use

Land use conversions during 2000–2023 show pronounced spatial heterogeneity across the Kaidu–Kongque River Basin, manifested as the contraction of ecological land and the expansion of productive land (Figure 5, Table 7). Using the land use transition matrix (Table 7) and Sankey diagram (Figure 6), this subsection further identifies spatial conversion patterns among different land-cover types, which directly shape the zonal divergence of regional habitat conditions.

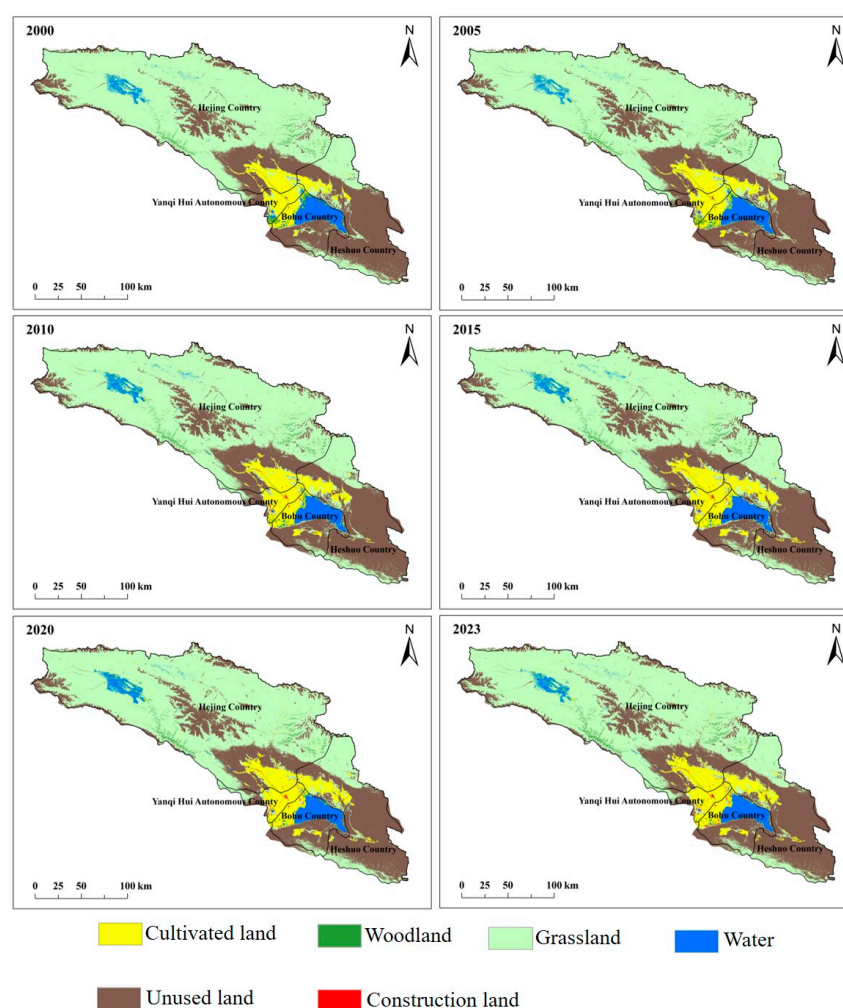


Figure 5. Land Use Distribution Patterns Across the Kaidu–Kongque Basin: 2000–2023.

Table 7. Land-use transition matrix of the Kaidu–Kongque River Basin from 2000 to 2023 (km²)

2000–2023	Cultivated Land	Woodland	Grassland	Water	Unused Land	Construction Land
Cultivated land	1988.05	5.07	188.34	24.49	9.82	30.56
Woodland	94.18	232.48	72.78	8.84	0.04	7.52
Grassland	505.65	187.29	23,535.87	157.01	1057.90	45.57
Water	91.57	11.07	137.34	1260.11	24.31	12.84
Unused land	378.16	0.60	1246.45	16.64	12,103.98	14.96
Construction land	1.32	0.00	2.27	0.17	0.47	6.17

Cultivated land is mainly distributed within the Yanqi Basin and has expanded outward from core oases toward the southern periphery. Over the 23-year study period, the total outflow of cultivated land (converted to other land types) amounted to 258.28 km², and the total inflow (converted from other land types) was 1070.88 km². The primary sources of cultivated land inflow were grassland (47.2%) and unused land (35.3%). Notably, rapid cropland expansion during 2010–2015 was driven primarily by the conversion of grassland (283.53 km²) and unused land (102.86 km²). The outward sprawl of cultivated land compresses surrounding natural ecological space, fragments formerly continuous grassland habitats, and reduces landscape connectivity in mid-stream oasis zones.

Forests are concentrated in south-central and northeastern mountainous zones. Local forest recovery in the northeast corroborates the effectiveness of mountain ecological protection projects. As the core natural ecological component of the basin, grassland accounts for 58.7% of the total basin area in 2000 and is mostly distributed across western upstream zones. Although portions of unused land were converted back to grassland, the total grassland area still declined by 306.24 km² between 2000 and 2023. The loss of upstream and mid-stream grassland diminishes high-quality vegetated habitats and impairs the basin's ecological conservation capacity.

Centered on Bosten Lake, the aquatic system sustains the basin's key hydrological framework. While some peripheral water-body areas shrank under combined anthropogenic and climatic pressures, the main lake area remained stable owing to targeted ecological protection policies. The stable lacustrine environment supports downstream riparian habitats, whereas localized water loss triggers partial habitat degradation along terrestrial-aquatic ecotones.

Widely distributed across central and downstream desert zones, unused land experienced net area reduction through large-scale conversion to grassland and water bodies. The total area of unused land converted to other land types was 1656.81 km², most of which was converted into grassland (1246.45 km²; 75.2%); a further 16.64 km² (1.0%) was converted to water. This ecological restoration mitigates local desertification and optimizes habitat configurations across desert-oasis ecotones. Even so, the inherently fragile background of unused land keeps downstream habitats at low stability. The net area of unused land decreased by 564.27 km² over the study period.

Construction land is mainly located in Yanqi Hui Autonomous County and Bohu County and exhibits the highest relative growth rate. The total inflow of construction land (converted from other land types) amounted to 111.45 km², and the total outflow (converted to other land types) was 4.23 km². New built-up areas are primarily transformed from grassland (40.9%), cultivated land (27.4%), and unused land (13.4%). Urban sprawl and infrastructure construction generate intensive anthropogenic disturbance hotspots in mid-stream oases, leading to persistent habitat fragmentation and quality deterioration in urban fringe zones.

Overall, land use conversion intensity presents a clear disturbance gradient from upstream mountainous regions, through mid-stream oases, to downstream deserts. This spa-

tially heterogeneous pattern of human interference directly produces the typical “upstream improvement-downstream degradation” divergence in habitat quality, and provides a land-surface-based interpretation for subsequent InVEST simulation outputs.

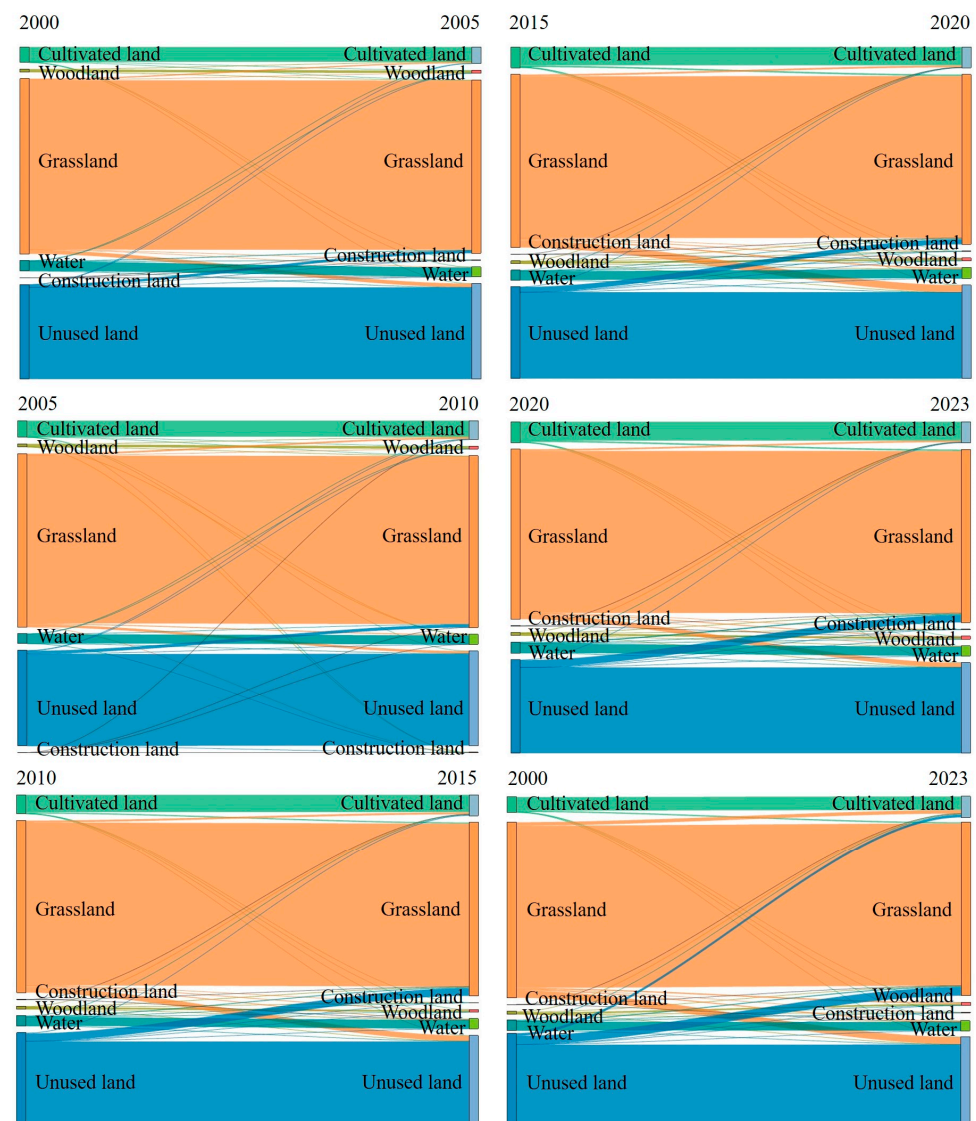


Figure 6. Sankey Diagram of Land Use Transitions in the Kaidu–Kongque River Basin (2000–2023). Each color corresponds to a land use type, including cultivated land, woodland, grassland, water, construction land, and unused land.

3.2. Analysis of Spatiotemporal Changes in Habitat Quality in the Kaidu–Kongque River Basin

This study systematically evaluated the habitat quality of the Kaidu–Kongque River Basin spanning the years 2000 to 2023. A systematic analysis was performed using the habitat quality module embedded in the InVEST model, and the evaluation results were optimized via ArcGIS spatial analysis technology. To clearly present the spatial variations in the basin's ecological environment and uncover the specific conditions across different ecological zones, habitat quality was meticulously classified into five levels corresponding to diverse ecological statuses: Low-quality Zone (0–0.2), Lower-quality Zone (0.2–0.4), Medium-quality Zone (0.4–0.6), High-quality Zone (0.6–0.8), and Higher Zone (0.8–1).

Over the span of 2000–2023, the habitat quality in the Kaidu–Kongque River Basin underwent substantial spatial heterogeneity and phased evolutionary trends (Figure 7). The basin exhibits obvious divergence among upstream, midstream and downstream

reaches under distinct environmental backgrounds. The upstream mountainous area is dominated by high-grade habitat quality; the midstream oasis-desert transition zone presents moderate and fluctuating habitat conditions; the downstream desert fringe is characterized by low habitat quality under intensive human-land conflicts. High-quality habitats were mainly distributed in the alpine forests and natural grasslands of the upper Kaidu River region. In this area, the dense vegetation and low human activity have contributed to the formation of stable ecosystems, which offer optimal habitats for a wide variety of wildlife. High-quality habitats were also concentrated in the extensive grasslands in the upstream areas of the Kaidu River and the waters around Bosten Lake. These areas, characterized by grassland and aquatic ecosystems, exert a pivotal influence on preserving robust biodiversity and ecological services within the basin.

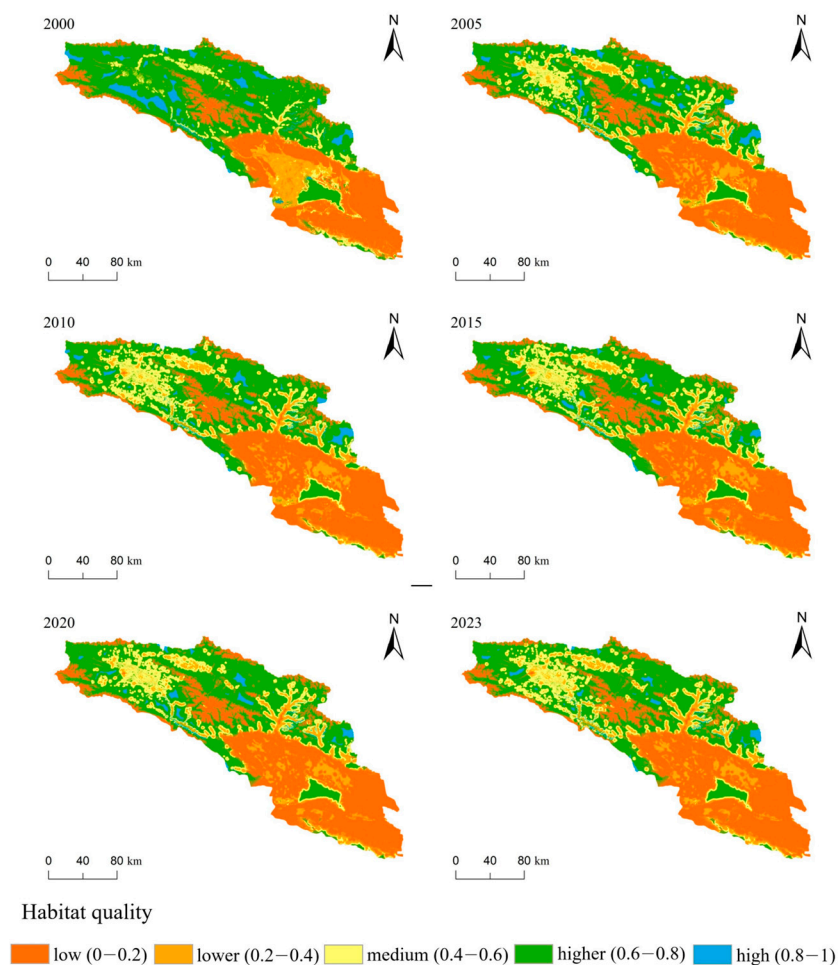


Figure 7. Temporal Shifts in Habitat Quality Distribution across the Kaidu–Kongque Basin (2000–2023).

Medium-quality habitats are primarily located along the Upper Kaidu River and the surrounding areas of the Peacock River. These areas are characterized by sparse vegetation cover and moderate ecosystem stability and are shaped by natural conditions with minimal human interference. In contrast, low-quality habitats are mainly concentrated in the Yanqi Basin.

Data from Table 8 reveal phased changes in habitat quality across different periods. From 2000 to 2010, the rapid expansion of construction land and intensified resource exploitation increased human disturbance intensity, resulting in continuous degradation of habitat quality across the whole basin. The area of low-quality habitats expanded from

13,892.52 km² to 16,153.87 km² (a net increase of 2261.35 km²), while the area of high-quality habitat decreased sharply from 21,486.96 km² to 16,126.54 km². This highlights the continuous ecological erosion caused by intensive human development. This set of data reflects the severe ecological erosion brought by large-scale human development activities.

Table 8. Multi-Temporal Habitat Quality Class Areas (km²) in the Kaidu–Kongque River Basin.

Habitat Quality	2000	2005	2010	2015	2020	2023
0–0.2	13,892.52	15,854.52	16,153.87	15,998.87	16,355.81	16,111.84
0.2–0.4	2773.74	3720.10	3743.36	4041.31	3718.39	3854.53
0.4–0.6	3161.53	5584.36	6373.83	6116.86	5910.23	6316.08
0.6–0.8	21,486.96	16,875.43	16,126.54	16,389.98	16,443.76	16,341.06
0.8–1	2152.89	1433.22	1070.03	920.54	1039.44	844.04

Between 2010 and 2020, under the promotion of a series of ecological protection and restoration policies, the changing trend of habitat quality in the basin showed obvious fluctuation characteristics. Although the area of low-quality habitat still expanded to a certain extent after 2015, the area of high-quality habitat achieved a moderate recovery, with a cumulative increase of 317.22 km² in the decade. This indicates that the implementation of ecological restoration projects has alleviated the long-term degradation trend of local habitats and restored part of the basin's ecosystem service functions.

From 2020 to 2023, the ecological conditions of natural habitats in the basin experienced significant fluctuations again. Comprehensive monitoring data revealed a substantial decrease in the area of low-quality habitats, with a reduction of 243.97 km². Simultaneously, the area of relatively high-quality habitats also showed a downward trend, shrinking by 102.70 km². This contradictory phenomenon indicates that although local ecological restoration efforts have achieved certain outcomes, the Kaidu–Kongque River Basin still faces dual challenges from climatic variability and anthropogenic disturbances. Frequent extreme climatic events further disrupt the spatiotemporal distribution patterns of water resources, while ongoing agricultural expansion and urbanization continue to encroach on ecological spaces. These factors collectively pose severe threats to ecosystem stability, meaning more targeted ecological conservation measures and adaptive management strategies are urgently needed (zoning criteria; see Section 2.1).

As depicted in Figure 8, the downstream section of the Kaidu–Kongque River Basin is undergoing the most severe ecological degradation, demonstrating distinct evolutionary stages and spatial variation patterns. From 2000 to 2010, the pressure on the agricultural ecosystem in the Yanqi Basin intensified significantly due to the expansion of farming operations. Areas affected by mild degradation expanded rapidly, primarily driven by agricultural irrigation systems and land reclamation activities. From 2010 to 2020, the accelerated extraction of mineral resources and the construction of transportation infrastructure led to a marked expansion of moderately degraded zones. During this period, extensive engineering projects triggered a sharp rise in the level of moderate degradation, resulting in multi-faceted disruptions to the ecosystem structure and functionality.

After 2020, ecological changes will show a spatial differentiation pattern characterized by “upstream-downstream” contrast. While the degradation trends in some upstream regions have been initially curbed through ecological restoration projects, the downstream oasis fringe areas have seen intensified conflicts in water resource allocation and continuous deterioration of land use quality. This forms a clear “upstream improvement-downstream degradation” pattern. Notably, since 2015, continuous ecological water replenishment projects have given rise to multiple localized ecological improvement zones around Bosten Lake, which have produced remarkable demonstration effects.

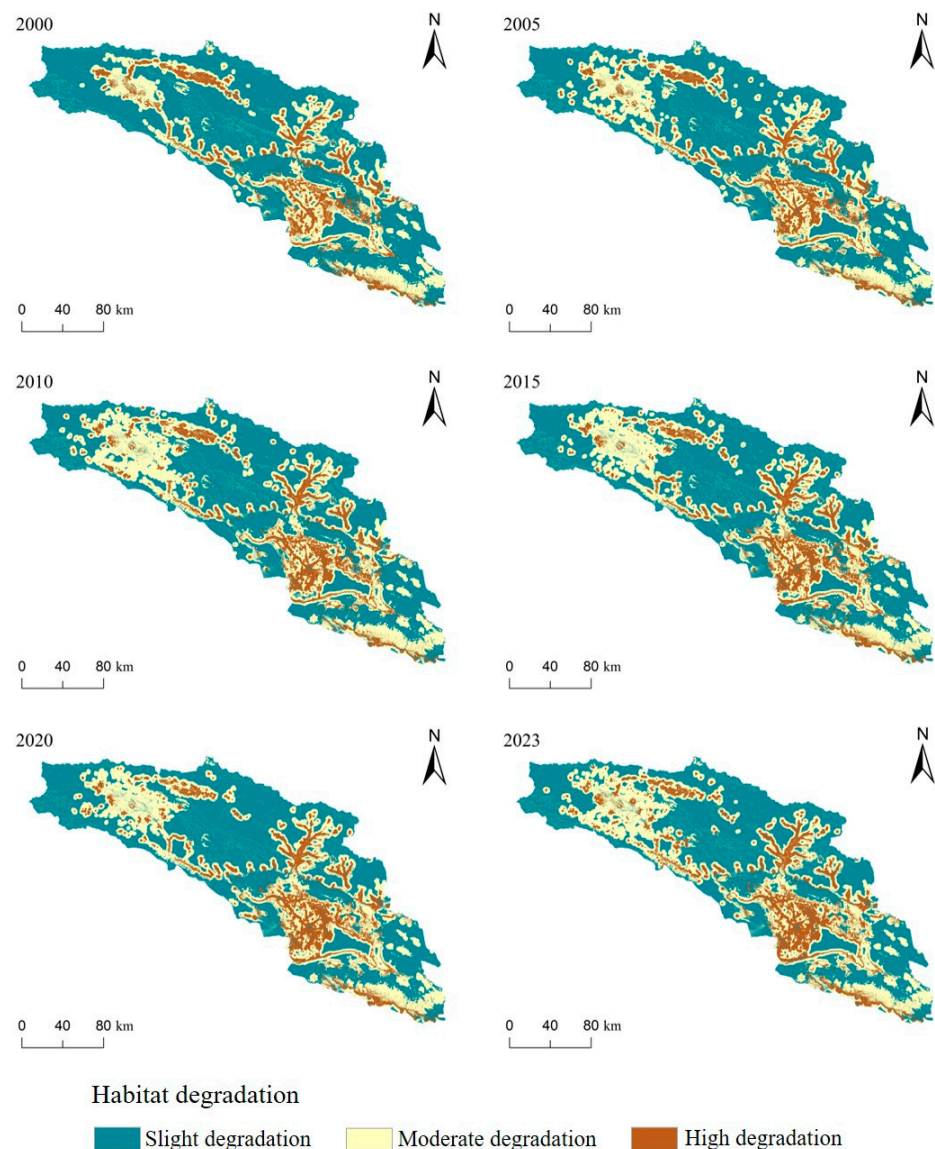


Figure 8. Mapping habitat quality loss across the Kaidu–Kongque River Basin.

The above-mentioned zonal habitat divergence at watershed scale is closely related to land-cover composition. Habitat suitability differences among various land use categories are further analyzed in Section 3.3.

3.3. Spatiotemporal Variations in Habitat Suitability Among Various Land Use Categories

Table 9 comprehensively illustrates the spatiotemporal dynamic characteristics of habitat suitability levels across different land use types in the KKRBB. Distinct habitat quality disparities exist among diverse land-cover categories, which further explains the zonal habitat differentiation patterns described in Section 3.2.

Table 9. Habitat quality grade shifts by land use type (2000–2023).

Land Type	Habitat Quality	2000	2005	2010	2015	2020	2023
Cultivated land	low(0–0.2)	116.55	1282.04	1568.73	1712.34	1877.18	1950.69
	lower (0.2–0.4)	2129.79	1125.33	1172.16	1292.88	1138.14	1108.30
Woodland	lower (0.2–0.4)	0	6.18	6.43	3.41	3.77	4.11
	medium (0.4–0.6)	0	67.37	43.16	15.35	16.51	13.36
	higher (0.6–0.8)	73.91	119.84	108.09	101.96	97.41	136.56

	high (0.8–1)	341.94	241.31	245.78	255.13	282.69	282.48
	low(0–0.2)	0	632.82	751.01	848.33	787.12	842.05
	lower (0.2–0.4)	643.95	2394.10	2384.07	2579.26	2377.22	2554.12
Grassland	medium (0.4–0.6)	2832.90	4917.57	5658.22	5437.73	5144.00	5649.73
	higher (0.6–0.8)	20,204.43	16,097.01	15,391.75	15,671.58	15,675.72	15,578.21
	high (0.8–1)	1810.94	1191.91	824.25	665.41	756.76	561.56
	lower (0.2–0.4)	0	194.49	180.71	165.76	199.27	187.99
Water	medium (0.4–0.6)	328.63	599.43	672.45	663.78	749.72	653.00
	higher (0.6–0.8)	1208.62	658.58	626.70	616.44	670.63	626.28
Unused land	low(0–0.2)	13,765.56	13,907.15	13,768.65	13,361.68	13,602.89	13,201.48
Construction land	low(0–0.2)	10.41	32.50	65.48	76.53	88.63	117.63

Woodland ecosystems maintained the most stable habitat conditions throughout the study period. High-quality habitats (0.8–1.0) consistently accounted for more than 39% of the total woodland area, making woodland the most stable core ecological barrier in the basin. Grassland areas were predominantly covered with relatively high-quality habitats (0.6–0.8). However, long-term overgrazing and grassland reclamation continuously undermined native vegetation conditions, resulting in sustained shrinkage of high-quality grassland habitats.

Cultivated land generally exhibited low habitat suitability, dominated by medium-to-low quality grades (0.2–0.4) in 2000. The continuous expansion of low-quality cultivated land habitats during the study period reflects the negative ecological effects of intensive agricultural activities and simplified field vegetation structures. Water bodies presented a relatively balanced habitat grade distribution, indicating high ecological complexity and sensitivity of aquatic and riparian ecosystems under changing water and land conditions.

In contrast, unused land and construction land were mainly concentrated in the lowest habitat grade (0–0.2). Extremely sparse natural vegetation in unused land and strong human disturbance in built-up areas severely limit local ecological functions, forming the main low-quality habitat source in the basin.

From 2000 to 2023, each land use type exhibited distinct temporal variations in habitat suitability. Cultivated land experienced a substantial increase in low-quality habitats by 1834.14 km², following a typical trend of “expanding low-grade areas and shrinking medium- and high-grade areas”. This continuous degradation is primarily driven by long-term intensive tillage and irrational irrigation patterns that weaken soil and vegetation stability.

Although woodland high-quality habitat area only decreased by 17.4%, this downward trend before 2020 indicates that forest ecosystems are persistently vulnerable to regional environmental changes. Grassland degradation was the most prominent among all land types, with high-quality habitat areas declining sharply by 69%. The most severe degradation occurred during 2005–2015, which was closely associated with widespread grassland reclamation and overgrazing.

Water body habitat quality showed an overall improving trend. The area of medium-grade aquatic habitats increased by 98.7%, especially after 2015, demonstrating the positive ecological effects of ecological water diversion and basin-scale water resource management. For unused land, low-quality habitat area decreased by 4.1%, partly attributed to ecological restoration and land use transformation. Nevertheless, some of these positive effects were offset by rapid urban occupation of unused land.

Construction land expansion significantly amplified regional habitat degradation. The expansion of construction land contributed to a 107.22 km² increase in low-quality

habitat area after 2015. Accelerated urbanization continuously occupied peripheral ecological land, intensifying the conflict between ecological conservation and socio-economic development in the oasis area.

Overall, habitat quality variations across land use types reveal two typical characteristics. First, natural ecosystems (woodland and grassland) maintain dominant high habitat suitability owing to intact vegetation structures and self-regulating ecological functions, while artificial land types (cultivated land and construction land) constitute the main degraded habitat areas. Second, the period of 2010–2015 was a critical turning point for basin ecological changes, during which drastic land use restructuring reshaped the overall habitat pattern. In general, the coexistence of stable natural ecosystems and expanding artificial ecosystems further intensified the spatial heterogeneity of basin habitat quality.

3.4. Correlation Analysis: Habitat Quality in Relation to Hydroclimatic Conditions

Pearson correlation analysis was applied to quantify statistical associations between habitat quality and hydroclimatic variables, including meteorological water deficit and surface soil moisture. Significant correlation coefficients were detected, indicating strong statistical co-variation between these variables. It should be noted that such correlation-based statistics cannot directly prove causal mechanisms; potential ecological pathways are further interpreted in the Section 4.

To explore the hydrological underpinnings of the spatiotemporal patterns of habitat quality (HQ), this study analyzed the relationships between habitat quality, meteorological water deficit (WD, calculated as Precipitation minus Potential Evapotranspiration), and surface soil moisture content (SMC).

At the basin scale, HQ showed a positive correlation with WD from 2000 to 2023, with Pearson correlation coefficients ranging from 0.942 to 0.959 (Table 10). This suggests that WD was closely associated with HQ variation at the basin scale. The spatiotemporal distribution of WD is shown in Figure 9.

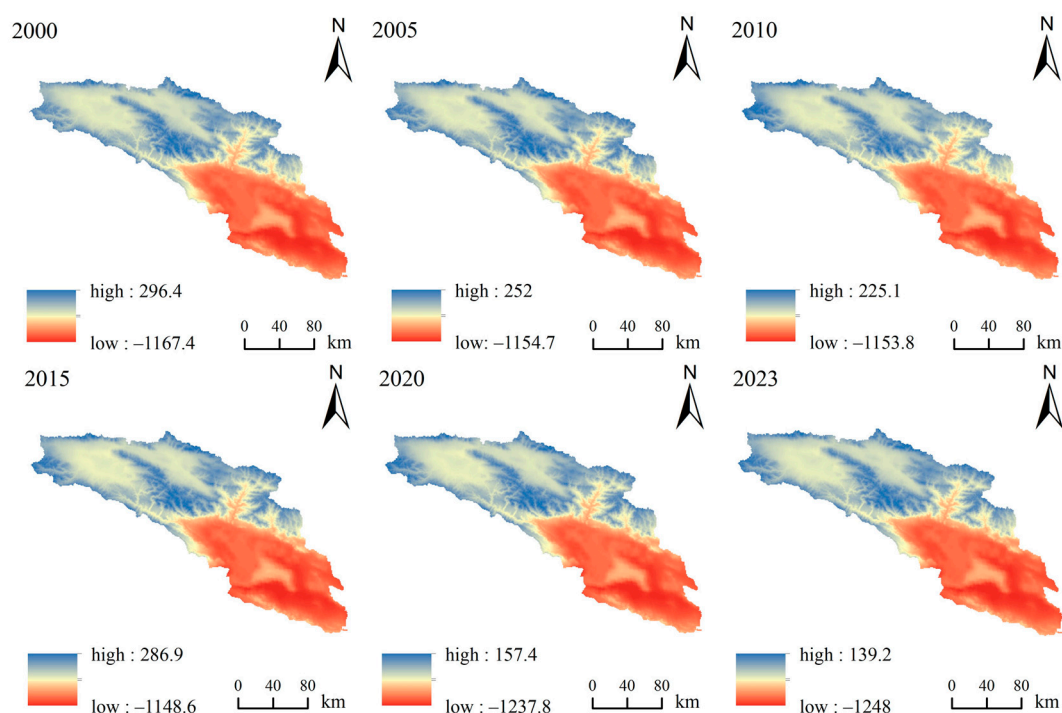
To further disentangle the confounding effects of topographic gradients on the WD–HQ association, we implemented a pixel-level partial correlation analysis by controlling for elevation. To reduce potential statistical bias induced by spatial autocorrelation among adjacent raster pixels, we randomly sampled 5000 valid pixels across the entire basin for each time period.

After accounting for elevation effects, WD was significantly positively correlated with HQ across 2000–2023 ($p < 0.001$), with partial correlation coefficients ranging from 0.306 to 0.386. Despite inter-annual fluctuation in correlation magnitude, moisture conditions serve as an inherently persistent driver for the spatial patterns of regional habitat quality regardless of large-scale topographic variability. Notably, the partial correlation magnitude exhibited an overall upward trend throughout the study period.

In contrast to the linear relationship with WD, the association between HQ and SMC exhibited a distinct non-linear pattern. The mean SMC did not increase monotonically with HQ. As shown in Table 11, SMC generally increased from low- and high-HQ areas to lower-, higher-, and medium-HQ areas, with the highest mean SMC occurring in medium-HQ areas. Although the relative SMC values of the low- and high-HQ categories varied slightly among years, their overall SMC levels remained lower than those of the lower-, higher-, and medium-HQ categories.

Table 10. Mean WD corresponding to different HQ levels from 2000 to 2023.

2000		2005		2010		2015		2020		2023	
HQ	WD	HQ	WD	HQ	WD	HQ	WD	HQ	WD	HQ	WD
0.1036	−821.1562	0.1003	−771.1709	0.101	−779.5989	0.1021	−744.0057	0.10178	−854.4239	0.1017	−873.5798
0.3037	−752.2862	0.3037	−768.1536	0.3027	−764.1322	0.2992	−763.6299	0.3017	−854.2271	0.3032	−834.183
0.5102	−448.3675	0.5097	−450.3478	0.5126	−435.1979	0.5122	−415.646	0.5109	−531.5991	0.5081	−519.7827
0.7315	−283.5377	0.7329	−272.0592	0.7288	−292.6105	0.7293	−247.3554	0.7302	−363.7762	0.7291	−368.4316
0.8274	−302.3741	0.8194	−286.5658	0.8251	−335.1648	0.829	−284.125	0.8305	−402.1623	0.8341	−419.9887

**Figure 9.** Spatiotemporal distribution of WD from 2000 to 2023.**Table 11.** SMC corresponding to different HQ levels from 2000 to 2023.

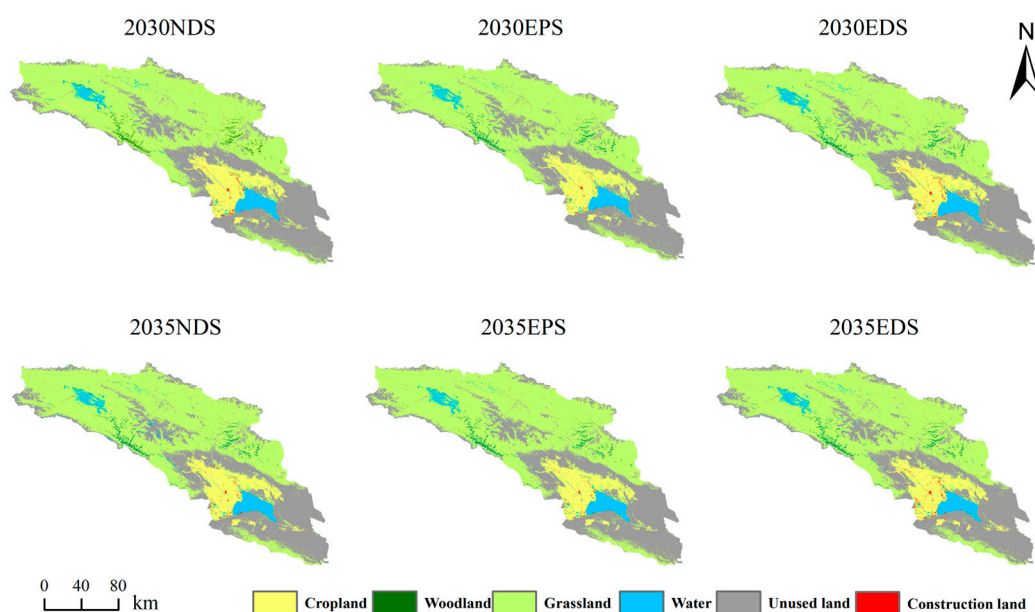
2000		2005		2010		2015		2020		2023	
SMC	HQ	SMC	HQ	SMC	HQ	SMC	HQ	SMC	HQ	SMC	HQ
0.1562	low	0.1548	low	0.1499	low	0.1543	low	0.1518	low	0.1573	high
0.1628	high	0.1703	high	0.1552	high	0.1646	high	0.1587	high	0.1574	low
0.1813	lower	0.1789	lower	0.1801	lower	0.1774	lower	0.1692	lower	0.1763	lower
0.1905	higher	0.196	higher	0.1819	higher	0.1874	higher	0.1876	higher	0.1891	higher
0.1947	medium	0.1965	medium	0.1927	medium	0.1905	medium	0.1881	medium	0.1896	medium

3.5. Future Land Use Analysis

By 2030, within the framework of the Natural Development Scenario (NDS), grass-land constitutes the major component of the land use pattern in the study area, accounting for 57.47%. It is followed by unused land at 30.35% and cultivated land at 7.40%. Water bodies (3.54%), Woodland (1.00%), and constructed land (0.23%) occupy relatively small proportions, signifying an overall stable land use pattern (Table 12 and Figure 10).

Table 12. Area proportion of each land use type under different scenarios from 2030 to 2035 (%).

Land Type	2030NDS	2030EPS	2030EDS	2035NDS	2035EPS	2035EDS
Cultivated land	7.40	6.79	7.33	7.66	6.99	7.66
Woodland	1.00	1.00	1.00	1.03	1.03	1.03
Grassland	57.47	58.31	57.47	57.46	58.43	57.46
Water	3.54	3.38	3.53	3.63	3.38	3.54
Unused land	30.35	30.35	30.35	29.99	29.99	29.99
Construction land	0.23	0.16	0.31	0.23	0.16	0.31

**Figure 10.** Spatial pattern projection of land use under diverse scenarios for the years 2030 and 2035.

In comparison to the NDS, the Ecological Protection Scenario (EPS) features a clear trend of ecological land growth. Specifically, the area of grassland experiences a substantial increase of 365.9 km², while cultivated land undergoes the most notable decrease, shrinking by 265.46 km². Additionally, the areas of water bodies and construction land decrease by 66.9 km² and 33.56 km², respectively, suggesting that ecological protection policies impose limitations on construction activities and certain water resource utilization (Table 13).

Under the Economic Development Scenario (EDS), the evolution of land use reveals a distinct shift toward increased construction land. The area of construction land rises by 32.63 km², while cultivated land shows the most significant reduction, declining by 30.88 km². Water bodies also experience a slight decrease of 1.75 km², whereas changes in other land use types remain relatively minor, reflecting the prominent influence of urbanization on the occupation of cultivated land.

By 2035, under the NDS, the land use structure largely maintains the distribution pattern observed in 2030. Grassland (57.46%) and unused land (29.99%) continue to be the

dominant land use types, while the respective proportions of cultivated land (7.66%), water bodies (3.63%), woodland (1.03%), and construction land (0.23%) exhibit minimal variation, indicating a stable land use pattern under natural evolution.

Compared with the NDS, the EPS further promotes the expansion of ecological land. Grassland shows a significant increase of 420.61 km², while cultivated land continues to register the largest decrease, dropping by 284.55 km². Meanwhile, water bodies and construction land decrease by 106.31 km² and 29.75 km² respectively, suggesting that ecological protection measures consistently drive the growth of ecological land and suppress the expansion of construction land.

Under the EDS, the enlargement of construction land areas becomes more prominent, with an increase of 38.63 km². Cultivated land again experiences the most substantial reduction, decreasing by 38.63 km². Changes in other land use types are not significant, suggesting that economic development primarily achieves spatial expansion through the occupation of cultivated land, exerting a relatively concentrated impact on the overall land use structure.

Table 13. Area of land use types and changes relative to the natural development scenario in 2030 and 2035 (km²).

Land Type	2030NDS	2030EPS	2030EDS	2035NDS	2035EPS	2035EDS
Cultivated land	3215.89	−265.46	−30.88	3328.37	−284.55	−
Woodland	436.63	−	−	449.09	−	−
Grassland	24,982.06	+365.90	−	24,976.04	+420.61	−
Water	1537.20	−66.89	−1.75	1577.58	−106.31	−
Unused land	13,193.55	−	−	13,038.20	−	−38.63
Construction land	102.22	−33.56	+32.63	98.28	−29.75	+38.63

3.6. Habitat Quality Forecasting Across Multiple Development Scenarios

Habitat quality is projected by modeling future land use changes across three development scenarios. (Figure 11).

In 2030, under the NDS and EDS scenarios, the combined proportion of low- and medium-quality habitats exceeds 65%, whereas high-quality habitats account for less than 1%. The average habitat quality reaches 0.3723 and 0.3762, respectively, suggesting an overall state of obvious degradation.

Conversely, the EPS leads to a significant enhancement in the habitat quality pattern. The combined proportion of low-quality and medium-quality habitats declines to 52.12%, while the shares of relatively high- and high-quality habitats increase notably, with high-quality habitats reaching 6.42%.

The average habitat quality reaches 0.4382, representing increases of 17.7% and 16.9% compared to the NDS and EDS scenarios, respectively, demonstrating the substantial efficacy of ecological protection measures in habitat restoration (Table 14).

Table 14. Multi-scenario habitat quality grade assessment results for 2030 and 2035.

Habitat Quality	2030NDS	2030EPS	2030EDS	2035NDS	2035EPS	2035EDS
Low	39.02%	38.32%	39.27%	38.25%	38.06%	38.41%
Lower	16.43%	9.51%	16.65%	19.86%	9.29%	18.70%

Medium	28.20%	13.80%	28.46%	27.40%	13.56%	26.90%
Higher	22.74%	22.09%	22.79%	20.13%	21.85%	19.86%
High	0.64%	6.42%	0.68%	0.61%	6.34%	0.71%
Mean	0.3723	0.4382	0.3762	0.3630	0.4404	0.3653

By 2035, the habitat quality patterns under the NDS and EDS scenarios exhibit minimal change and remain at a generally low level. The proportion of low-quality habitats remains stable at approximately 38–39%, and high-quality habitats still account for less than 0.72%. The mean habitat quality values are 0.3630 and 0.3653, respectively, slightly lower than those in 2030, indicating that the trend of ecological degradation has not been effectively alleviated.

In contrast, under the EPS, habitat quality continues to improve. The proportion of low- and medium-quality habitats further decreases to 51.62%, while the combined proportion of relatively high- and high-quality habitats exceeds 28%. The mean habitat quality increases to 0.4404, which is 21.3% and 20.6% higher than those under the NDS and EDS scenarios, respectively, highlighting the cumulative impacts of long-term ecological interventions.

Overall, the EPS significantly optimizes the habitat quality structure and represents the most effective approach for promoting sustained improvement in watershed habitat quality. By contrast, neither the NDS nor the EDS is adequate to reverse the trend of ecological degradation, and both may even exacerbate ecosystem vulnerability.

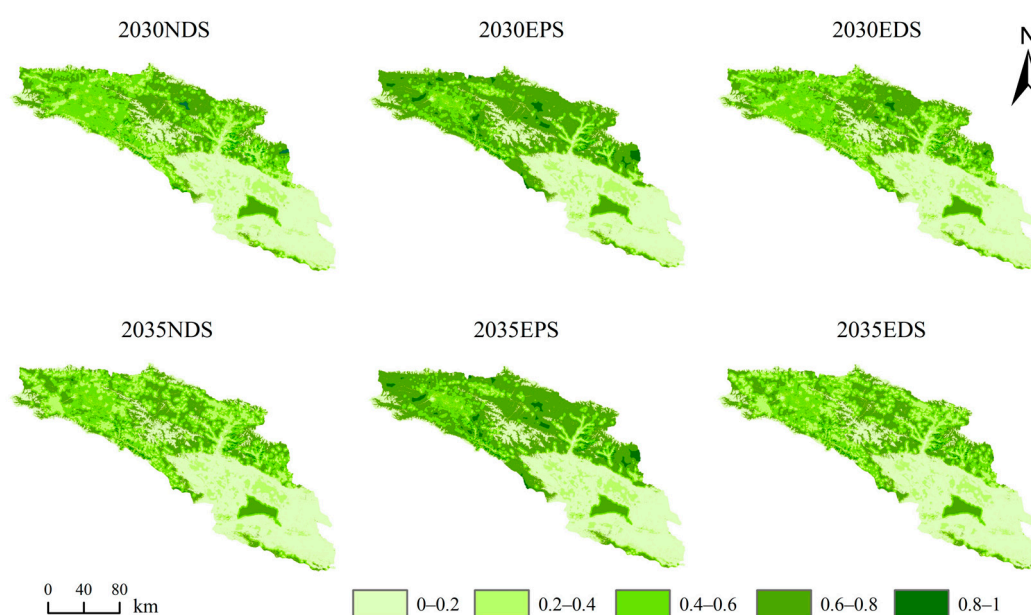


Figure 11. Habitat quality prediction results under different scenarios for 2030 and 2035.

4. Discussion

4.1. The Direct Impact of Land Use Change on Habitat Quality

This study systematically analyzes land use and habitat quality dynamics across the Kaidu–Kongque River Basin during 2000–2023 using the CLCD dataset and the habitat quality module of the InVEST model.

Land use transformation constitutes one of the most influential anthropogenic factors shaping habitat quality in arid inland river basins. Unlike humid regions, where ecosystem conditions are strongly modulated by climate variability, habitat status in water-limited arid basins is highly sensitive to land use conversions driven by human activities.

The basin exhibits a typical pattern of “productive land expansion and ecological land contraction”, in which cropland and built-up areas expand largely at the expense of natural grasslands. Such land use conversions replace complex native ecosystems with simplified human-modified landscapes, which is associated with reduced vegetation cover and weakened soil-water retention capacity. Our simulation results reveal a distinct “upstream improvement–downstream degradation” dichotomy of habitat quality across the whole basin. Similar spatial patterns have also been documented in other arid inland river basins [15].

Upstream habitat improvement aligns with the beneficial effects of local ecological restoration measures, including grazing exclusion and afforestation, implemented in source-water conservation zones [40]. In contrast, downstream oasis regions face growing habitat fragmentation, which coincides with the intensive agricultural reclamation and urban expansion observed in comparable arid basins [1]. Grassland degradation warrants particular attention, given the critical role of grasslands in soil conservation and biodiversity maintenance in arid environments [41,42]. This unfavorable trend is closely linked to grassland conversion for agricultural development, as recorded in earlier regional studies [43].

Beyond direct landscape transformation, cropland expansion paired with intensive irrigation may exert indirect pressures on regional ecosystems. For example, farmland development in the Yanqi Basin can trigger excessive groundwater extraction and falling water tables, which in turn threaten riparian vegetation such as *Populus euphratica* forests. This secondary ecological risk has also been highlighted in previous research on the study basin [8,9]. Changes in water-related land-cover types further illustrate how land use patterns can reshape the hydrological conditions that support desert-oasis ecosystems.

Taken together, land use change not only alters surface vegetation and landscape patterns but also interacts with regional hydrological processes. Most existing studies on arid-basin habitat quality focus primarily on the direct association between land-cover shifts and habitat degradation. Drawing on our simulated outputs together with existing regional findings, this study suggests that land use conversions can transmit ecological impacts through hydrological pathways. Such a land-water interactive perspective complements conventional interpretations and provides a more holistic understanding of habitat evolution under human interference in arid inland watersheds.

4.2. Future Trajectories Under Multi-Scenario Simulation and Management Implications

The PLUS model simulations for 2035 present three distinct development pathways with clear ecological consequences (Figures 10 and 11; Tables 12–14). Both the Natural Development Scenario (NDS), projecting current trends, and the Economic Development Scenario (EDS), prioritizing growth, fail to reverse habitat degradation, with HQ stagnating at a low level (0.3631 for NDS) or declining further. This mirrors the unsustainable development trajectory observed in many arid regions globally, where economic growth often comes at the expense of ecosystem health [2,3]. Critically, only the Ecological Protection Scenario (EPS)—which enforces the conservation and expansion of ecological land—achieves substantial improvement, projecting an average HQ of 0.4404 by 2035, a 21.3% increase over NDS. This result unequivocally demonstrates that proactive, stringent land use planning focused on ecological conservation is the only viable strategy to enhance ecosystem resilience in this arid basin, a conclusion supported by the effectiveness

of localized model parameterization seen in other studies [14]. These findings reveal the inherent and intensifying contradiction between agricultural/urban sprawl and long-term ecological security in water-limited environments [6,7]. Effective watershed management must, therefore, transition decisively towards the EPS framework. This involves (1) enforcing strict ecological protection redlines; (2) promoting sustainable agricultural practices within the carrying capacity of local water resources; and (3) restoring critical ecological corridors to mitigate habitat fragmentation, actions consistent with broader calls for integrated watershed management [12]. Ultimately, achieving a sustainable future for the KKRBB hinges on recognizing ecosystem health as the foundation for socio-economic stability, necessitating land use decisions that prioritize ecological integrity within the ultimate constraint of regional water availability [17].

4.3. The Hydrological Driving Mechanism of Habitat Quality in Arid Regions

The observed statistical coupling may suggest a potential cross-scale regulatory pathway: basin-scale water deficit shapes overall habitat patterns by constraining large-scale vegetation productivity, while local soil moisture imposes threshold-dependent non-linear effects on habitat suitability.

Beyond the direct impact of land use change on habitat quality, water availability is a fundamental constraint on the dynamics of arid ecosystems. Based on the correlation analysis conducted in Section 3.4, this study reveals the cross-scale coupled association between climate, habitat, and hydrology that underpins the observed habitat quality (HQ) patterns, which is summarized in Figure 12.

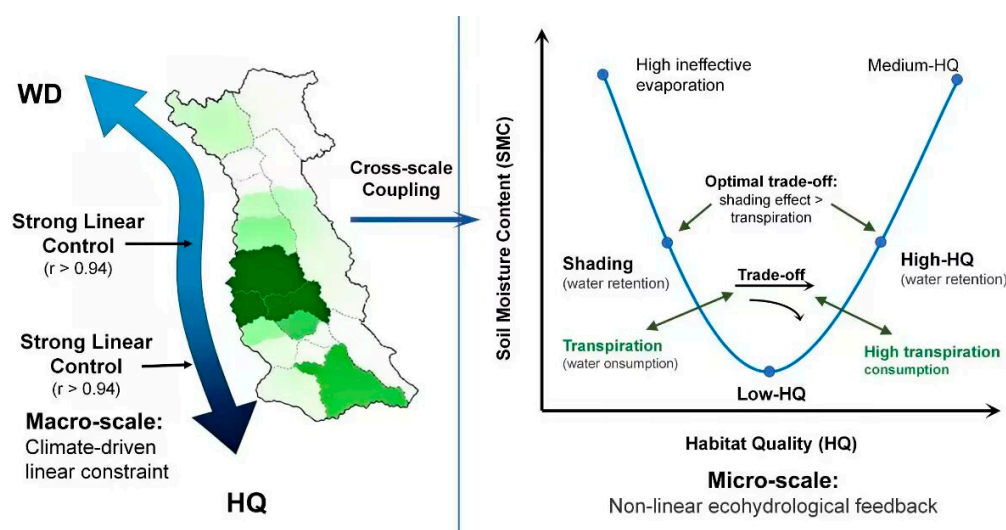


Figure 12. Conceptual diagram of cross-scale hydrological drivers of habitat quality in arid basins. The green gradient in the schematic region represents the spatial gradient of habitat quality, from low (light green) to high (dark green).

As shown in Figure 12, the correlation results integrate the macro-scale linear spatial association and the micro-scale non-linear ecohydrological relationship, which jointly correspond to variations in habitat quality. At the whole-basin scale, the spatial gradient of meteorological water deficit (WD) has an extremely significant positive linear correlation with habitat quality, indicating that the regional climatic water budget is closely associated with the overall spatial pattern of habitat quality in arid inland river basins.

At the micro scale, habitat quality (HQ) shows a clear inverted U-shaped non-linear relationship with surface soil moisture content. In low HQ areas dominated by desert and bare land, sustained high levels of ineffective evaporation continuously consume surface soil water, resulting in the lowest soil moisture content in this group. Areas with moderate

vegetation coverage achieve an optimal water balance: the water retention effect from vegetation shading outweighs the water consumed by transpiration, thus maintaining the highest soil moisture content. In high-coverage forests and shrublands with high HQ, increased transpiration water consumption drives a decline in soil moisture, even though the overall habitat quality of these areas is higher. Based on the correlation results, the macro-scale climatic water gradient is strongly associated with the overall spatial pattern of regional habitat quality, while the micro-scale interaction between vegetation and soil moisture corresponds to local habitat heterogeneity. The coupling of these two cross-scale relationships effectively explains the observed spatial differentiation of habitat quality in the study area.

4.3.1. The Deterministic Role of Meteorological Water Deficit

At the basin scale, a highly significant positive linear correlation was observed between habitat quality (HQ) and meteorological water deficit (WD, calculated as Precipitation minus Potential Evapotranspiration), with Pearson correlation coefficients ranging from 0.942 to 0.959 (Table 10). This robust statistical relationship indicates that the regional climatic water budget acts as a fundamental constraint, or a “physical ceiling,” for ecological potential in arid regions.

The spatiotemporal evolution of WD from 2000 to 2023 further confirms its dominant role in shaping the macro-scale HQ pattern. As shown in Figure 9, WD consistently exhibited a spatial gradient of “high in the northern upstream mountainous area and low in the southern downstream desert-oasis area” over the study period. This spatial congruence strongly suggests that net water availability (P-PET) sets the absolute upper limit for vegetation productivity, thereby controlling the long-term trajectory and overall spatial distribution of HQ. This finding underscores the principle of “water-defined ecology”, implying that any ecological restoration target must be realistic within the basin’s climatic hydrological context.

4.3.2. The Non-Linear Trade-Off Between Vegetation and Soil Moisture

Contrary to the macro-scale linearity, the relationship between HQ and surface soil moisture content (SMC) at the local scale was distinctly non-linear. The mean SMC varied across HQ levels from 2000 to 2023, with generally lower values in low- and high-HQ areas and higher values in lower-, higher-, and medium-HQ areas, reaching its highest level in medium-HQ areas (Table 11).

This inverted U-shaped pattern is likely driven by a trade-off between vegetation’s physical and biological functions: its canopy provides shading (reducing evaporation and retaining water) while its roots and leaves drive transpiration (consuming water). In the lowest HQ areas (predominantly bare land and deserts), intense ineffective evaporation due to the lack of vegetation cover leads to minimal SMC. In medium and higher HQ areas (characterized by moderately covered grasslands), vegetation can effectively suppress evaporation, and their root systems may improve soil structure, allowing SMC to reach its peak. Notably, in the highest HQ areas (dominated by dense forests and shrubs), strong transpiration driven by high biomass can deplete substantial soil water, leading to a decline in local SMC despite the high overall habitat quality.

This finding carries significant implications for ecological restoration: blindly pursuing maximum vegetation cover or afforestation in arid regions can trigger “ecological water consumption” that exceeds the soil moisture carrying capacity, potentially leading to deep soil desiccation and unsustainable outcomes. Therefore, restoration efforts should adhere to the principle of “determining vegetation by water availability,” aiming for a moderate, sustainable vegetation scale that aligns with local soil water resources.

By integrating localized InVEST simulation, multi-source hydrological datasets, and multi-scenario projections, this study yields two key scientific outputs. First, we quantitatively distinguished basin-scale linear and local-scale inverted-U-shaped non-linear responses of habitat quality to water constraints in arid inland basins. Second, scenario simulations further quantified the effectiveness of different ecological management pathways under combined land use and water-resource pressures. Most existing arid-region habitat assessments rely predominantly on land use information and overlook multi-scale hydrological regulation effects. Our findings advance existing understanding by explicitly disentangling how land use change and water constraints jointly shape habitat-quality spatial heterogeneity, rather than attributing habitat variations merely to land use conversion.

4.4. Study Limitations and Future Research Directions

Despite the robust findings of this study, several limitations remain that require further improvement in future work.

First, although this study used localized parameters for the InVEST habitat quality model, it still lacks explicit coupling with dynamic hydrological processes—especially the groundwater-vegetation interaction, which is a core mechanism shaping arid ecosystem dynamics. Additionally, the future land use projections from the PLUS model do not incorporate the impacts of future climate change on regional water availability, which may introduce uncertainty to scenario simulation results.

Second, this study relies heavily on remote sensing products and model simulations and still lacks sufficient in situ validation and quantitative assessment. On the one hand, the habitat quality results are only validated via cross-comparison with another remote sensing-based index (CHEQ), without ground-truthing from field-measured biodiversity and habitat survey data. On the other hand, we fail to quantitatively assess the direct impacts of specific human activities (e.g., grazing intensity, agricultural irrigation, water resource exploitation) on habitat quality degradation.

Third, multiple sources of uncertainty exist throughout the research process: (1) Data uncertainty: the CLCD land use dataset inevitably has classification errors that affect simulation accuracy; (2) Model parameter uncertainty: subjective bias may exist in the setting of key parameters such as threat factor weights and distance attenuation coefficients in the InVEST model; (3) Scenario uncertainty: parameters for future development scenarios (e.g., land use conversion probability) are calibrated based on historical trends, which may deviate from actual future development trajectories; (4) Spatiotemporal scale uncertainty: the study period is limited to 2000–2023, and targeted differentiated analysis for different ecological functional zones within the watershed is still lacking.

To address the above limitations, future research should focus on the following directions: (1) Develop coupled eco-hydrological models (e.g., coupling InVEST with SWAT or other hydrological models) to explicitly capture the interaction between hydrological processes and habitat dynamics, improving the mechanistic interpretation of assessment results; (2) Integrate long-term field monitoring data and ground survey data (e.g., biodiversity inventories, pastoral household questionnaires, land use intensity observation records) for model validation and quantitative analysis of human activity impacts; (3) Incorporate future climate change scenarios into land use projection to improve the practical utility of simulation results for watershed management; (4) Conduct multi-scale differentiated analysis to explore the heterogeneous response of habitat quality to land use change in different ecological zones.

5. Conclusions

From 2000 to 2023, obvious human-land conflicts existed in the Kaidu–Kongque River Basin, manifested as continuous expansion of productive land at the cost of ecological land. Cropland and construction land mainly occupied grassland resources, while water-body areas shrank and unused land faced prominent desertification risks, suggesting growing ecological pressure induced by land use transformation.

Habitat quality exhibited significant spatiotemporal differentiation and an overall degrading trend, with a typical pattern of “upstream improvement and downstream degradation” (zoning criteria, see Section 2.1). The high-quality habitat area in upstream forests and grasslands decreased by 60.8%, while the low-quality habitat area in downstream regions expanded to 16,111.84 km². Habitat quality deteriorated continuously from 2000 to 2010, improved slightly during 2010–2020 under ecological restoration projects, but fluctuated and declined again after 2020.

Human activities acted as the major factor driving habitat changes, while climate change further aggravated habitat degradation. Ecological water-diversion measures produced partial positive effects yet could not reverse the overall degradation tendency. Scenario simulation results indicate that the ecological protection scenario can effectively improve habitat quality by 2035. By contrast, both natural-development and economic-development scenarios fail to restrain ecosystem degradation.

Combined with meteorological water-deficit and surface soil-moisture datasets, this study provides a plausible interpretation for habitat evolution in arid basins. Statistical correlations imply that macro-scale water conditions are closely associated with overall habitat patterns, and there exists a nonlinear relationship between local soil moisture and vegetation status. These inferences, supported by existing ecohydrological knowledge, offer one potential understanding of habitat-quality responses under water-limited conditions.

To promote ecological restoration and sustainable development, targeted strategies are proposed: strictly control the oasis development boundary to curb disorderly expansion of cultivated land and construction land; carry out farmland-to-grassland conversion to restore degraded grasslands; strengthen the implementation of ecological water diversion projects; and integrate glacier protection and desertification control to establish a synergistic “mountain-oasis-desert” conservation system.

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