Assessment of River Basin Habitat Quality and Its Relationship with Disturbance Factors: A Case Study of the Tarim River Basin in Northwest China (Postprint)

Authors: HE Bing, CHANG Jianxia, GUO Aijun, WANG Yimin, WANG Yan, Zhehao Li, CHANG Jianxia, GUO Aijun

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Abstract

The status of regional biodiversity is determined by habitat quality. The effective assessment of habitat quality can help balance the relationship between economic development and biodiversity conservation. Therefore, this study used the InVEST model to conduct a dynamic evaluation of the spatial and temporal changes in habitat quality of the Tarim River Basin in southern Xinjiang Uygur Autonomous Region of China by calculating the degradation degree levels for habitat types that were caused by threat factors from 1990 to 2018 (represented by four periods of 1990, 2000, 2010 and 2018). Specifically, we used spatial autocorrelation analysis and Getis-Ord G* i analysis to divide the study area into three heterogeneous units in terms of habitat quality: cold spot areas, hot spot areas and random areas. Hemeroby index, population density, gross domestic product (GDP), altitude and distance from water source (DWS) were then chosen as the main disturbance factors. Linear correlation and spatial regression models were subsequently used to analyze the influences of disturbance factors on habitat quality. The results demonstrated that the overall level of habitat quality in the TRB was poor, showing a continuous degradation state. The intensity of the negative correlation between habitat quality and Hemeroby index was proven to be strongest in cold spot areas, hot spot areas and random areas. The spatial lag model (SLM) was better suited to spatial regression analysis due to the spatial dependence of habitat quality and disturbance factors in heterogeneous units. By analyzing the model, Hemeroby index was found to have the greatest impact on habitat quality in the studied four periods (1990, 2000, 2010 and 2018). The research results have potential guiding significance for the formulation of reasonable management policies in the TRB as well as other river basins in arid areas.

Full Text

Preamble

Assessment of River Basin Habitat Quality and Its Relationship with Disturbance Factors: A Case Study of the Tarim River Basin in Northwest China

Bing He, Jianxia Chang, *Aijun Guo*, Yimin Wang, Yan Wang, Zhehao Li
State Key Laboratory of Eco-hydraulics in Northwest Arid Region of China, Xi' an University of Technology, Xi' an 710048, China

Abstract: Regional biodiversity status is fundamentally determined by habitat quality. Effective assessment of habitat quality can help balance the relationship between economic development and biodiversity conservation. This study employed the InVEST model to conduct a dynamic evaluation of spatiotemporal changes in habitat quality across the Tarim River Basin in southern Xinjiang Uygur Autonomous Region, China, by calculating degradation degree levels for habitat types resulting from threat factors from 1990 to 2018 (represented by four periods: 1990, 2000, 2010, and 2018).

Specifically, we used spatial autocorrelation analysis and Getis-Ord G*i analysis to divide the study area into three heterogeneous units based on habitat quality: cold spot areas, hot spot areas, and random areas. The Hemeroby index, population density, gross domestic product (GDP), altitude, and distance from water source (DWS) were selected as the main disturbance factors. Linear correlation and spatial regression models were subsequently used to analyze the influences of disturbance factors on habitat quality. The results demonstrated that the overall level of habitat quality in the TRB was poor, showing a continuous degradation state. The intensity of the negative correlation between habitat quality and Hemeroby index was strongest across cold spot areas, hot spot areas, and random areas. The spatial lag model (SLM) was better suited to spatial regression analysis due to the spatial dependence of habitat quality and disturbance factors in heterogeneous units. Model analysis revealed that the Hemeroby index had the greatest impact on habitat quality across the four study periods (1990, 2000, 2010, and 2018). These research results offer potential guidance for formulating reasonable management policies in the TRB and other river basins in arid regions.

Keywords: habitat quality; biodiversity; InVEST model; spatial heterogeneity; spatial lag model; human activities; Tarim River Basin

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1 Introduction

Biodiversity represents the combination of organisms, complex environments, and various related ecological processes, serving as the material basis for human survival (Ma et al., 1998). As human activities intensify and socioeconomic development accelerates, anthropogenic disturbance to ecosystems has affected biological habitat quality and caused biodiversity reduction. According to statistical data (2011-2020), over 1.5×10^{4} species have disappeared, and the trend of biodiversity loss has not been effectively curbed; biodiversity is anticipated to decrease further in the future (Isbell et al., 2013; Terrado et al., 2016a; Dai et al., 2018). Habitat quality represents the ability of an ecosystem to provide suitable living conditions for the sustainable development of individuals and populations within a certain spatiotemporal range, reflecting regional biodiversity status to a certain extent (Fellman et al., 2015; Hillard et al., 2015). Therefore, exploring changes in regional habitat quality and analyzing the influencing factors of these changes are of great significance for regional biodiversity protection and ecological management.

Habitat quality is regarded as an important representation of regional biodiversity and ecosystem services, and assessing, simulating, and predicting its trends and status constitute an effective means for studying regional ecosystem services (Wu et al., 2021). Currently, the main methods used for habitat quality assessment include traditional biodiversity and habitat surveys (Mark et al., 2008; Miller et al., 2010), ecological index evaluation methods (Maes et al., 2012; Coates et al., 2016), and ecological assessment models (Costa et al., 2010; Terrado et al., 2016a, b). Due to a lack of long-term and continuous species detection data, field biodiversity surveys cannot evaluate temporal and spatial dynamic changes in biodiversity (Balasooriya et al., 2008; Sun et al., 2010). The ecological index evaluation method uses habitat quality evaluation index systems and criteria, such as the biological abundance index and vegetation coverage, which have certain limitations in evaluating dynamic changes in habitat quality and its spatial agglomeration state. With the wider application of 3S technology (geographic information system (GIS), global positioning system (GPS), and remote sensing (RS)) and mathematical models, ecological assessment models have become powerful tools for quantitative, visual, and fine-scale monitoring and assessment of spatiotemporal changes in habitat quality (Leh et al., 2013). Currently, the main ecological assessment models include the Habitat Suitability Index (HSI) model (Liu et al., 2006), Social Value for Ecosystem Services (SolVES) model (Sherrouse et al., 2014), and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (Sharp et al., 2016; Aneseyee et al., 2020). Among these, the InVEST model offers advantages of relatively few operational parameters, easily accessible basic data, and quantifiable assessment results with spatial visualization, making it widely used for studying habitat quality, particularly in large-scale basins or regions. For example, Chu et al. (2018) combined the InVEST model with the Cellular Automaton (CA)-Markov method to study landscape pattern evolution and habitat quality in the

Hubei section of the Three Gorges Reservoir Area in China, demonstrating that habitat degradation and landscape pattern change are causing continuous biodiversity decline in the region. Aneseyee et al. (2020) used the InVEST model to analyze spatiotemporal changes in habitat quality across different land use types in the Winike Basin (in the Omo-Gibe Basin, Southwest Ethiopia) and discussed the influence of population density, altitude, land use intensity, and other factors on habitat quality.

Changes in habitat quality result from many factors, whereby variations in land use (landscape pattern) caused by anthropogenic factors represent an important indicator that threatens habitat quality (Zheng et al., 2018; Zhang et al., 2020). In addition, habitat quality distribution is also affected by natural factors and other anthropogenic factors, including topography, terrain, GDP, and population density. Most previous studies have focused on the impact of land use and spatial pattern change on regional habitat quality (e.g., Zheng et al., 2018). Researchers have generally directly associated land use change with habitat quality models when studying the impact of land use change on habitat quality (Chu et al., 2018; Wang et al., 2019; Wang et al., 2020). Studies have also focused on analyzing the correlation between habitat quality and natural and anthropogenic factors, including altitude, slope, GDP, and land use intensity, as a means of quantifying the impact of different disturbance factors on habitat quality (Sun et al., 2019). However, relatively few studies have examined the relationship between comprehensive indicators of human disturbance and habitat quality. Furthermore, the heterogeneity of habitat quality has been largely ignored, which can distort the relationship between habitat quality and human disturbance (Zhang et al., 2018). Previous studies (Hu et al., 2015; Han et al., 2020) have demonstrated that the Getis-Ord G*i spatial statistical method can be used to describe and visualize the spatial distribution of related elements and can effectively identify heterogeneous units related to clusters. Therefore, conducting research on the spatial heterogeneity of habitat quality and the impact of different interference factors on habitat quality can help reveal habitat quality evolution under human activity influence and scientifically guide ecological environmental protection and sustainable land resource use.

The Tarim River Basin (TRB) is located in southern Xinjiang Uygur Autonomous Region, China. It is a typical inland arid area and an important region for landscape biodiversity protection. The region has abundant natural resources and plays a crucial role in strategic development, but it has a fragile ecological environment (Xue et al., 2019). The geographic components of vegetation found in the TRB include desert vegetation flora. Plant species are relatively limited, mainly including *Populus euphratica*, *Tamarix chinensis*, *Glycyrrhiza uralensis*, and *Phragmites communis*. The desert riparian forest with *Populus euphratica* and *Tamarix* sp. as constructive and dominant species is the main barrier against oasis desertification (Yu et al., 2017). In recent decades, increased human, social, and economic activities have caused unreasonable development and utilization of water and soil resources in the TRB, leading to several ecological and environmental problems, including vegetation degradation, lake drought, desertification, massive biodiversity loss, and habitat degradation (Tan et al., 2011; Ling et al., 2018). Following the implementation of the Belt and Road Initiative, as the core area of the Silk Road Economic Belt (Chen et al., 2016), the habitat quality of the TRB is of great significance for social and economic development, ecosystem balance, and biodiversity protection. However, most existing research on the TRB has focused on climate change, optimization of water resource allocation, land use change, and ecological water transfer effects, whereas comparatively little research has addressed biodiversity from an ecosystem service perspective.

The main objectives of this study are as follows: (1) evaluate habitat quality between 1990 and 2018 and analyze its temporal and spatial changes by determining habitat suitability and threats to biodiversity caused by different land use types in the TRB; (2) identify and divide spatial heterogeneity units of habitat quality; (3) clarify differences in influencing factors on habitat quality across different heterogeneous units using linear regression methods; and (4) clarify the spatial dependence of habitat quality on disturbance factors in different units using a spatial regression model. It is anticipated that the results of this study will provide a reference for rational land resource planning and utilization and coordinated ecological environment development in the TRB.

2.1 Study Area

The TRB is located in the Tarim Basin (34°55 -43°08 N, 73°10 -94°05 E) in southern Xinjiang Uygur Autonomous Region of China and covers an area of 1.02$×10^{6}$ km^2, including nine water systems and 114 rivers (Yu et al., 2016). The TRB is located far from the ocean and surrounded by mountains on all sides. It is a closed inland hydrological region with a relatively independent water cycle and water balance (Fig. 1 [Figure 1: see original paper]) (Xue et al., 2017). The Tarim River is China' s largest inland river with a mainstream that is 1321 km long and does not produce any flow. Historically, water from nine water systems in the TRB flowed into the mainstream of the Tarim River, but due to changes in the natural environment and the development of modern oasis agriculture, only three upstream rivers (Aksu River, Yarkant River, and Hotan River) now have a natural hydraulic connection with it (Chen et al., 2013; Xu et al., 2013). The TRB encompasses five states, 42 counties (cities), four production and construction companies, and 55 regiments. According to statistical data, in 2018, the total population of the TRB was 13.14$×10^{\{6\}, the crop planting area was 2.23×10}\{6\}$ hm^2, the gross national product was 411.77$×10^{9}$ CNY, and the total water resources were 42.04$×10^{9}$ m^3.

Fig. 1 Overview of the Tarim River Basin (TRB). ARB, Aksu River Basin; YRB, Yarkant River Basin; HRB, Hotan River Basin; CRB, Cherchen River Basin; WRB, Weigan-Kuche River Basin; KRB1, Kaxgar River Basin; KRB2, Keriya River Basin; KRB3, Kaidu-Konqi River Basin.

2.2 Data Sources and Preprocessing

In this study, we used five different data sources to calculate and analyze spatiotemporal variations in habitat quality and spatial heterogeneity with disturbance factors. Specifically, Landsat series RS images with a resolution of 30 m$×30mfrom1990, 2000, 2010, and2018intheTRBwereselectedasthebasicdatasources, providedbytheDataCe
//www.resdc.cn).RSimageswithnocloudsorfewcloudsbetweenJuneandSeptemberwereselected.UsingENVI5
computerinteractionmethod, andinterpretationresultswereverifiedandcorrectedusingGPStechnology.Fina
//www.gscloud.cn/).The1km×$1 km GDP data (1990, 2000, 2010, and 2018) were obtained from the RESDC. River system data (1:1,000,000) were obtained from the RESDC. Population data (1991-2019) were obtained from the Xinjiang Statistical Yearbook (Statistics Bureau of Xinjiang Uygur Autonomous Region, 1990–2018).

2.3.1 Model

The InVEST model was developed by the US Natural Capital Project team in 2007, and the habitat quality module is one that assesses multiple ecosystem services (Sharp et al., 2016). The habitat quality module reflects the impact of human activities on the ecological environment; therefore, greater human disturbance creates greater threats to habitat, resulting in lower quality and lower biodiversity. Habitat type and threat source factors must be set when running the habitat quality module (Zhang et al., 2011). Due to the different sensitivities of various land use types to threat source factors (Yang et al., 2018), this study considered the current situation and expert opinions of the TRB and selected cultivated land, construction land, and unused land as threat source factors. The other land use types (forestland, grassland, and water body) represent different habitat types. After referring to the InVEST model user manual and examining previous research results (Zhang et al., 2011; Liu et al., 2020; Wang et al., 2021), we determined the weight of threat source factors, the maximum influence distance of source factors on ecological land (Table 1), and the sensitivity of ecological land to stress factors (Table 2). The core objective of the habitat quality module is to establish the relationship between habitat types and threat source factors or to obtain habitat degradation degree by calculating the negative impact of threat source factors on habitat and then determining habitat quality based on habitat suitability and degradation degree. Before running the model, all land use data and threat source factor data were rasterized using ArcGIS software. The specific calculation equations are as follows (Han et al., 2019):

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

where j is the habitat type; D_{xj} is the habitat degradation degree of grid x in habitat type j; r is the number of threat source factors ($r = 3$ in this study); Y_r

is the total number of grids of threat source factor r; W_r is the weight of threat source factor r; r_y is the stress value of threat source factor r to grid y; β_y is the accessibility of grid y; S_{jr} is the sensitivity of habitat type j to the threat source factors r, where values closer to 1 indicate greater sensitivity; i_{rxy} is the stress value of grid y; d_{xy} is the distance between grid x and grid y; and $d_{r_{max}}$ is the influence range of threat source factor r.

$$i_{rxy} = \begin{cases} 1 - \left(\frac{d_{xy}}{d_{r_{max}}}\right) & \text{if linear} \\ \exp\left(-2.99\frac{d_{xy}}{d_{r_{max}}}\right) & \text{if exponential} \end{cases}$$

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

where Q_{xj} is the habitat quality index of grid x in habitat type j; H_j is the habitat suitability of habitat type j; K is the semi-saturation constant, generally half of the maximum value of D_{xj}; and z is the normalization constant, which defaults to 2.5.

Table 1 Attribute table of habitat threat source factors

Threat source factor (R)	$d_{r_{max}}$ (km)	Weight	Spatial decay function
Cultivated land			Linear
Construction land			Exponential
Unused land			Linear

Note: $d_{r_{max}}$ is the maximum influence range of threat source factor r.

Table 2 Sensitivity of land use types to each threat source factor

Land use type	Habitat suitability	Sensitivity
Cultivated land		
Forestland		
Grassland		
Water body		
Construction land		
Unused land		

To compare and analyze habitat quality changes in different years in the TRB, we used the natural break (Jenks) classification in ArcGIS with four grades: low (0.00–0.25), lower (0.25–0.50), higher (0.50–0.75), and high (0.75–1.00).

2.3.2 Methods

Due to the large area of the TRB, we divided the study area into 113,916 grid units with a spatial resolution of 3 km$\times$3 km using the "create fishing net" function module of ArcGIS 10.5 software to analyze the spatial heterogeneity of habitat quality and its relationship with disturbance factors. Subsequent spatial autocorrelation analysis, cold-hot spot analysis, ecological disturbance degree assessment, and analysis of the relationship between habitat quality and disturbance factors were all based on these created grids. The software used for calculations included ArcGIS 10.5, GeoDa 1.1, and SPSS 24.0.

The Hemeroby index is a comprehensive indicator of human disturbance determined based on the combined impact of human activity frequency and intensity on an ecosystem (Hill et al., 2002; Chen et al., 2010). The calculation equation is as follows:

$$H = \sum_{i=1}^{m} \frac{HI_i \times S_i}{S}$$

where H is the Hemeroby index of a grid cell; HI_i is the Hemeroby coefficient of the ith land use type (Table 3); S_i is the area of the ith land use type in a grid cell; and S is the total area of the grid units.

Based on natural break points, we divided the Hemeroby index into three levels: low (0.0000–0.4000), medium (0.4000–0.6000), and high (0.6000–1.0000).

Table 3 Hemeroby coefficient (HI) corresponding to each land use type

Land use type	HI
Cultivated land	
Forestland	
Grassland	
Water body	
Construction land	
Unused land	

Spatial autocorrelation analysis is a method used to test the potential dependence of spatial variables with regular patterns at different spatial positions based on classical statistics (Rey, 2001). As an important field of spatial statistical research, the combination of global and local spatial autocorrelation analysis has been widely applied to various spatial problems (Zhang et al., 2011). Spatial heterogeneity results from different degrees of spatial autocorrelation (Han et al., 2020). Therefore, this study used global spatial autocorrelation analysis to test the heterogeneity of habitat quality within the study area. Generally, the global Moran' s I index was used for measurement, with the calculation equation as follows:

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

where I is the Moran' s I index; n is the total number of grids; W_{ij} is the spatial weight matrix of raster i and raster j (if i is adjacent to j, its spatial weight is 1; otherwise, it is 0); x_i is the habitat quality value in the ith grid; and $\bar{x}$ is the mean value of habitat quality.

When conducting spatial autocorrelation analysis, habitat quality values for the four periods were extracted using 3 km$×$3 km grids and processed and calculated using GeoDa software.

Hotspot analysis is a method for studying the clustering distribution characteristics of local regions, used to identify statistically significant high-value areas (hot spots) and low-value areas (cold spots) in the spatial distribution of habitat quality (Han et al., 2019). In this study, ArcGIS software was used to analyze habitat quality in the TRB for 1990, 2000, 2010, and 2018 using the Getis-Ord G*i index (Getis et al., 1992). Based on the calculation results of the Getis-Ord G*i index, we divided the study area into cold spot areas, hot spot areas, and random areas. Compared with the Moran' s I index, the Getis-Ord G*i index can determine the spatial distribution of habitat quality heterogeneity units. The calculation equation is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij}x_j - \bar{x}\sum_{j=1}^{n} W_{ij}}{S\sqrt{\frac{n\sum_{j=1}^{n} W_{ij}^2 - (\sum_{j=1}^{n} W_{ij})^2}{n-1}}}$$

where x_j is the habitat quality of raster j; and S is the standard deviation of habitat quality.

Using the 3 km$×$3 km grid element as the calculation scale, the Pearson correlation coefficients of habitat quality and disturbance factors in the three habitat quality heterogeneous units (cold spot areas, hot spot areas, and random areas) were calculated for 1990, 2000, 2010, and 2018 using the linear regression tool of SPSS software. The three habitat quality heterogeneity units were determined using cold-hot spot analysis.

In this study, the ordinary least squares (OLS), spatial lag model (SLM), and spatial error model (SEM) proposed by Anselin (1988) were used to perform regression analysis of habitat quality and disturbance factors using GeoDa software. The model calculation equation is as follows (Anselin, 2005):

$$y = \rho W_1 y + \beta x + \mu, \quad \mu = \lambda W_2 \mu + \varepsilon$$

where y is the dependent variable (habitat quality); ρ is the regression coefficient of the spatial lag term $W_1 y$; W_1 and W_2 are the spatial adjacency weight matrices of the dependent variable and residual, respectively; β is the regression coefficient of the independent variable; x is the independent variable (relevant interference factor); μ is a random error term; α is a constant; λ is the regression coefficient of the spatial residual term; and ε is a random error with mean value of 0 and variance of δ^2.

When different parameters in Equation 7 are equal to 0, four types of spatial regression models can be formed (Anselin, 2005). When $\rho \neq 0$ and $\beta = \lambda = 0$, this is a first-order spatial autoregressive model that does not consider the influence of independent variables on dependent variables. Therefore, only the OLS, SEM, and SLM models were considered for use in this study. When $\rho = 0$ and $\lambda = 0$, the OLS model is defined, and the observed values of dependent and independent variables in space are unaffected by spatial differences. When $\rho \neq 0$ and $\lambda = 0$, the SLM model is defined, and there is spatial correlation between dependent variables in space, with observed values of dependent variables being related to corresponding independent variables and dependent variables in adjacent areas. When $\rho = 0$ and $\lambda \neq 0$, the SEM model is defined. In this case, there is no spatial correlation between dependent variables in space, and only independent variables with spatial correlation are considered. In addition, observation values of dependent variables in space are related to corresponding independent variables as well as independent and dependent variables in adjacent areas.

3.1 Temporal and Spatial Variations of Habitat Quality in the TRB

Based on dynamic changes in land use types in the TRB between 1990 and 2018, we evaluated habitat quality for four periods (1990, 2000, 2010, and 2018) using the habitat quality module of the InVEST model. In ArcGIS, habitat quality values were divided into four grades: 0.0000–0.2500, 0.2500–0.5000, 0.5000–0.7500, and 0.7500–1.0000, where smaller values indicated worse habitat quality. Figure 3 [Figure 3: see original paper] shows that the overall habitat quality level for the entire TRB was poor (in the range of 0.2500–0.5000), and the average habitat quality continuously decreased from 0.3000 in 1990 to 0.2700 in 2018, indicating that habitat quality in the study area was in a state of degradation. Between 1990 and 2018, habitat quality in each sub-basin exhibited different degrees of degradation (with the exception of the Hotan River Basin (HRB)).

The spatial distribution of habitat quality demonstrated differences between sub-basins in the study area (Tables 4 and 5). Habitat quality in northern sub-basins (Kaxgar River Basin (KRB1), Aksu River Basin (ARB), Weigan River Basin (WRB), and Kaidu-Konqi River Basin (KRB3)) was higher than that in southern sub-basins (HRB, Keriya River Basin (KRB2), and Cherchen River Basin (CRB)), and habitat quality in high-altitude areas (gradient 3 (3000–4500 m) and gradient 4 (4500–8439 m); Table 5) was higher than that in low-altitude areas (gradient 1 (41–1500 m) and gradient 2 (1500–3000 m); Table 5).

Spatial differences in habitat quality between 1990 and 2018 were obvious. With the exceptions of the Taklimakan Desert and Kumtag Desert, the lowest habitat quality was mostly concentrated in oasis areas with frequent human activities, while the highest habitat quality was generally concentrated in mountains and water bodies.

3.2 Heterogeneity of Habitat Quality in the TRB

Based on the spatial distribution of habitat quality in the TRB across the four periods (1990, 2000, 2010, and 2018) and according to the calculation process of Equation 4, we tested the spatial autocorrelation of habitat quality using GeoDa software. The results shown in Figure 4 [Figure 4: see original paper] demonstrated that when $P < 0.05$, the global Moran' s I index values of habitat quality during the four periods from 1990 to 2018 were 0.8465, 0.8437, 0.8429, and 0.8395, respectively, thereby confirming the existence of spatial autocorrelation in habitat quality, indicating heterogeneity. Generally, the global autocorrelation index displayed a continuous weakening trend between 1990 and 2018, but the decreasing range was very small, indicating that spatial heterogeneity had a weak decreasing trend.

We divided the spatial heterogeneity units of habitat quality in the TRB into three types according to Equation 5: cold spot areas, hot spot areas, and random areas. Habitat quality in the TRB from 1990 to 2018 was then analyzed using the Getis-Ord G*i index in ArcGIS, with results shown in Figure 5 [Figure 5: see original paper]. According to ArcGIS statistics, cold spot areas accounted for 42.03%, 41.67%, 54.27%, and 63.97% of the study area in 1990, 2000, 2010, and 2018, respectively; hot spot areas accounted for 26.07%, 25.79%, 22.89%, and 20.25%, respectively; and random areas accounted for 31.90%, 32.54%, 22.84%, and 15.78%, respectively. Spatially, the distribution pattern of cold spot areas and hot spot areas of habitat quality was "cold inside and hot outside, cold in the east and hot in the west," displaying obvious heterogeneity. Cold spot areas were mainly concentrated in the Taklimakan Desert and Kumtag Desert, and the KRB and CRB had more cold spot areas than other sub-basins. Land use types in cold spot areas were mainly alpine desert, bare rock land, or grassland with low vegetation coverage; therefore, habitat quality was low, with average habitat quality of 0.1240. Hot spots were mainly located in oasis areas, mountain areas, and the mainstream of the Tarim River (ecological protection area). Due to relatively high vegetation coverage in these areas, there was generally high habitat quality (average habitat quality of 0.6594). Regarding temporal change, the range of cold spot areas exhibited a continuously increasing trend from 1990 to 2018, whereas hot spots in mountainous areas showed an increasing trend.

3.3 Analysis of the Change in Hemeroby Index

Based on the spatial distribution of land use types in the Tarim River Basin between 1990 and 2018, we calculated the spatial distribution of the Hemeroby index in the TRB using Equation 4, with results shown in Figure 6 [Figure 6: see original paper]. According to statistics (Table 6), the Hemeroby index of the TRB during the four periods (1990, 2000, 2010, and 2018) was at high levels: 0.6459, 0.6472, 0.6586, and 0.6608, respectively. This showed a general upward trend, indicating that the impact of human disturbance on the ecological environment was intensifying between 1990 and 2018. In terms of spatial distribution, the Hemeroby index was similar to the distribution pattern of cold spots and hot spots, displaying a pattern of "high inside and low outside, high in the east and low in the west." In addition to desert areas, high-level Hemeroby index was mainly distributed in low-altitude areas (gradient 1 and gradient 2). These areas were mainly oases with frequent human activities; therefore, the Hemeroby index was high. Medium-level Hemeroby index was mainly distributed in mountainous areas (gradient 3) with less human activity, more precipitation, and higher vegetation coverage. There were few areas with low-level Hemeroby index, and they were mainly distributed around lakes and other water bodies. In terms of temporal scale, the areas of low- and medium-level ecological interference continued to decrease (with the exception of desert areas) between 1990 and 2018, and the ecological interference degree of the same altitude area displayed an increasing trend, showing that the impact of human activities on the ecological environment was intensifying.

3.4.1 Selection of Disturbance Factors

Results in Section 3.3 showed that from 1990 to 2018, the Hemeroby index in the TRB displayed an increasing trend, and habitat quality was in a state of degradation. As the premise and foundation of ecosystem service functions, habitat quality has numerous disturbance factors (Fellman et al., 2015; Hillard et al., 2015; Han et al., 2020). The Hemeroby index is a comprehensive indicator of human disturbance that reflects the degree of disturbance of landscape type (or land use type) change on an ecological environment. Therefore, when analyzing habitat quality and disturbance factors, it is also necessary to consider other natural and human factors, in addition to data availability. Relevant studies (Sun et al., 2019; Aneseyee et al., 2020) have shown that population density, socioeconomic factors, topography, and geomorphology impact habitat quality distribution. The water system structure of the TRB is separate, and "water is oasis, no water is desert" is the typical characteristic of the basin. Water plays a crucial role in the ecological environment of the basin (particularly the mainstream of the Tarim River). Based on these characteristics, this study selected the Hemeroby index, population density, GDP, altitude, and distance from water source (DWS) as the main disturbance factors. These five variables were diagnosed using collinearity analysis (Fig. 7 [Figure 7: see original paper]), and the results demonstrated that the variance inflation factor (VIF) values for each disturbance factor in different years were less than 5.0, indicating no collinearity between the factors.

Fig. 7 Results of variance inflation factor (VIF) in collinearity diagnostics for the main disturbance factors. Cold, cold spots; Hot, hot spots; Random, random areas. H, Hemeroby index; PD, population density; GDP, gross domestic product; DWS, distance from water source.

3.4.2 Linear Relationship Between Habitat Quality and Disturbance Factors

The correlation between habitat quality and disturbance factors in the three heterogeneous units can be seen in Figure 8 [Figure 8: see original paper]. Different disturbance factors had different correlations with habitat quality in different years. A significant and negative linear relationship was found between habitat quality and Hemeroby index in the three heterogeneous units ($P < 0.01$), with the largest correlation coefficient, indicating that the Hemeroby index was the key disturbance factor causing habitat quality degradation. Habitat quality showed a positive linear relationship with population density and GDP in cold spot areas and random areas and a significant and negative linear relationship in hot spot areas, indicating that population density and GDP facilitated habitat quality degradation in hot spot areas but not in cold spot areas and random areas. The reason for this difference is that hot spot areas were the main population gathering regions with frequent human activities, which can directly or indirectly affect habitat.

Fig. 8 Relationship between habitat quality and disturbance factors in cold spot areas, hot spot areas, and random areas. *, statistically significant at the 5% level; **, statistically significant at the 1% level.

There was a significant and positive correlation between habitat quality and altitude, indicating that habitat quality improved with increasing altitude, but the correlation coefficient in hot spot areas decreased between 1990 and 2018. There was a significant and negative linear relationship between habitat quality and DWS in cold spot areas and random areas, and the correlation coefficient increased (from 1990 to 2018), indicating that habitat quality worsened in these areas farther from water sources. Further, there was a significant and negative linear relationship between habitat quality and DWS during 1990–2000, followed by a significant and positive correlation during 2010–2018, indicating that the ecological environment of the TRB improved following the implementation of ecological management projects (particularly the ecological water conveyance project) after 2000.

3.4.3 Spatial Relationship Between Habitat Quality and Disturbance Factors

The spatial relationship between habitat quality and disturbance factors (Hemeroby index, population density, GDP, altitude, and DWS) across the three heterogeneous units (cold spot areas, hot spot areas, and random areas) in the TRB between 1990 and 2018 was statistically tested and compared using the regression modeling tool of GeoDa software to enable selection of the optimal spatial regression model. The evaluation indices of the spatial regression model included correlation coefficient (R^2), log(Likelihood) (logL), Akaike information criterion (AIC), and Schwartz criterion (SC). The range of R^2 values was 0.0000–1.0000, with values closer to 1.0000 indicating better regression effect. In addition, larger logL values and smaller AIC and SC values indicated better regression model performance. According to OLS results, it was necessary to judge the significance of the Lagrange multiplier (LM) and Robust Lagrange multiplier (RLM). Larger values of these two statistics indicated better regression effect of the spatial regression model. Table 7 shows that the global Moran' s I (error) values of the three heterogeneous units between 1990 and 2018 were significant at $P < 0.01$ level, indicating spatial dependence in all spatial regressions. Furthermore, LM (lag) and LM (error) all passed the 1% significance test. Therefore, SEM or SLM regression was better suited to studying habitat quality and disturbance factors than OLS regression. The regression model with the best fitting effect was chosen following comparison between LM and RLM values of the three heterogeneous units for each year. After examining the advantages and disadvantages, the SLM was deemed more suitable for spatial regression analysis.

Table 7 Comparison of statistical test goodness-of-fit for spatial regression models in different heterogeneous units in 1990, 2000, 2010, and 2018

Heterogeneous unit	Statistic	1990	2000	2010	2018
Cold spot areas	Moran' s I (error)	198,929.0	198,940.0	59,972.3	50,485.7
	LM (lag)	-397,845.0	-397,868.0	-119,933.0	-100,959.0
	RLM (lag)	-397,791.0	-397,813.0	-119,877.0	-100,904.0
	LM (error)	68.9**	72.0**	347.3**	388.0**
	RLM (error)	556.4**	415.0**	84,837.9**	116,775.9**
Hot spot areas	Moran' s I (error)	4,736.6**	5,182.9**	120,561.3**	150,482.0**
	LM (lag)	4,181.4**	4,819.5**	35,817.7**	34,834.2**
	RLM (lag)	47,430.2	45,911.6	17,201.2	15,911.7
	LM (error)	-94,848.3	-91,811.2	-34,390.4	-31,811.3
	RLM (error)	-94,796.2	-91,759.1	-34,338.4	-31,759.4
Random areas	Moran' s I (error)	245.0**	242.3**	192.2**	188.8**
	LM (lag)	3,771.4**	4,116.7**	20,683.1**	21,503.1**
	RLM (lag)	3,638.0**	3,501.3**	1,402.6**	778.3**
	LM (error)	59,975.4**	58,627.1**	36,908.3**	35,592.3**
	RLM (error)	59,842.0**	58,011.8**	17,627.7**	14,867.5**

*Note: R^2, correlation coefficient; logL, log(Likelihood); AIC, Akaike information criterion; SC, Schwartz criterion; LM, Lagrange multiplier; RLM, Robust Lagrange multiplier; **, statistically significant at the 1% level.*

According to the spatial regression coefficients (Table 8), the regression coefficients of habitat quality with Hemeroby index, altitude, and DWS in each heterogeneous unit between 1990 and 2018 were negative ($P < 0.01$), indicating significant negative correlation between habitat quality and these disturbance factors. However, the correlation differed across the three heterogeneous units. The negative correlation coefficient between habitat quality and Hemeroby index was the largest, indicating that the Hemeroby index had the greatest impact on habitat quality. The impact of Hemeroby index on habitat quality in cold spot areas and random areas was greater than that in hot spot areas. There was a significant and positive correlation between habitat quality and GDP ($P < 0.01$), with greater correlation in hot spot areas. There was a positive correlation between habitat quality and population density in cold spot areas and random areas, but a negative correlation in hot spot areas, indicating that human aggregation in hot spot areas was more likely to affect habitat quality. Generally, the effects of habitat quality in different heterogeneous units on the spatial dependence of disturbance factors were different.

Table 8 Spatial regression results of habitat quality with disturbance factors in different heterogeneous units in 1990, 2000, 2010, and 2018 based on the spatial error model

Heterogeneous unit	Variable	1990	2000	2010	2018
Cold spot areas	Constant	1.8829**	1.8855**	1.2565**	1.1626**
	Altitude	-2.4739**	-2.4775**	-1.5976**	-1.4406**
	H	0.0068**	0.0051**	0.0014**	0.0043**
	PD	-0.0068**	-0.0069**	-0.0016**	-0.0017**
	GDP	-0.0073**	-0.0075**	-0.0019**	-0.0041**
	DWS	1.6167**	1.6592**	1.2711**	1.2653**
Hot spot areas	Constant	-1.901**	-1.8900**	-1.2942**	-1.2416**
	Altitude	-0.0028**	-0.0026**	-0.0045**	-0.0057**
	H	0.0169**	0.0580**	0.0876**	0.0303**
	PD	-0.0025**	-0.0021**	-0.0017**	-0.0021**
	GDP	-0.0019**	-0.0021**	-0.0034**	-0.0043**
	DWS	1.8317**	1.8260**	1.3339**	1.3222**

Heterogeneous unit	Variable	1990	2000	2010	2018
Random areas	Constant	- 2.3133**	- 2.2993**	- 1.4637**	- 1.3628**
	Altitude	0.0117**	0.0097**	0.0048**	0.0071**
	H	0.0146**	0.0652**	0.0935**	0.0103**
	PD	- 0.0016**	- 0.0016**	- 0.0047**	- 0.0016**
	GDP	- 0.0023**	- 0.0025**	- 0.0074**	- 0.0010**
	DWS	1.8829**	1.8855**	1.2565**	1.1626**

*Note: H, Hemeroby index; PD, population density; GDP, gross domestic product; DWS, distance from water source. **, statistically significant at the 1% level.*

4.1 Spatial and Temporal Characteristics of Habitat Quality Heterogeneity

This study discovered that habitat quality in the TRB displayed a continuous degradation trend between 1990 and 2018, and the sub-basins (with the exception of the HRB) also showed different degrees of degradation. There were differences in habitat quality across different sub-basins and altitudes. Habitat quality was generally better in the northern region of the study area than in the southern region and better in high-altitude areas than in low-altitude areas. This could be because there was greater vegetation coverage in the northern region than in the southern region and lower frequency of human activities in high-altitude areas. These results are consistent with those obtained by Liu et al. (2020) on spatiotemporal changes in habitat quality in Xinjiang, China: overall habitat quality in Xinjiang displayed a degradation trend, and areas with high habitat quality values were mainly located at the edge of mountains and basins (Liu et al., 2020). Simultaneously, our study results are similar to those obtained by Huang et al. (2020) on landscape biodiversity in the YRB of the TRB: areas with low habitat quality values were mainly distributed in regions with poor natural environments, while areas with high habitat quality values were mainly distributed in natural forests and grassland reserves (Huang et al., 2020). Our study also confirmed significant spatial heterogeneity in habitat quality in the TRB, and the study area can be divided into three heterogeneous units based on habitat quality: cold spot areas, hot spot areas, and random areas (Fig. 5). In these three heterogeneous units, cold spot areas were mainly concentrated in low-altitude areas that were the main regions of human activities, in addition to the two large deserts (Taklamakan Desert and Kumtag Desert). Hot spot areas were mainly distributed in high-altitude mountainous regions or ecological protection regions, as these areas had relatively high vegetation coverage.

4.2 Effects of Different Disturbance Factors on Habitat Quality

The Hemeroby index quantifies the disturbance degree of human activities on an ecosystem by considering the degree of disturbed landscape or habitat in relation to the natural landscape or habitat (Anselin, 1988; Chen et al., 2010). Cultivated land, construction land, and unused land were threat source factors to habitat quality, and their changes significantly impacted habitat quality. Figure 9 [Figure 9: see original paper] showed that the proportion of threat source factors in the three heterogeneous units was largest (with the exception of natural vegetation), which explained the significant and negative correlation between habitat quality and Hemeroby index. However, the negative correlation between habitat quality and Hemeroby index has decreased since 2000, potentially because the comprehensive management policy of the TRB has effectively restrained ecological environment deterioration in the region. Among other disturbance factors, population density and GDP exhibited opposite correlations in cold spot areas, random areas, and hot spot areas. Combined with the gradual deterioration of habitat quality in oasis areas in Figure 3 and the increasing proportion of cultivated land in Figure 9, this showed that human activities had a negative impact on habitat quality in hot spot areas.

Fig. 9 Area percentages of land use types in the three heterogeneous units. The arrow direction and years indicated that the circles from outside to inside were 1990, 2000, 2010, and 2018, respectively. Values in the table represented the area percentages of land use types. The colors for area percentages of land use types were consistent with those of years.

4.3 Limitations of the InVEST Model

The InVEST model compensates for the shortcomings of traditional ecosystem service assessment methods and provides an effective way to assess ecosystem services. In recent years, habitat quality assessment as a function module of the InVEST model has been widely conducted (Sharp et al., 2016; Babbar et al., 2021). However, the model has some shortcomings when assessing habitat quality. For example, it obtains habitat quality in a study area by accumulating the influence of threat source factors on habitat quality, but the simple accumulation of threat source factors is not exactly equal to the comprehensive impact of these stress factors. Therefore, the model requires further improvement in terms of the usage process. The parameters of threat source factors and habitat sensitivity are subjective and require further study in the future.

5 Conclusions

Through analysis of spatiotemporal changes in habitat quality in the TRB between 1990 and 2018, this study discussed the spatial heterogeneity of habitat quality and quantified its relationship with interference factors, thereby providing a new comprehensive method for quantifying the impact of threat source factors on habitat quality. The main conclusions are as follows.

Temporally, the overall level of habitat quality in the TRB was poor and in a state of continuous degradation. Spatially, habitat quality in the northern region was greater than that in the southern region and greater in high-altitude areas than in low-altitude areas. The results showed that habitat quality exhibited spatial heterogeneity in the TRB, represented by cold spot areas, hot spot areas, and random areas. There was a significant negative linear relationship between habitat quality and Hemeroby index in the three heterogeneous units, and the correlation coefficient was greater than the correlation coefficients of habitat quality with population density, GDP, altitude, and DWS.

There was spatial dependence between habitat quality and disturbance factors in the three heterogeneous units. During the four periods (1990, 2000, 2010, and 2018), habitat quality in each heterogeneous unit had a significant and negative correlation with Hemeroby index, altitude, and DWS, but the correlation coefficient with Hemeroby index was the largest, indicating that the Hemeroby index had the greatest impact on habitat quality.

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Note: Figure translations are in progress. See original paper for figures.