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Dynamic Changes in Habitat Quality and the Driving Mechanism in the Luoxiao Mountains Area from 1995 to 2020

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The strengthening of regional habitat quality is crucial to protect biodiversity and fully utilize ecosystem services such as those provided by forestry and aquatic ecosystems. However, the long-term patterns of change in the habitat quality of the Luoxiao Mountains area, which is both an important ecological barrier area and a concentrated poverty-stricken area, and the driving mechanism remain unclear. In this study, the InVEST model was used to assess the habitat quality of the Luoxiao Mountains area in 1995 to 2020, and the spatial autocorrelation model was used to explore the spatial and temporal variation and distribution characteristics of habitat quality. Further, ordinary least squares (OLS) model, geographically weighted regression (GWR) model, and random forest (RF) algorithm were combined with multidimensional datasets to explore the underlying mechanisms driving changes in habitat quality. According to the results, the habitat quality indices of the Luoxiao Mountains area in 1995, 2005, 2015, and 2020 were 0.822, 0.818, 0.817, and 0.813, respectively, with an overall decreasing trend. The RF model was the best fit for habitat quality, better than the GWR and OLS models. Physical geographic factors such as slope and precipitation, as well as socioeconomic factors such as gross domestic product, were key drivers of habitat quality in the Luoxiao Mountains. Precise implementation of ecological protection and restoration measures, improvements in the efficiency of spatial utilization, and exploration of the value of ecological products are key factors in maintaining a balance between habitat quality and economic growth into the future.

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Introduction

Habitat quality is a representation of an ecosystem's ability to provide living conditions for the sustainable development of individuals and populations [1–4]. It can reflect the state of regional biodiversity to a certain extent. Studies have shown that a series of ecological chain reactions, such as habitat fragmentation [5,6], invasion of exotic species [7,8], and loss of biodiversity [9,10] due to land use changes as a result of intensified human activities, have led to degradation of regional habitat quality, increased vulnerability, and reduced suitability, which have, in turn, affected ecosystem productivity and service capacity [11,12]. This poses a threat to human well-being and the sustainable development of ecosystems utilized by humans, including mountains, water, forests, fields, lakes, and grasses [13]. The strengthening of regional habitat quality is crucial for the full utilization of ecosystem services, the protection of biodiversity, and the maintenance of regional ecological security. Research on the spatial and temporal changes in habitat quality and the driving mechanisms has become a focus in the international field of ecology and geography [8,14–16].

To date, studies of habitat quality have been conducted on different scales and different contents and using different methods. The research scales include the micro scale [8,17] and macro scale [18], and the research contents involve the response of habitat quality to land use changes [19], the relationship between habitat quality changes and factors such as socioeconomic conditions and landscape patterns [20–23], habitat quality and ecological security patterns [24], and the simulation prediction of habitat quality under different future scenarios and land use structures [25,26]. The above studies have generally shown that habitat quality decline is closely related to land use, and the rapid expansion of construction land is the main reason underlying the yearly decline in habitat quality. There are 2 main types of habitat quality evaluation methods. First, the sample field measurement method, which can obtain accurate data and allows for objective evaluation of the spatial and temporal dynamics of habitat quality. However, data collection for this method is difficult, labor and material intensive, and spatially discontinuous. Thus, this method is commonly used for habitat quality assessments in small areas and nature reserves [27,28]; it is difficult to apply this method to large-scale habitat quality studies [19]. Second, the model evaluation method, which involves rapid real-time and large-scale habitat quality evaluations using models such as the SolVES model [29], MIMES model [30], HSI model, and InVEST model [31]. Among them, the InVEST model was developed based on biodiversity threat factors. It uses land use data as input variables to assess habitat quality based on the distance, weight, and habitat sensitivity of ecological threat factors (arable land, roads, construction land, and other types of land use that are highly influenced by human activities) [32]. It has the advantages of a small amount of input data, a large amount of derived data, and the ability to quantitatively analyze abstract ecosystem service functions. Thus, it is widely used in studies related to habitat quality and ecosystem service function assessment [8,33,34]. For example, Leh et al. [35] used the InVEST model to investigate the evolution of habitat quality in different phases of land use change and to provide an overall assessment of habitat quality levels in 2 West African countries. Sallustio et al. [5] assessed habitat quality in Italy and found that habitat quality degradation depended on the anthropogenic impact location and intensity; the authors also identified priority areas for national-scale biodiversity conservation strategies. Gao et al. [36] discussed the impact of land use change on habitat quality in the mountainous areas of Dali Prefecture and found that habitat degradation was inextricably linked to urban expansion in low-slope areas and that the development of reforestation, the fruit industry, and tourism improved the habitat quality in the area. Overall, the use of the InVEST model to assess habitat quality is scientifically valid and has important implications for the development of management strategies for land use and biodiversity conservation.

Socioeconomic factors reflected by land use change are known to be the main factors influencing habitat quality [37]. The distribution pattern of habitat quality is also influenced by physical geographic factors such as elevation, slope, rainfall, and population density, as well as anthropogenic factors. Many studies have focused on the spatial and temporal dy namics of habitat quality [13,16,25], but there are few studies on the mechanisms underlying changes in habitat quality, and the relationships between habitat quality and influencing factors such as physical geography and socioeconomic factors still require further investigation. In revealing the drivers of habitat quality, ordinary least squares (OLS) and geographically weighted regression (GWR) models are useful for detecting subtle changes in the process mechanism of habitat quality over time and space and are important research methods for exploring the drivers of objective objects [38,39]. Each of these approaches has a different focus. OLS models provide "average" and "global" estimates of influences through least squares, which makes it difficult to reveal the spatial variability of each influence [40]. In contrast, GWR is unique for exploring the drivers of habitat quality change because it allows for spatial variation in local parameters with spatial location [41,42]. In addition, with improvements in computer power and data acquisition techniques, machine learning is becoming an accurate and effective means to model nonlinear complex systems. The random forest (RF) algorithm is a widely used machine learning method for fitting statistical models; it expresses the nonlinear characteristics of the data, is not prone to overfitting, and performs well in impact factor analysis [43,44], making it a suitable method for modeling and analyzing the mechanisms driving spatial and temporal changes in habitat quality. However, to date, few studies have applied this method. Therefore, this study used OLS, GWR, and RF models to simulate habitat quality changes. The optimal model was selected by comparing the fit of each model. This not only effectively identified the main driving factors underlying habitat quality changes but also provides a basis for model selection in future similar studies.

The Luoxiao Mountains area is an important ecological barrier in the southern red-soil ecologically fragile area; it is also a concentrated area of extreme poverty and has been designated as a concentrated poverty-stricken area by the Chinse government. In recent decades, to achieve economic growth and eradicate poverty, large areas of forest, grassland, and other ecological lands in the region have been overtaken by human activities, resulting in habitat fragmentation. Thus, there is an urgent need to explore the long-term patterns in habitat quality change in the region and the driving mechanism. This would provide a reference for future approaches to ecological poverty alleviation, the formulation of ecological protection and restoration measures, and the optimization of the ecological security barrier network. To this end, this paper assessed habitat quality in the Luoxiao Mountains area and explored the driving mechanisms in 4 years: 1995, 2005, 2015, and 2020. The research objectives were to (a) clarify the characteristics of land use changes in the Luoxiao Mountains area, (b) apply the InVEST model to assess and map habitat quality from 1995 to 2020 and analyze its spatial and temporal patterns, and (c) use OLS, GWR, and RF to analyze the factors influencing habitat quality. This study not only offers a scientific baseline for exploring the dynamic change characteristics and driving mechanisms of habitat quality in concentrated poverty-stricken areas but also provides a scientific reference for ecological restoration practices and land use planning in other concentrated poverty-stricken areas.

Materials and Methods

Study site

The Luoxiao Mountains area is located at 112°37′ to 116°38′E, 24°30′ to 27°45′N (Fig. 1) and includes the middle and southern sections of the Luoxiao Mountain Range and the area connecting with the Nanling and Wuyi Mountains. The Luoxio Moun tains area spans the Jiangxi and Hunan provinces, with a total area of about 53,000 km^2. The Luoxiao Mountains area is also an old revolutionary area with a large population of low-income regional farmers (in 2010, the per capita net income of farmers was equivalent to 53.6% of the national average, and the incidence of poverty was 10.2%). In 2011, the Luoxiao Mountains area was identified as one of 11 “concentrated contiguous special hardship areas” to be supported by the state. According to the "Luoxiao Mountain Area Regional Development and Po verty Alleviation Plan (2011-2020)", the area covers 24 counties in Jiangxi and Hunan. In 2020, the Luoxiao Mountains area achieved full poverty eradication, but it still faces problems such as relative poverty and the risk of returning to poverty [45]. The region has a subtropical humid monsoon climate, with an altitude of 30 to 2,108 m and an annual precipitation of 1,414 to 1,866 mm. The topography is characterized by

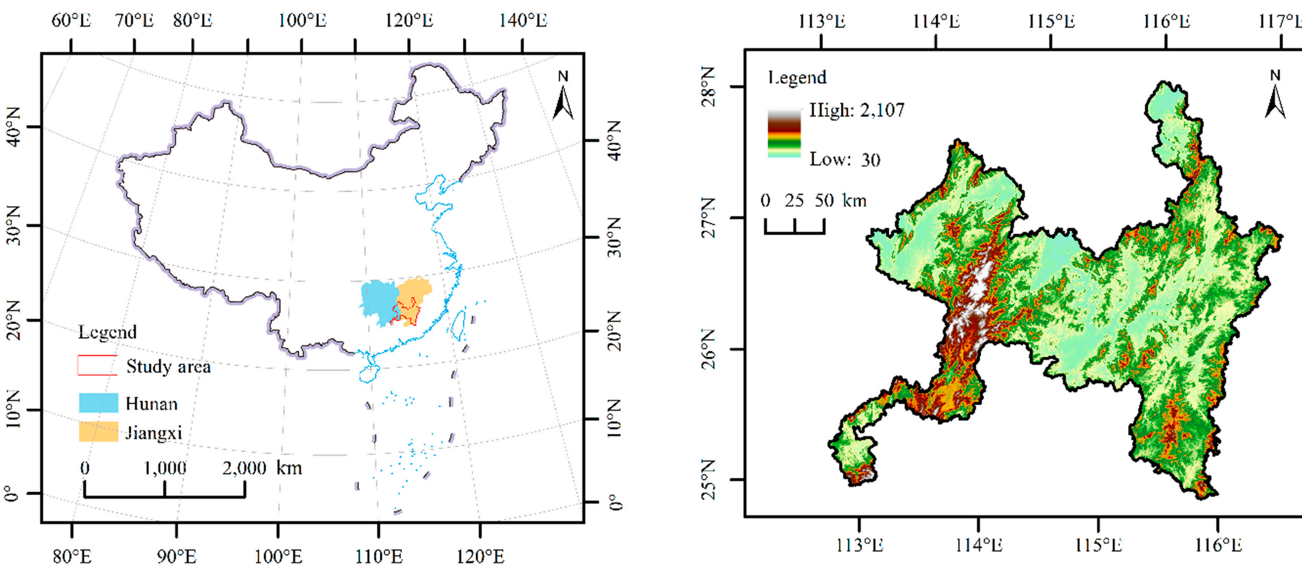

Fig. 1. Location of the Luoxiao Mountains area.

mountains and hills, with extensive distribution of red soil, rich biodiversity, and a forest coverage rate of 75%.

The Luoxiao Mountains area, dominated by forest land (72%) and arable land (18%), is an important ecological security barrier for the Ganjiang, Dongjiang, and Xiangjiang river basins. It is also an ecologically fragile area in the southern red-soil hills and mountains. It faces many ecological problems such as overcultivation of land, forest irrigation and woodcutting, obvious vegetation degradation, and severe soil erosion. With intensive agriculture and animal husbandry, industrial activities, and urban expansion, the regional ecosystem and biodiversity are under threat. In recent years, the level of anthropogenic disturbance in the Luoxiao Mountains has increased, the vegetation area has continued to decrease, the ecological functions in some areas have been degraded, and the habitat quality of the region is under severe threat.

Data source

This study used land use data (accuracy: 100 m × 100 m), digital elevation model (DEM) data (30 m × 30 m), slope data (Slope), temperature data (Tem), precipitation data (Pre), road data, county-level administrative district maps, gross domestic product (GDP), population distribution maps (POP), and nighttime lighting data. The dataset was provided by the Data Center for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The land use data included 4 periods, 1995, 2005, 2015, and 2020, and the land use types were divided into 6 categories: grassland, cropland, forest land, construction land, water, and bare land. The accuracy of these data and classifications met the needs of this study [46]. Slope parameters were extracted or computed based on the DEM (10 × 10 resolution), using the Geographic Info rmation System (ArcGIS 10.0). The annual night light dataset was based on the DMSP/OLS from 1992 to 2013 and the Suomi National Polar-Orbiting Partnership-Visible Infrared Imaging Radiometer Suite satellite night light remote sensing image data from 2012 to the present. The annual night light brightness data for the whole country since 1992 were processed and generated. Since this dataset was obtained from different satellite sensors (DMSP/OLS and Suomi National Polar-Orbiting Partnership-Visible Infrared Imaging Radiometer Suite), the 2 datasets were aligned. In addition, the data resolution affects the accuracy of the study results and facilitates spatial calculations and analysis. Therefore, using land use data as the standard, the resampling tool of ArcGIS was used to resample the resolution of the other data to 100 m × 100 m. The unified coordinate system for all data was WGS_1984_UTM_Zone_50N.

Research methodology

The research framework for this paper can be roughly divided into 3 parts (Fig. 2). Firstly, land use dynamics were analyzed using the land use transfer matrix. Secondly, habitat quality was assessed using the InVEST model, and its spatial and temporal change characteristics were analyzed. Thirdly, the relationships between habitat quality and physical–geographical and socioeconomic factors were simulated using 3 methods: OLS, GWR, and RF. The optimal model was selected by comparing and analyzing the simulation effects. Then, the driving mechanism of habitat quality was analyzed.

Land use change transfer matrix

A land use transfer matrix provides a quantitative description of land class state and state transfer. It provides information on the dynamic process of mutual transformation between the beginning and end of a period of time for each type of area in a study area [19,47,48]. The dynamic process of land use change was quantitatively analyzed using the ArcGIS vectorization calculation and EXCEL pivot table function to obtain a land use transfer matrix of the Luoxiao Mountains area over 4 periods, from 1995 to 2020. The calculation formula is as follows:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \tag{1}$$

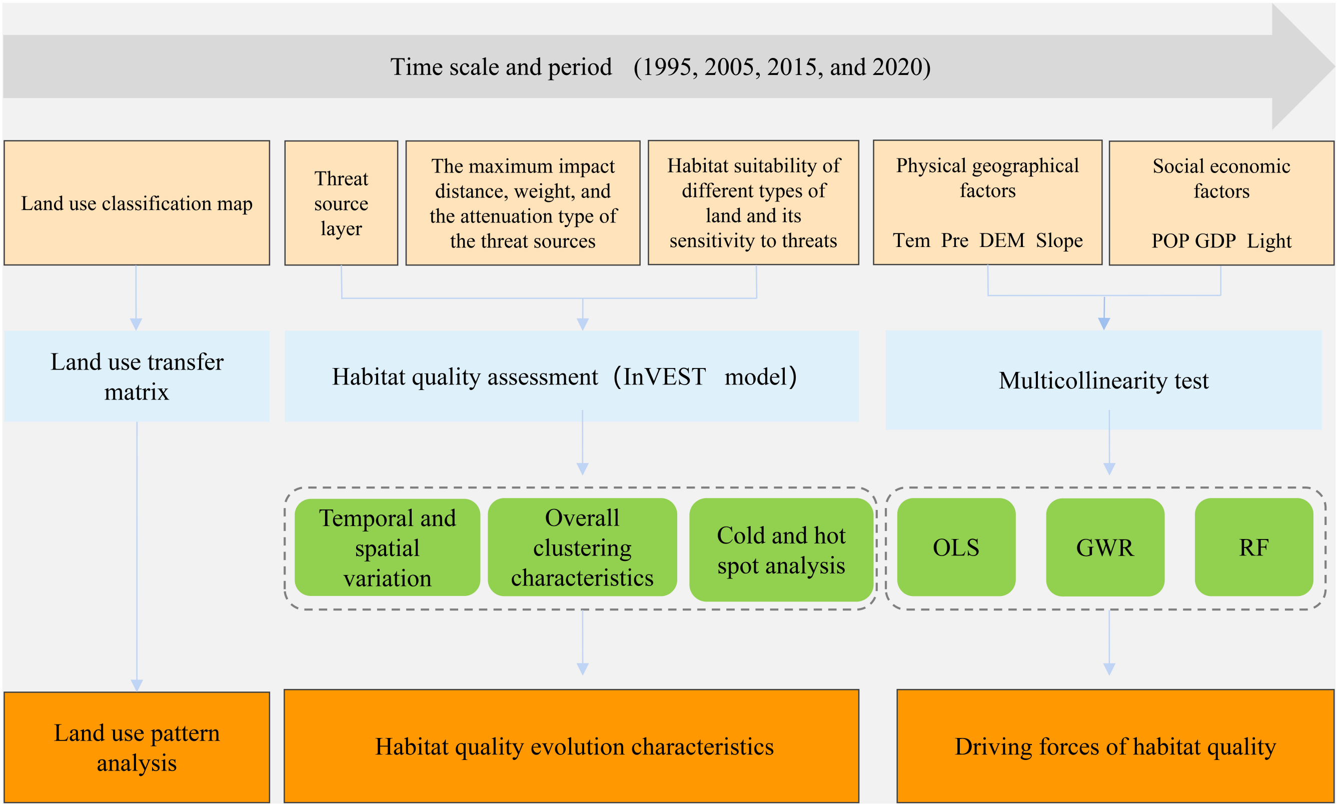

Fig. 2. Research framework of this paper Tem, temperature; Pre, precipitation; DEM, digital elevation model; POP, population distribution maps; GDP, gross domestic product; Light, night lighting index; OLS, ordinary least squares; GWR, geographically weighted regression; RF, random forest.

where S is the area, S_{ij} is the area of land class i transformed into land class j during the study period, and n is the number of land classes.

InVEST habitat quality model and parameterization

The habitat quality module of the InVEST 3.7.0 model [32] was used to quantitatively assess the level of habitat quality in the Luoxiao Mountains area. The better the habitat quality, the higher the regional biodiversity and the more stable the ecosystem [49,50]. The calculation formula is as follows:

$$Q_{xj} = H_j\left(1 - \left(\frac{D_{xj}^z}{D_{xj}^z + k^z}\right)\right) \quad (2)$$

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{Yr}\left(W_r / \sum_{r=1}^{R} W_r\right) r_y i_{rxy} \beta_x S_{jr} \quad (3)$$

$$i_{rxy\ l} = 1 - \left(\frac{d_{xy}}{d_{r\ max}}\right) \quad (4)$$

$$i_{rxy\ e} = \exp\left(-\left(\frac{2.99}{dr_{\ max}}\right) \times d_{xy}\right) \quad (5)$$

where Q_{xj} is the habitat quality of raster x in land use type j, H_j is the habitat suitability of land use type j, Q_{xj} is the habitat degradation of raster cell x in land use type j, k is the half-saturation coefficient (the default value of the model is 0.5), z is the normalization constant (the model is set to 2.5), R is the number of threat factors, W_r is the weight of threat factor r, y is the number of raster cells of threat factor type r, Y_r is the total number of raster cells of threat factor r, i_{rxyl}、i_{rxye} is the stress value of raster y obtained by linear or exponential decay, respectively, and the stress degree of raster x, β_x is the accessibility of various threat factors to raster x, S_{jr} is the sensitivity of land use type j to threat factor r,and d_{xy} is the maximum threat distance of threat factor r.

Based on the actual situation of land use in the Luoxiao Mountains area, land use types with intensive human activities and great impacts, such as paddy fields, drylands, urban land, rural settlements, other construction land, and traffic land (national roads, provincial roads, highways, and railroads) were selected as habitat threat factors. In this study, the habitat quality module parameters were determined based on the InVEST model manual [32] and related studies [33,39].

Spatial statistical analysis

Exploratory spatial data analysis is used to describe the spatial clustering and anomalies in the spatial distribution patterns of visualized things or phenomena by calculating spatial autocorrelation coefficients. It is widely used in socioeconomic and ecological analyses. In this study, Moran's I index was used to describe the global autocorrelation characteristics of habitat quality change. The Getis-Ord G_i^* index was used to explore the aggregation and divergence characteristics of habitat quality change, i.e., the distribution patterns of "hot spots" and "cold spots". The values of Moran's I index range from [−1,1]. Values greater than 0 indicate a positive spatial correlation; the larger the value, the more significant the positive correlation and the stronger the spatial agglomeration; values less than 0 indicate a negative spatial correlation; values equal to 0 indicate no spatial correlation, i.e., the spatial units are randomly distributed. The P value of the Getis-Ord G_i^* index indicates the typical probability; 0.01 and 0.05 correspond to the typical confidence interval of 99% and 95%, respectively. These values reflect the degree of aggregation and divergence of hot spots (or cold spots) in spatial units. The calculation equations are as follows:

$$\text{Moran } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2\left(\sum_i\sum_j w_{ij}\right)} \tag{6}$$

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{(n-1)}}} \tag{7}$$

$$\overline{X} = \frac{1}{n}\sum_{j=1}^{n} x_i \tag{8}$$

$$S = \sqrt{\frac{1}{n}\sum_{j=1}^{n} x_j^2 - \left(\overline{X}\right)^2} \tag{9}$$

where:n is the number of spatial grid cells, x_i and x_j denote the observations of units and cells, respectively, $\left(x_i - \overline{x}\right)$ is the deviation of the observation on the ith spatial cell from the mean, $\left(x_j - \overline{x}\right)$ is the deviation of the observation on the jth spatial cell from the mean, and w_{ij} is the spatial weight matrix based on spatial adjacency relationships [51].

In order to ensure that the spatial unit habitat quality has certain regional characteristics and sufficient accuracy to reflect the spatial heterogeneity of drivers, such as physical geographic factors and socioeconomic factors, the study area was divided into 2 km × 2 km square grid cells using the fishing net tool in ArcGIS 10.3 software. Then, the raster map of habitat quality change at different stages was partitioned into numerical statistics using the neighborhood statistics tool. These were then assigned to the grid cells for spatial statistical analysis of habitat quality changes to obtain the hot-spot map of habitat quality changes in the Luoxiao Mountains area during different periods.

Global spatial autocorrelations can only reflect whether there are cohesive features in a study area as a whole; they cannot clarify the location distribution of cohesive features. Using the ArcGIS 10.6 platform, hot-spot analysis was conducted based on the grid, and hot and cold spots with confidence levels above 90% were selected to reflect the distribution of high- and low-value habitat quality clusters in the Luoxiao Mountains area.

GWR model

The GWR technique integrates Tobler's first law of geography [52] with the local spatial statistics method. It obtains the spatial regression coefficients corresponding to spatial locations, one by one, by solving the regression analysis model for independently sampled analysis points separately. Then, it quantitatively charac terizes the heterogeneity of spatial relationships by parameter estimates that vary with spatial locations. The basic GWR model is calculated as follows.

$$y_i = \beta_0\left(u_i, v_i\right) + \sum_{k=1}^{m}\beta_k\left(u_i, v_i\right)x_{ik} + \varepsilon_i \tag{10}$$

where y_i is the value of the dependent variable at position i, x_{ik} (k = 1, 2...m) is the value of the independent variable at position i, (u_i, v_i) is the coordinate of the regression analysis point i, $\beta_0(u_i, v_i)$ is the intercept term, $\beta_k(u_i, v_i)$ (k = 1, 2...m) is the regression analysis coefficient, and ε_i is the residual at position i.

RF

RF is based on classification and regression trees [53]. It produces numerous independent trees to reach a final decision through 2 randomization approaches to the selection of training samples and the selection of variables at each node of a tree. This randomness alleviates the typical drawbacks of classification and regression trees, such as overfitting and sensitivity to the training sample configuration [53]. Using out-of-bag data from random selection, RF provides internal cross-validation and the relative importance of a variable when samples are held in out of bag [43,54,55]. RF was implemented by MATLAB 2018.

Results

Land use change characteristics

The land use types in the Luoxiao Mountains area are diverse and structurally complex. The land use types in the study area were classified as cropland, woodland, grassland, water, construction land, and bare land. The 5-phase land use type distribution map (Fig. 3) showed that the land use types in the study area were mainly woodland, cropland, and grassland, among which, the area of woodland was the largest, accounting for more than 72% of the total study area, followed by cropland and grassland, accounting for about 18% and more than 6% of the total area of the region, respectively. Overall, the areas of forest land, grassland, and arable land accounted for more than 97% of the total study area and had a greater impact on the overall landscape, while the proportions of construction land, water, and bare land were smaller, accounting for less than 3% of the total study area. From 1995 to 2020, the area of construction land in the Luoxiao Mountains area increased the most, reaching 436.19 km^2, followed by water, with an area increase of 39.03 km^2. The area of forest land decreased the most, amounting to 338.59 km^2, followed by arable land and grassland, with these areas decreasing by 74.31 and 60.69 km^2, respectively; the area of unused land decreased by 1.63 km^2.

To fully understand the structural characteristics of land use type changes in the Luoxiao Mountains area, a land use shift matrix was constructed to calculate the number of mutual land use shifts (Table 1). As shown in the table, from 2000 to 2005, land use transfer mainly occurred among cropland, forest land, grassland, and construction land, with a large amount of forest land and grassland shifting to cropland; the area of cropland increased by 79.09 km^2. From 2005 to 2015, construction land

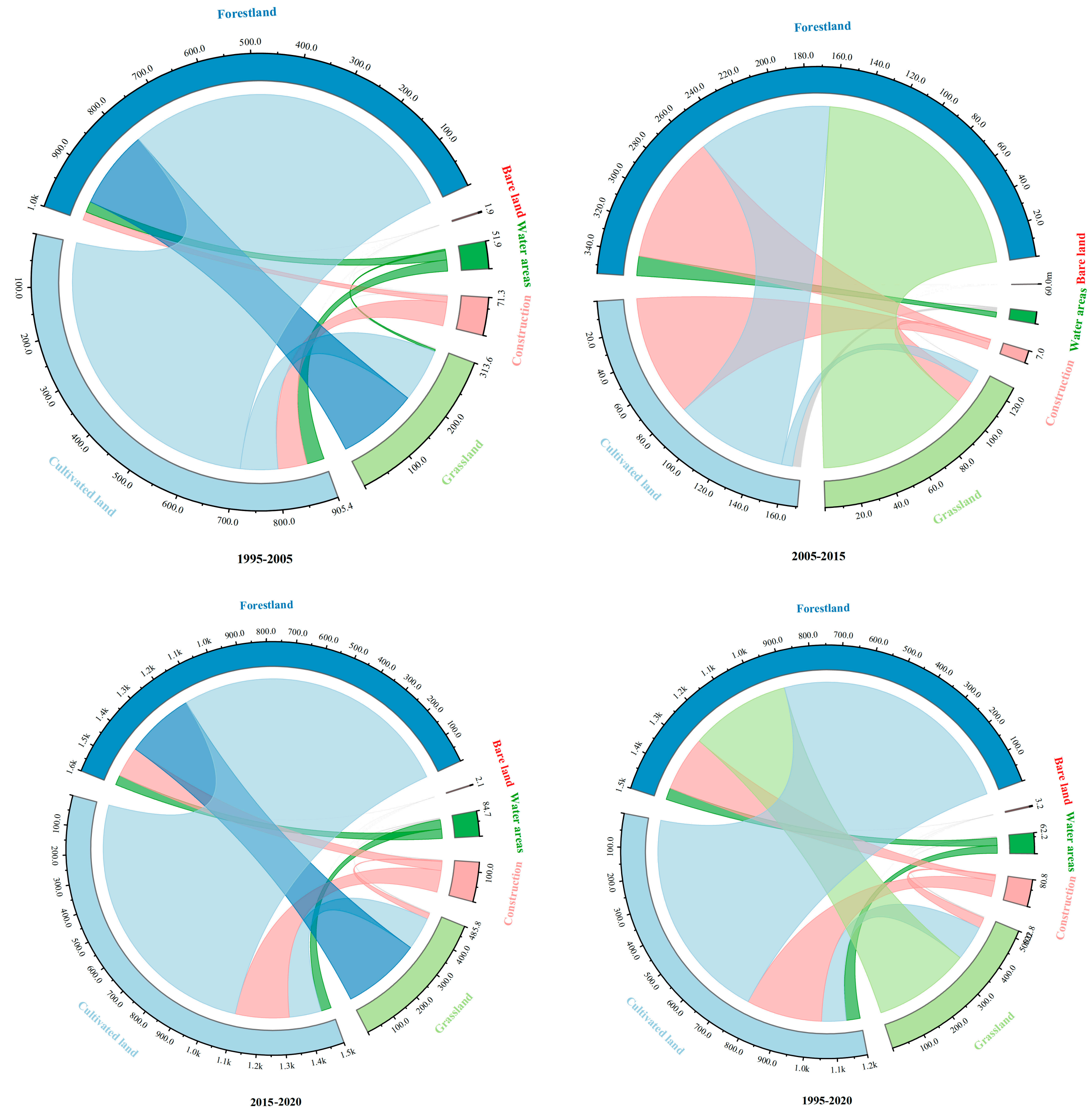

Fig. 3. Sankey diagram of land use transfer.

increased significantly (177.61 km^2), with the main sources of inflow being cropland and forest land. The area of grassland also increased (44.43 km^2), with the main source of inflow being forest land. From 2015 to 2020, arable land, forest land, and grassland were substantially transformed into construction land, and the area of construction land continued to increase significantly (239.43 km^2).

Habitat quality variability characteristics

Spatial and temporal variation in habitat quality

The habitat quality index (HQI) is a continuous value between 0 and 1; the closer to 1, the stronger the ability of the regional ecological environment to resist threat factors and the better the habitat quality. The average HQI of the Luoxiao Mountains region in 1995, 2005, 2015, and 2020 was 0.822, 0.818, 0.817, and 0.813, respectively, indicating that the overall habitat quality of the Luoxiao Mountains region decreased over time. The declines during 1995 to 2005 and 2015 to 2020 were the largest.

To accurately describe the dynamic trend in habitat quality, the HQI in the Luoxiao Mountains area was divided into 5 grades using the equal spacing classification method; the 5 classes and range of values were as follows: very low (0 to 0.2), low (0.2 to 0.4), medium (0.4 to 0.6), high (0.6 to 0.8), and very high (0.8 to 1.0) [56]. Overall, the habitat quality of concentrated areas of forest land, grassland, and water was high, while the habitat quality of arable land, construction land,

Table 1. Land use transfer matrix for the Luoxiao Mountains area (km^2).

Years	Type	Cropland	Forestland	Grassland	Water	Construction	Bare land
1995–2005	Cropland	–	712.69	85.72	40.13	66.73	0.16
	Forestland	782.03	–	180.24	24.94	19.11	0.51
	Grassland	122.24	183.72	–	4.25	3.27	0.11
	Water	25.80	21.29	3.08	–	1.70	0.00
	Construction	54.14	13.57	2.20	1.37	–	0.05
	Bare land	0.31	0.65	0.86	0.04	0.07	–
2005–2015	Cropland	–	75.63	7.37	5.75	82.11	0.02
	Forestland	90.47	–	164.35	13.34	86.47	0.16
	Grassland	9.12	103.00	–	0.42	15.33	0.01
	Water	2.24	3.34	0.38	–	0.65	0.00
	Construction	4.70	1.80	0.20	0.25	–	0.00
	Bare land	0.02	0.02	0.01	0.01	0.00	–
2015–2020	Cropland	–	1101.72	131.46	42.26	220.43	0.33
	Forestland	1146.57	–	280.61	40.38	124.25	1.01
	Grassland	134.05	322.59	–	5.62	23.51	0.03
	Water	37.74	38.76	4.63	–	3.52	0.04
	Construction	88.82	36.32	4.41	3.35	–	0.07
	Bare land	0.34	0.79	0.30	0.01	0.69	–
1995–2020	Cropland	–	774.21	89.36	50.57	275.19	0.26
	Forestland	901.47	–	366.61	42.96	199.61	1.23
	Grassland	127.78	351.36	–	5.35	38.26	0.05
	Water	28.65	27.14	3.22	–	3.17	0.00
	Construction	56.94	19.49	1.99	2.32	–	0.02
	Bare land	0.44	1.09	0.93	0.01	0.72	–

and bare land were low (Fig. 4). As shown in Table 2, from 1995 to 2020, the total area of very high-grade habitat quality areas accounted for the largest proportion, with all greater than 55%, indicating that the overall habitat quality of the Luoxiao Mountains area was good. However, the area of very high-grade habitat quality first decreased and then increased, from 29,871.87 km^2 in 1995 to 29,228.15 km^2 in 2015, and then increased to 29,300.11 km^2 in 2020; the proportion also decreased from 56.91% to 55.69% and then increased to 55.82%. The area of very low-grade habitat quality area first decreased and then increased, from 664.95 km^2 in 1995 to 648.31 km^2 in 2005, and then continuously increased to 1196.78 km^2 in 2020; the proportion also decreased from 1.27% to 1.24% and then continuously increased to 2.28%. The areas of the other habitat quality grades remained consistent (Table 2). This indicates that there was spatial heterogeneity in the habitat quality of the Luoxiao Mountains over time, with both a trend of deterioration followed by gradual improvement and a trend of improvement followed by continuous deterioration.

Global spatial autocorrelation analysis of habitat quality

The Moran's I calculations for the 4 periods of 1995, 2005, 2015, and 2020 showed that the Z scores of the 4 periods were all greater than 2.58, and all $P = 0.0000 < 0.01$. This indicates that the spatial distribution of habitat quality in the Luoxiao Mountains area was not random but had a strong spatial correlation.

The Moran's I values for all 5 periods from 1995 to 2020 were above 0.6, indicating a significant clustering pattern, i.e., high values of habitat quality clustered spatially and low values tended to be adjacent to each other. In addition, the values from 1995 to 2020 first decreased and then gradually increased (Table 3), indicating that the spatial correlation of habitat quality in the region first decreased (1995 to 2005) and then gradually increased (2005 to 2020). This is primarily because the areas with high habitat quality were affected by the expansion of urban land, which eroded the original woodland, grassland, and other ecological landscapes and caused habitat fragmentation. The development of large amounts of urban land has resulted in the increasingly widespread distribution of areas with low habitat quality.

Analysis of cold spots and hot spots of habitat quality changes

From 1995 to 2020, the hot-spot areas of habitat quality in the Luoxiao Mountains area were mainly concentrated in the areas where the national key ecological function areas are located, especially Jinggangshan City, Yanling County, and Anyuan County, where the habitat quality is high. The cold-spot areas were mainly located in provincial key development areas

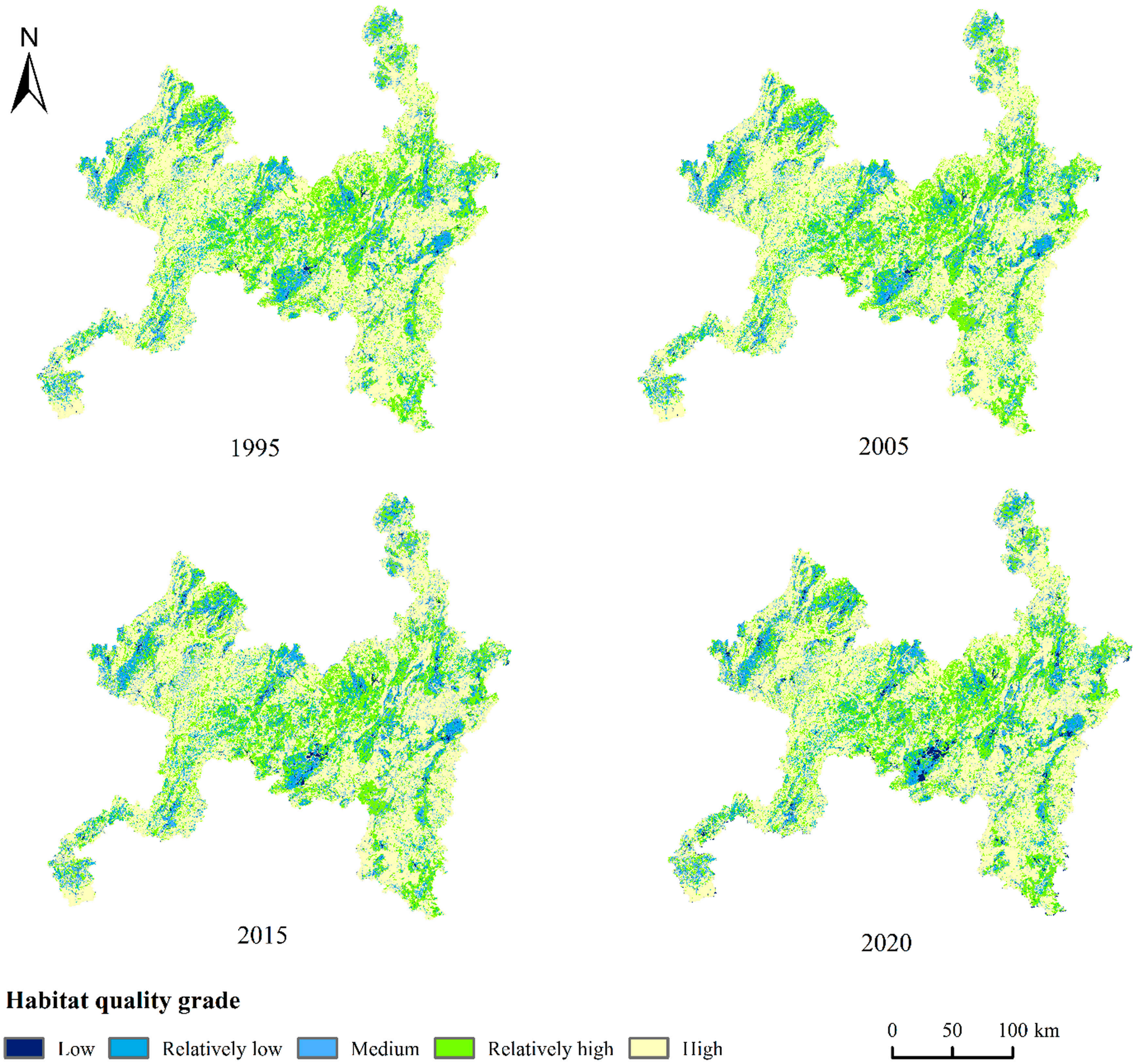

Fig. 4. Spatial distribution of habitat quality in the Luoxiao Mountains area, 1995 to 2020.

(Nankang District, Ganxian District, and Ganzhou District) and national agricultural main production areas (Xingguo County, Yudu County, Ningdu County, and Anren County) (Fig. 5). The above areas are flat, densely populated, and subject to strong interference from human activities, such as agricultural production and rapid urban expansion, resulting in low regional habitat quality.

Analysis of factors influencing the changes in habitat quality

Fitting effects of the OLS, GWR, and RF models

The spatial pattern of habitats reflects that human activities and natural factors have important influences on the spatial and temporal changes in habitat quality. In this paper, natural geographic factors such as the average annual rainfall, average annual temperature, altitude, and slope, and socioeconomic factors such as the spatial distribution of the population, GDP, and luminosity index were selected as independent variables to compare and verify the fitting effects of the OLS, GWR, and RF models.

First, the variance-inflated factor (VIF) diagnostic method was used to test the multicollinearity among the independent variables in order to exclude the factors with significant multicollinearity. Usually, VIF = 10 is used as the criterion; when VIF < 10, there is no multicollinearity, when 10 ≤ VIF < 100, there is strong multicollinearity, and when VIF ≥ 100, there is serious multicollinearity [39,41]. The test results indicated that the VIF values of the respective variables were less than 10, and thus, it can be concluded that there was no multicollinearity between the respective variables. This satisfies the requirements of the explanatory variables.

Table 2. Habitat quality percentage statistics for the Luoxiao Mountains, 1995 to 2020.

Level	1995		2005		2015		2020	
	Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%
Very low	664.95	1.27	648.31	1.24	873.28	1.66	1196.78	2.28
Low	3385.50	6.45	3320.02	6.33	3415.35	6.51	3357.08	6.40
Medium	6179.78	11.77	6216.73	11.84	6566.87	12.51	6342.19	12.08
High	12387.77	23.60	12758.13	24.31	12407.38	23.64	12294.92	23.42
Very high	29871.87	56.91	29543.51	56.29	29228.15	55.68	29300.11	55.82

Table 3. Global Moran's I index table.

Year	Global autocorrelation index statistics			
	Moran's I	Z-score	*P* value	Result
1995	0.664	149.777	0.0000	Gather
2005	0.660	147.412	0.0000	Gather
2015	0.666	150.246	0.0000	Gather
2020	0.717	113.795	0.0000	Gather

The explanatory power of the OLS model was less than 50% for habitat quality, and the GWR model had a significantly better fit than the OLS model for all 5 time periods, with an explanatory power of more than 65%. Meanwhile, both the Sigma and Akaike's Information Corrected criterion of the GWR model were lower than those in the OLS model, indicating that the GWR model had better explanatory power for factors affecting habitat quality and its model accuracy was better.

When simulated using the RF algorithm, the mean square error (MSE) reached a minimum once the number of categorical regression trees increased to 100 and the number of leaf nodes was 5. Therefore, in the subsequent analysis, the number of categorical regression trees was set to 100 and the number of leaf nodes was set to 5. The simulation accuracy R^2 of the RF algorithm in 1995, 2005, 2015, and 2020 was 0.845, 0.861, 0.864, and 0.865, and the MSE was 0.073, 0.070, 0.070, and 0.074, respectively. This indicates that the RF algorithm was the best fit and outperformed the OLS and GWR models.

Habitat quality change influencing factors

According to the GWR results (Fig. 6), the correlation coefficients between each influencing factor and habitat quality during the 5 periods from 1995 to 2020 showed more dispersed regional distribution characteristics. Among the natural geographic factors, temperature and elevation were negatively cor related with habitat quality, and the regression coefficients were negatively correlated in the eastern region and positively correlated in the central and western regions. Precipitation and slope were positively correlated with habitat quality, and the regression coefficients were positively correlated in the central and eastern regions and negatively correlated in the western region. Socioeconomic factors such as the population density and nighttime light index showed more significant negative correlations with habitat quality, and the correlations increased over time (Fig. 6), indicating that the spatial heterogeneity in the effect of socioeconomic factors on habitat quality became more significant with increases in the urbanization rate.

The RF results revealed that the ranking of the importance values of the influencing factors during the 5 periods from 1995 to 2020 exhibited relative consistency, with the highest importance values for slope and precipitation among the natural factors, and the highest importance value for GDP among the socioeconomic factors. In addition, the importance values of the different influencing factors varied across the different years. In particular, the nighttime lighting factor showed the most obvious performance, and its importance value increased over time (Fig. 7).

Discussion

Spatial and temporal changes in land use and habitat quality in the Luoxiao Mountains

In this study, the InVEST model was used to assess the habitat quality of the Luoxiao Mountains area during 4 periods from 1995 to 2020. In terms of the spatial distribution, the overall habitat quality of the Luoxiao Mountains area showed a spatial distribution pattern of low in the central urban area and high in the peripheral urban area, with an obvious hierarchical structure. This is highly compatible with the topographic characteristics of the Luoxiao Mountains area. In terms of temporal changes, the overall habitat quality in the Luoxiao Mountains showed a decreasing trend from 1995 to 2020; this trend was more obvious between 1995 to 2005 and 2015 to 2020. There was an overall decrease of 0.5%, which was closely related to land use changes. The changes from 1995 to 2005 were mainly driven by economic interests, such as grain commodities; this led to the reclaiming of a large amount of forest and grassland for cultivation. From 2005 to 2015 and 2015 to 2020, construction land increased significantly. On the one hand, this is due to the implementation of the poverty eradication policy, the vigorous development of regional specialty industries, and a large increase in the construction of agricultural and forestry product bases. On the other hand, the accelerated urbanization process has led to the large-scale expansion and occupation of construction land. Land use changes due to enhanced anthropogenic activities have resulted in the degradation of habitat quality levels at an accelerated rate with increased spatial autocorrelations. This is consistent with the gradual decline in habitat quality in the Poyang Lake basin in Jiangxi Province [57], Guangdong Province [19], and the Beijing-Tianjin-Hebei region [25], where the common cause is a rapid increase in construction land due to urbanization expansion. In addition, the habitat quality in the Luoxiao Mountains area showed spatial heterogeneity over time, with the distribution of cold and hot spots being closely related to the regional functional zoning; there was a trend of deterioration followed by gradual improvement, which is due to the implementation of ecological projects such as natural forest protection and the return of farmland to forest in the context of regional urbanization construction; these projects help to improve habitat quality.

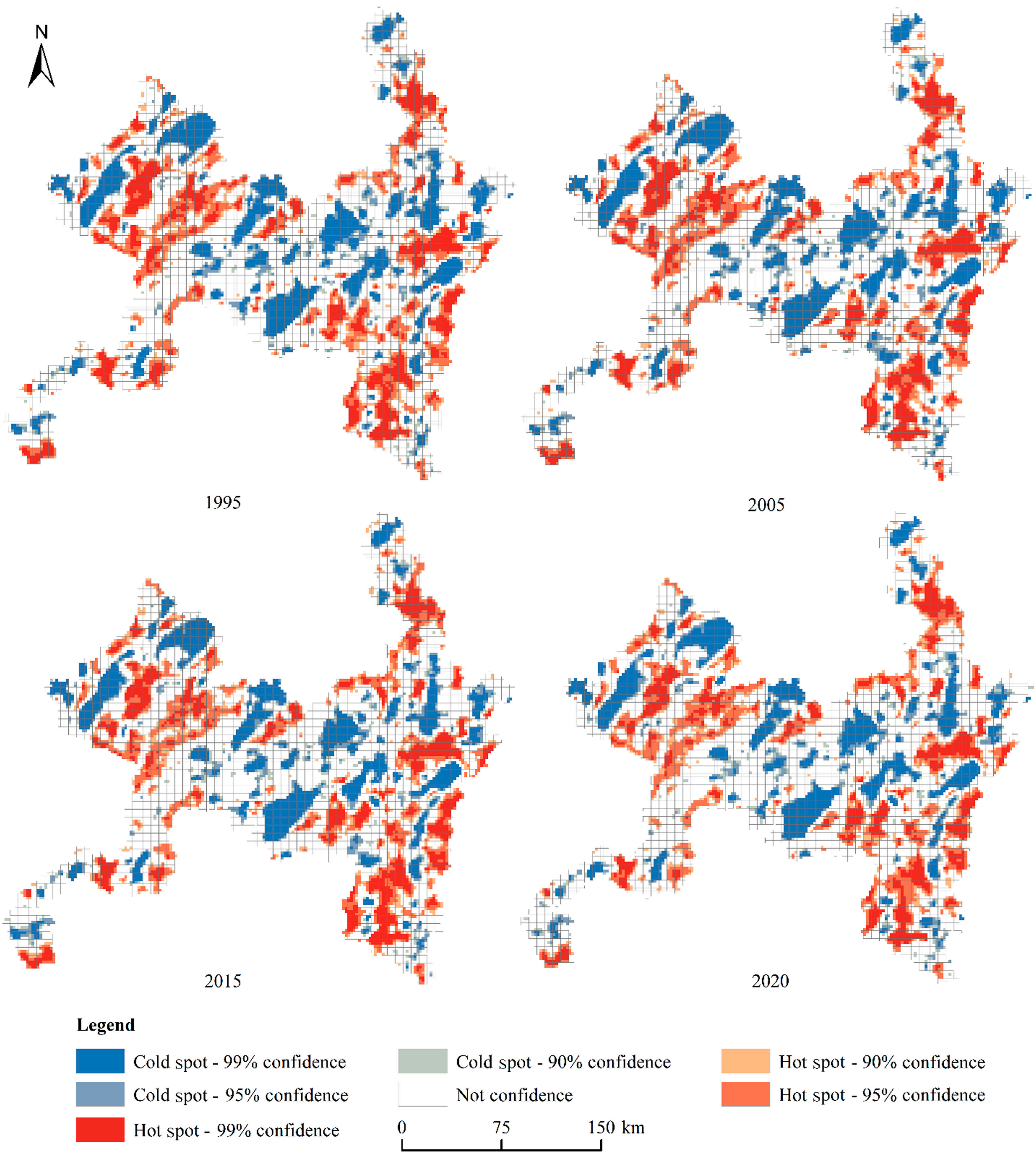

Fig. 5. Habitat quality "hot-spot" analysis in the Luoxiao Mountains area, 1995 to 2020.

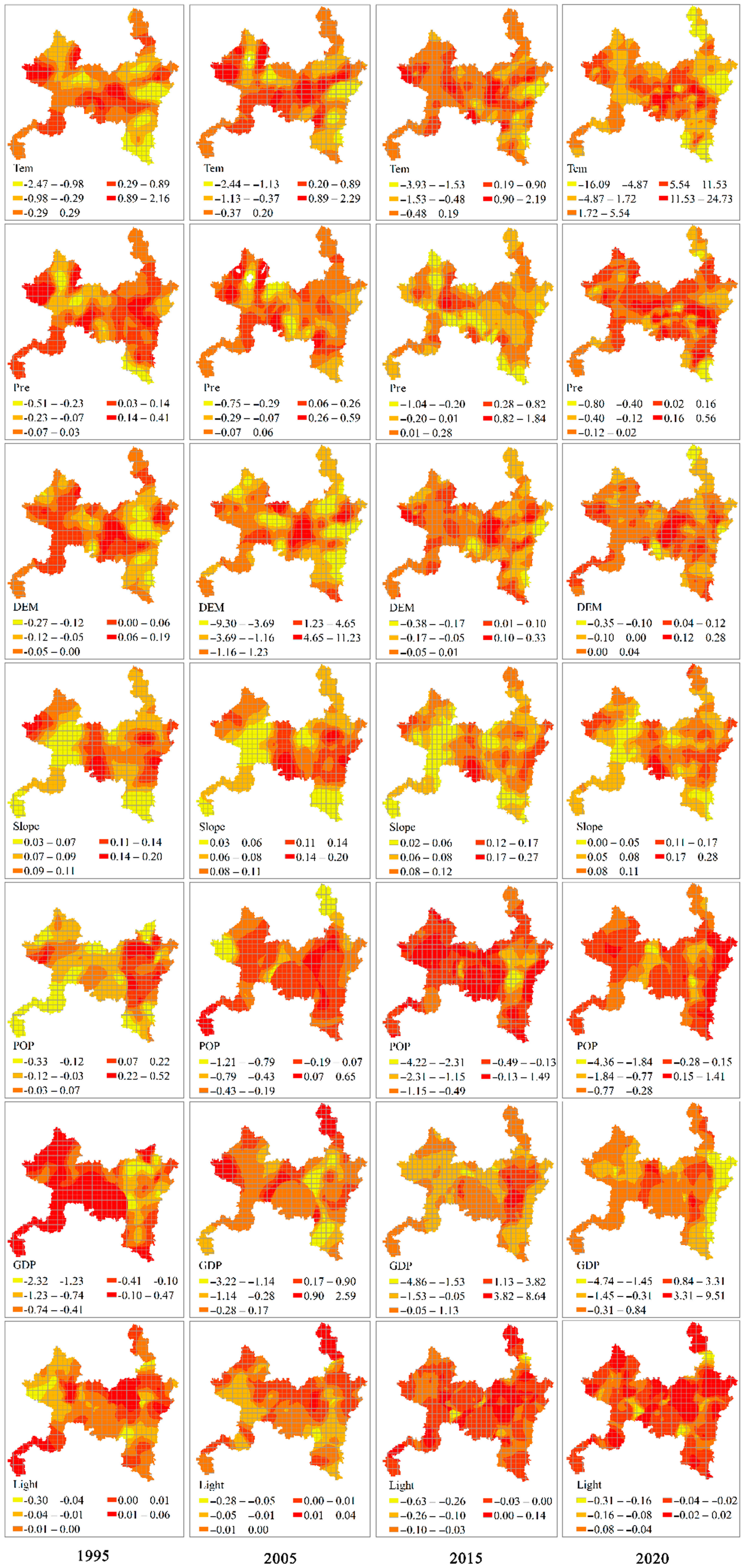

Fig. 6. Spatial distribution patterns of GWR regression coefficients.

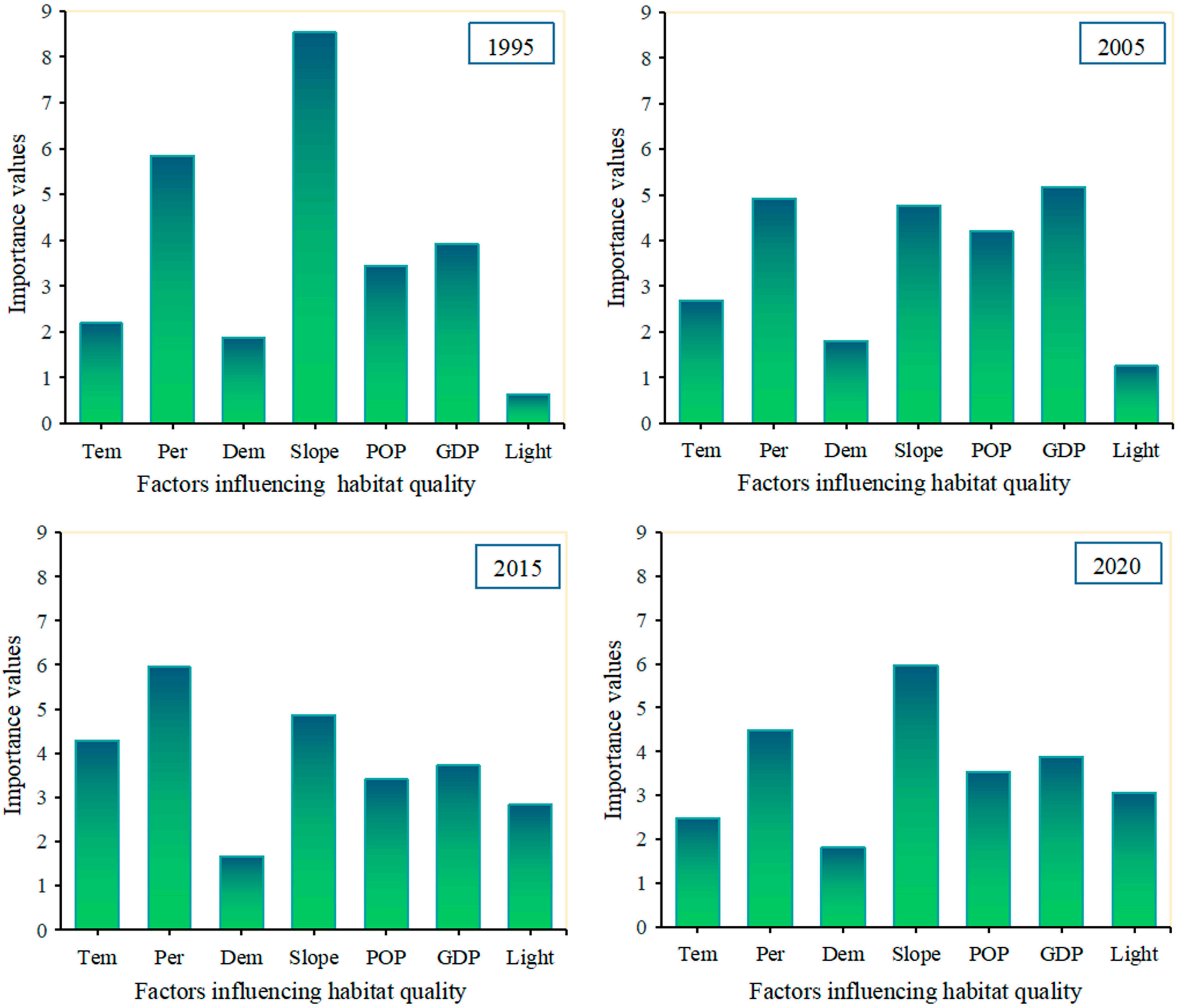

Fig. 7. The importance values of different factors influencing on habitat quality.

Habitat quality driving mechanisms in the Luoxiao Mountains

In this study, OLS, GWR, and RF were used to quantify the effects of physical geographic and socioeconomic factors on habitat quality. The GWR model explained the factors influencing the changes in the spatial patterns of habitat quality at the spatial location level better than the OLS model during different time periods. In addition, the machine learning RF algorithm had the highest simulation accuracy and showed good predictive performance. This indicates that RF model is robust, especially when a large number of samples are used [44,55,58].

Overall, natural geographic and socioeconomic factors jointly drove the spatial pattern changes in habitat quality in the Luoxiao Mountains. The spatial heterogeneity of the effects of socioeconomic factors on habitat quality became more significant with increasing urbanization. Among the natural geographic factors, those with the greatest influences on habitat quality changes, from high to low, were slope, precipitation, temperature, and DEM. In general, habitat quality showed a tendency to increase with increasing DEM and slope [13,39]. This is because regions with larger DEM and slope generally have fewer socioeconomic activities and less ecosystem-disturbing factors, and thus, there is a relatively lower impact on habitat quality. It should be noted that previous studies have shown more significant effects of DEM on habitat quality [39]; however, in this study, the effect of DEM on regional habitat quality was lower. This may be due to the lower spatial heterogeneity of DEM in the Luoxiao Mountains area compared with other factors. Among the meteorological elements, precipitation had a higher value of importance on habitat quality and temperature had a smaller value. This is likely because the Luoxiao Mountains area is located in a subtropical region and the temperature was relatively stable during the study period; thus, precipitation was a key factor affecting vegetation growth.

The aggregation of various socioeconomic factors in the urbanization process is an important driver of regional habitat quality changes. Sun et al. showed that the distribution of GDP was not related to habitat quality in a study of the spatial and temporal dynamics of habitat quality in the Nansi Lake watershed in Eastern China [13]. In contrast, the current study found that the GDP contributed the most to habitat quality changes among the various socioeconomic factors. This difference may be due to differences in the study areas. To a certain extent, GDP reflects the process of urbanization construction in the Luoxiao Mountains area; in general, the higher the GDP, the higher the degree of regional urbanization construction, and the greater the impact on habitat quality. Notably, socioeconomic factors such as Pop and Light showed more significant negative correlations with habitat quality, and the correlations increased over time. POP and Light are representations of hu man activities and thus reflect indirect disturbance effects of urban socioeconomic development and the effects of high-intensity human activities on ecosystems. Together, these findings suggest that intensive socioeconomic activities threaten habitat quality and cause habitat loss and degradation.

Ecological restoration strategy analysis

The Luoxiao Mountains area is both an ecological barrier area and an ecologically fragile area; it faces problems such as relative poverty and the risk of returning to poverty [45]. Therefore, it is necessary to fully balance ecological protection and economic growth to achieve sustainable regional development in this specific region. Given that the hot-spot areas of habitat quality in the Luoxiao Mountains were mainly concentrated in national key ecological function areas such as Jinggangshan City, Yanling County, and Anyuan County, these areas should focus strongly on the realization of the ecological product value of the rich forest resources (e.g., ecological protection compensation, carbon trading, forest economy, and ecotourism) and should explore effective paths to transform typical ecological product endowments into economies for indigenous populations, with the aim of curbing the expansion of agricultural land to maintain better habitat quality and ecosystem service supply [59]. For habitat quality cold-spot areas such as the provincial key development areas (Nankang District, Ganxian District, and Ganzhou District) and national agricultural main production areas (Xingguo County, Yudu County, Ningdu County, and Anren County), spatial utilization efficiency should be improved, expansion of construction land should be mitigated, and ecological restoration measures should be implemented to improve habitat quality. Moreover, low-carbon green industries should be developed, and advantageous agricultural product bases created. In addition, the Luoxiao Mountains area should fully utilize the value of unused land to provide available space for the implementation of fallowing and reforestation project.

Research limitations

The application of the InVEST model for habitat quality studies mainly relies on expert knowledge to define model parameters [60], and the process of parameter selection is inevitably influenced by expert subjectivity. Thus, there is a need to enhance model parameter localization studies through field and long-term observational studies in order to optimize habitat suitability, threat impact characteristics, and threat sensitivity parameters for different land use types [8,61]. In terms of habitat quality driving mechanisms, this study explored the effects of physical geographic and socioeconomic factors on habitat quality, which provides a limited view of the driving mechanisms. Due to the complexity of regional ecosystems, other factors such as the spatial distribution of vegetation, culture, and policy can all influence habitat quality to some extent. Therefore, it is necessary for future studies to investigate other relevant factors in order to more comprehensively study the habitat quality driving mechanisms and their scale effects.

Conclusion

In this study, ArcGIS and InVEST models were used to quantitatively analyze the spatial and temporal change characteristics of land use and habitat quality in the Luoxiao Mountains area. Moreover, OLS, GWR, and RF were used to analyze the driving mechanisms of the spatial and temporal change characteristics of habitat quality in the Luoxiao Mountains area. The main results are as follows:

1. The land use type of the Luoxiao Mountains area is mainly forest land, accounting for more than 70% of the total area. From 1995 to 2020, the largest increase was in the area of construction land, amounting to more than 170 km^2; this was mainly due to the transformation of arable land to forest land.
2. During 2000 to 2020, the overall habitat quality of the Luoxiao Mountains area exhibited a decreasing trend, and its spatial distribution showed strong autocorrelations and significant aggregation. The spatial distribution of habitat quality was closely related to land use, and the hot spots were mainly concentrated in the areas where national key ecological function areas are located, while the cold spots were mainly distributed in provincial key development areas and national main agricultural products production areas.
3. OLS, GWR, and RF were used to analyze the habitat quality driving mechanism in the Luoxiao Mountains area, and RF was found to be superior to the other methods.
4. The physical geographic factors of slope and precipitation, and the socioeconomic factor GDP were the key drivers of habitat quality in the Luoxiao Mountains. The spatial heterogeneity in the influence of socioeconomic factors on habitat quality became more significant with the acceleration of the urbanization rate.

This study offers a comprehensive understanding of the long-term habitat quality change patterns and their driving mechanism in the Luoxiao Mountains and provides a basis for decision-making to maintain and enhance habitat quality. This can be achieved through the precise implementation of ecological protection and restoration measures, the improvement of spatial utilization efficiency, and the exploration of ecological product value realization. In addition, this study not only provides a scientific baseline for exploring the dynamic change mechanisms of habitat quality in concentrated poverty-stricken areas but also offers a scientific reference for ecological protection, restoration, and land use planning in other concentrated poverty-stricken areas.

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K.G.: Conceptualization, methodology, investigation, validation, visualization, and writing original draft. T.X.: Suggestions. X.M.: Language embellishment. X.N. and B.W.: Conceptualization, funding acquisition, project administration, and supervision. **Competing interests**: The authors declare that they have no competing interests.

Data Availability

The data are available from the authors upon a reasonable request.

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