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Spatial and temporal dynamics of habitat quality in response to socioeconomic and landscape patterns in the context of urbanization: A case in Zhengzhou City, China

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Abstract

With the rapid development of urbanization, the habitat quality (HQ) in urban areas has been eroded. This phenomenon is destroying the balance of ecosystems, triggering the reduction of biodiversity and the decay of ecosystem service functions. The study of the relationship between urbanization and HQ in Zhengzhou City is beneficial for the reference of sustainable urban ecological planning and management. Based on landscape classification data and socioeconomic data for three years, this study analyzes the spatial correlations between socioeconomic and landscape pattern factors and HQ, compares the dynamic changes in the explanatory power of different factors, and explores the joint effects between multiple factors. The results show that: (1) The overall value of HQ index in Zhengzhou City decreased by .10 during 2000–2020, mainly occurring in suburban areas, with a small amount of HQ improvement occurring in the core areas of ecological protection, such as mountains and river channels. (2) The spatial autocorrelation of all influencing factors with HQ increased during this period, while the negative impact from socioeconomic sources was stronger than the positive impact from landscape patterns. (3) Intensive human activities lead to a single habitat type, which reduces HQ; rich landscape types and complex landscape composition can enhance HQ. Improving the connectivity of blue-green landscapes helps to attenuate the negative effects of urbanization on HQ. (4) Changes of HQ in the study area and the development of multi-factor effects on HQ are driven by the Zhengzhou Metropolitan Area Plan. Urban development policies and management can build idyllic complexes at the edge of urban development, preserving pristine blue-green patches to avoid their homogenized distribution and thus slowing the decline of HQ. The above results provide new ideas for the development of sustainable urban ecology.

Keywords
Landscape pattern, policy, socioeconomic, urbanization, Zhengzhou Metropolitan Area Plan

1. Introduction

Habitat refers to the environment in which organisms live, and habitat quality (HQ) measures the ability of an ecosystem to provide conditions for individuals and populations to survive and reproduce (Hall et al. 1997; Nelson et al. 2009). HQ is indicative of the reflection of biodiversity status. Global urbanization rates are continuing to grow, with urban areas already doubling in 2020 compared to 1992, and may expand to 180% in 2100 (Knapp et al. 2021); the rapid expansion of cities is eroding the natural habitats where plants and animals live. The study shows that the fragmentation of the landscape and the complexity of the landscape structure continue to affect HQ as the expansion of towns and cities is accompanied by rapid changes in the surface pattern (Goldstein et al. 2012; Rosenberg et al. 2019; Chang et al. 2021). Areas with high HQ are more likely to have towns and cities, and the range of negative impacts of urbanization is much greater than that of ecosystems in urban areas (Knapp et al. 2021). Urbanization is considered to be an important cause of degradation and the loss of pristine habitats and thus a threat to ecosystem stability (Van Dolah et al. 2008; Mcdonald et al. 2009; Song et al. 2020). As a basic component of the ecosystem, changes in the quality of habitat are important for protecting biodiversity, building ecological security patterns, and enhancing ecosystem service functions (Termorshuizen and Opdam 2009; Krauss et al. 2010). In order to maintain the balance of the regional ecosystem, to create a near-natural and diverse habitat and promote a healthy symbiotic relationship between human and nature, research related to HQ is one of the hotspots in the field of urban ecology (John et al. 2019; Lanfredi et al. 2022).

Achieving regional ecological sustainability requires exploring the mechanisms by which urbanization affects ecosystem structure and function. Therefore, the responsive relationship between urbanization and HQ has attracted the attention of many scholars. The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model is commonly used to quantify HQ in recent studies (Moreira et al. 2018; Wu et al. 2021); this model can be used to obtain the HQ index based on the ecological suitability of the habitat and its sensitivity to different threat sources, and to derive spatial distribution maps of HQ index based on the composition of multiple habitats even when complete species distribution data are not available (He et al. 2017). The manifestations of urbanization can be divided into two forms, indirect and direct. The landscape pattern index is considered as an indirect representation of urbanization; it can express the changes in landscape patterns under the influence of human activity aggregation and land use change (Suo et al. 2016; Dadashpoor et al. 2019). To a certain extent, it reflects the impact of the urbanization process on the ecological environment. Several international scholars have conducted studies on the relationship between landscape pattern and HQ, and uncovered regional differences in the effects of landscape pattern indices on HQ (Sallustio et al. 2017; Dadashpoor et al. 2019; Chang et al. 2021). However, the indicative role of the landscape pattern index is limited because the causes of landscape pattern changes are very complex (Li et al. 2004). Socio-economic indicators are seen as a direct manifestation of urbanization (Zeng et al. 2022), visually reflecting the prosperity and expansion intensity of cities. Several studies have indicated a significant correlation between socioeconomic indices and HQ (Sun et al. 2019; Zhu et al. 2020), factors such as population density (POP) and Gross Domestic Product (GDP) have a negative impact on HQ (Bai et al. 2019), their model simulations predicted that the intensive development of cities and towns could slow habitat degradation (He et al. 2017; Chu et al. 2018; Li et al. 2018). Fewer studies have combined the two in a multi-temporal analysis and quantified the spatial correlation between socioeconomic indicators, landscape pattern indices and HQ. This paper will examine this perspective.

In related studies, when analyzing the influence of multiple influencing factors on HQ, SPSS correlation analysis was applied to screen the influencing factors with strong influence on HQ (Zhu et al. 2020), combined with statistical analysis models such as the ordinary least squares model (OLS) and the geographically weighted regression model (GWR) to infer the degree of association between different influencing factors on HQ in geographic space and to determine the relationship between multiple variables and HQ (Sun et al. 2019; Wu et al. 2021). These research methods reflect the relationship between individual influencing factors and HQ; they cannot reflect the intensity and magnitude of the aggregation of correlations in space, and cannot analyze the joint effect of different influencing factors on HQ. The bivariate autocorrelation analysis with GeoDA software (Huang et al. 2020a; Chang et al. 2021) and the interaction detector with Geodetector software (Wang et al. 2022) can solve the above mentioned problems.

As China's new first-tier city and one of the country's major transportation hubs, Zhengzhou City is a typical example of urbanization development with its high population flow and rapid urban renewal (Feng et al. 2005). Zhengzhou City is a core area for metropolitan development and also has a Yellow River Wetland Nature Reserve; it covers a wide range of landscapes including large rivers, mountains, hills, and plains. Because of its urban expansion rate, landscape pattern changes, and ecosystem composition, Zhengzhou City is an ideal study area for conducting research on urbanization and HQ change. This paper evaluated Zhengzhou's HQ from 2000 to 2020 through the InVEST model based on three phases of landscape classification data. With the technical support of GIS10.2 software, a grid cell of 1 km × 1 km was used to resample the study area, and GeoDA software was applied to analyze the spatial correlation between landscape pattern factors, socio-economic factors and HQ. Geodetector software was used to compare the influence of different factors on HQ and analyze the common effect between the influencing factors. The objectives of this study are: (1) to analyze the spatial and temporal evolutionary characteristics of HQ in Zhengzhou in multiple time series, (2) to reveal the spatial coupling relationship between socio-economics, landscape pattern and HQ, (3) to explore the optimization strategies of urban ecology in the context of urban regionalization development.

2 Materials and methods

2.1. Study area

Zhengzhou City is the capital of Henan Province (34°16'N–34°58'N, 112°42'E–114°14'E) and is located in the central-northern part of Henan Province. With a continental monsoon climate and four distinct seasons, it is hot and rainy in summer, but cold and dry in winter. The terrain is high in the west and low in the east, with plains and inclined plains dominating the whole territory, while the western mountainous areas belong to the Funiu Mountains and the rivers in the territory belong to the two major water systems, the Yellow River and the Huaihe River (Feng et al. 2005; Lei et al. 2012). Zhengzhou City is in charge of Zhongyuan District, Erqi District, Jinshui District, Huiji District, Shangjie District, Guanchenghuizu District, Xinzheng City, Dengfeng City, Xinmi City, Xingyang City, Gongyi City, Zhongmou County (Wang et al. 2021). In 2020, Zhengzhou's GDP exceeded EUR 0.17 trillion for the first time, ranking 16th among China's top 100 cities. According to the results of the seventh national census, Zhengzhou's resident population jumped into first place in Henan Province, attracting 74% of the province's new population over the last 10 years, demonstrating superb economic growth and population absorption capacity. As a national central city and a national ecological garden city, Zhengzhou City is gradually growing into the core city of the Central Plains City Cluster. Location and elevation image of Zhengzhou City is as follow (Fig. 1).

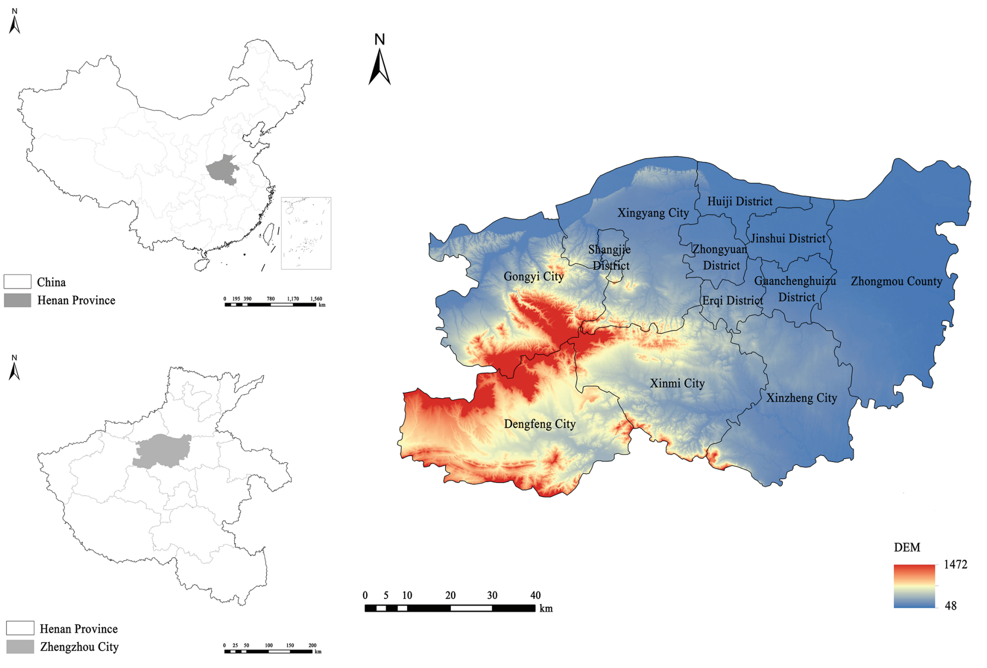

Figure 1. Location and elevation image of Zhengzhou City.

2.2. Data sources and pre-processing

The 30 m resolution landscape classification data for 2000, 2010 and 2020 were obtained from GlobleLand30 (http://www.globallandcover.com, accessed on 29 November 2021) released by the Ministry of Natural Resources of China, using the multispectral images without or with few clouds in the vegetation growing season as the information source, and classifying the land use types according to land use attributes and natural attributes. It is divided into 10 primary land use types, and after data merging and clipping, a total of 6 primary land use types are covered in the study area, namely, arable land, forest, grassland, wetland, water, and construction land, with a classification accuracy of more than 83%. The specific classification description is shown in Appendix 1. The nighttime light data come from the joint product developed by the GIS development and urban research team of the College of Geographical Sciences of East China Normal University and others (https://doi.org/10.7910/DVN/YGIVCD, accessed on 29 November 2021) (Chen et al. 2021b), using DMSP-OLS and NPP-VIIRS NTL as data sources, with the advantages of high spatial resolution of 500 m and long time span through cross-sensor calibration, verified by random pixel, with good accuracy in pixel-level (R^2: 0.87) and city-level (R^2: 0.95) (Chen et al. 2021a). Population data was obtained from worldpop's 100 m resolution demographic data set (https://www.worldpop.org/, accessed on 29 November 2021), the raster data were corrected by combining the population's numbers from Zhengzhou City Yearbooks and census results. The rural settlements were obtained from the Resource and Environmental Science and Data Center (https://www.resdc.cn/, accessed on 29 November 2021); it is used as a reference to extract the data of land urbanization space. The elevation data was obtained from the ALOS DEM data on the official NASA website (https://search.asf.alaska.edu/#/, accessed on 29 November 2021) with a spatial resolution of 12.5 m.

2.3. Methods

2.3.1. Habitat quality (HQ) evaluation

The InVEST model assesses the variability and distribution of HQ in the study area based on the sensitivity of different habitat types to stressors and the intensity of external threats to them, and evaluates the biodiversity service function of ecosystem in the study area by the level of the HQ index (Peng et al. 2018; Sun et al. 2019); these can replace a large number of field surveys and facilitate the optimization of biodiversity conservation strategies. The calculation formula is as follows:

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

$$D_{xj} = \sum_{i=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{\omega_r}{\sum_{r=1}^{R} \omega_r} \right) r_y i_{rxy} \beta_x S_{jr} \tag{2}$$

where Q_{xj} is the HQ of raster image element x in landscape type j, H_j is the habitat suitability, D_{xj} denotes the habitat threat level, k is the half-saturation constant, usually taken as half of the maximum value of D_{xj}, z is the normalization constant, usually taken as 2.5, R denotes the number of threat factors, y is all raster image elements of threat r, Y_r indicates the total number of raster image elements occupied by r, ω_r is the weight, β_x is the is the legal accessibility of raster image element x, S_{jr} is the sensitivity of land cover j to threat factor r, i_{rxy} means the coercive effect of raster image element y on habitat raster image element x.

In landscape classification, the more primitive, complex and large continuous ecosystems have higher suitability and stability, while land types with high intensity of human activities are more likely to threaten the surrounding habitats with strong expansiveness and need to be extracted as threat sources (Chang et al. 2021). Referring to the existing research results (Wang et al. 2020; Zhu et al. 2020; Chen and Li 2021) and the actual situation in the study area, the maximum impact distance, weight of threat factors, and the sensitivity of each type of habitat to threat factors were set as Table 1 and Table 2.

Table 1. The weight for threat factors.

Threat factor	dr_max/km	Weight/ω_r	Distance-decay function
Cropland	4	0.5	exponential
Construction Land	8	0.9	exponential

Table 2. The sensitivity of habitat types to threatening factors.

Landscape code	Habitat type	Habitat suitability	Cropland	Construction Land
10	Cropland	0.5	0	0.5
20	Forest	1	0.6	0.4
30	Grassland	0.8	0.8	0.6
50	Wetlands	1	0.4	0.9
60	Water area	0.9	0.4	0.4
80	Construction Land	0	0	0

2.3.2. Selection of impact factors

The landscape pattern indicators reflect the dynamic changes of the ecosystem under the influence of urbanization as indirect influence factors, and the socio-economic indicators reflect the direct influence of socio-economic development on the ecosystem as direct influence factors. Referring to the relevant literature (Huang et al. 2020a; Chang et al. 2021; Zeng et al. 2022), the following indicators were selected as impact factors (Table 3). In this paper, population density (POP) is selected to characterize the aggregation of population, night time light (NTL) to characterize the frequency of socio-economics, and land urbanization rate (LUR) to characterize the intensity of urban development, so that they represent the direct impact of urbanization (Chan and Vu 2017; Zeng et al. 2022). In the landscape pattern indices, SHDI and PD express the diversity of landscape patches and are used to characterize landscape types, CONTAG and ED express the shape and connectivity of landscape patches and are used to characterize landscape structure (Satir and Erdogan 2016; Zeng et al. 2022). The socioeconomic indicators are obtained from the corrected raster data, and landscape pattern indicators are calculated by Fragstats 4.0. The values of all factors are assigned to the grid with the help of ArcGIS's spatial analyst. The description of the factors' calculation formula is shown in Appendix 2.

Table 3. Descriptions of the impact factors.

Category	Metrics	Abbreviation	Description
Landscape pattern	Edge density	ED	Reflects the degree of differentiation or fragmentation of the overall landscape patches.(Xia et al. 2021)
	Contagion index	CONTAG	Reflects the degree of agglomeration or extension trend of the plaque.
	Shannon's diversity index	SHDI	Reflects landscape heterogeneity.(Li 2011)
	Patch density	PD	The number of patches in unit area.
Socio-economic	Population density	POP	The number of people per square kilometer.
	Night time light	NTL	Reflects the activity and agglomeration of socio-economic activities.
	Land urbanization rate	LUR	Proportion of urban land to urban-rural construction land.(Gao et al. 2018)

2.3.3. Grid analysis

The application of grid analysis can describe, compare, and analyze regional geographic phenomena in equivalent spatial conditions. 1 km × 1 km grid scale is often applied in articles for studying land use change (Zhu et al. 2020; Xia et al. 2021; Wang et al. 2022), so this paper uses this grid scale as the basic research scale for analysis and discussion.

2.3.4. Construct the spatial weight matrix

The spatial weight matrix is constructed by GeoDA software to define the spatial relationship between grids, and the queen contiguity is selected to construct the spatial weights with the grid number as the variable, with the following rules:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{3}$$

where n denotes the number of spatial units, w_{ij} denotes the adjacency between region i and j. If they have a common boundary or point, the value is 1, otherwise, the value is 0.

2.3.5. Bivariate spatial autocorrelation

Bivariate spatial autocorrelation analysis can reflect the degree of association between two attribute values of a spatial unit (Anselin 1995); the relationship is characterized by the Moran's *I* index, while the Moran's *I* scatter plot is generated. LISA (the Local Indicators of Spatial Association) clustering maps can characterize the degree of correlation between a unit and its neighboring units on the geographic space. There are generally four types of spatial patterns in the LISA clustering map: high-high (H-H), high-low (H-L), low-high (L-H), and low-low (L-L). The Moran's *I* index and LISA clustering map can show the degree of spatial association of different indicators with HQ and the distribution of clustered areas. The calculation formula is:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_j - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{4}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \tag{5}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_j \tag{6}$$

where I is the Moran's *I* index; n is the number of spatial cells, x_i and x_j are the observed values of cells i and j, respectively, and w_{ij} is the spatial adjacency of cells i and j. S^2 is the variance of the observed values. I takes values between [-1,1], and values less than 0 indicate negative spatial correlation, greater than 0 indicate positive spatial correlation, where equal to 0 indicates no correlation and random distribution in space.

2.3.6. Geodetector

The Geodetector can avoid the covariate interference of multiple factors and compare the magnitude of the driving force or explanatory force of multiple influencing factors on the geospatial distribution of something based on spatial heterogeneity (Wang et al. 2022). The Geodetector can not only reveal the influencing factors with important driving forces behind HQ, but also compare the magnitude of the explanatory power of the factors and evaluate the co-action among them (Wang and Xu 2017). The results of the Geodetector's analysis can be used to obtain influence factors that are more helpful to improve HQ and provide reference for urban planning adjustments. The formula is:

$$q = 1 - \frac{1}{n\sigma^2}\sum_{h=1}^{L} n_k \sigma_k^2 \tag{7}$$

where: q is the explanatory power; n_k and n are the number of samples within type h of factor A and within the entire study area, respectively; σ_k^2 and σ^2 are respectively the discrete variance within type h of factor A and within the entire study area. q takes values between [0,1], and larger values of q indicate greater explanatory power of factor A.

3. Results

3.1. Spatial distribution and dynamics of HQ

As shown in Fig. 2, the spatial pattern of HQ in Zhengzhou City changed significantly from 2000 to 2020. According to the values of HQ index, there are high quality zones (>0.75), relatively high quality zones (0.5~0.75), relatively low quality zones (0.25~0.5), and low quality zones (<0.25). Overall, the distribution of HQ in Zhengzhou City from 2000 to 2020 is "high in the northwest and low in the southeast". In conjunction with the landscape classification map of Zhengzhou City (Fig. 3), the northwestern and northeastern parts of the study area serve as the edge of the main urban area and the nature reserves; there are rich landscape compositions with intermingled agriculture and forestry, and concentrated high quality areas. The southeastern part of the study area is an agglomeration of arable land with lower quality zones distributed. Low quality areas are distributed in the main urban area, which is dominated by man-made surfaces in the central north.

From 2000 to 2020, the area of the low HQ changed greatly, increasing by 1451.68 km^2, with a percentage increase of 19.15%; the relatively low HQ zone and high HQ zone showed a decreasing trend, decreasing by 1401.16 km^2 and 70.42 km^2, with a percentage decrease of 18.45% and 0.92%, respectively, where the high HQ zone showed fluctuating changes. The relatively high HQ zone had the smallest change with an increase of 17.42 km^2 and a percentage increase of 0.23% (Table 4).

Table 4. HQ classification and area change.

Classification	Value	2000		2010		2020	
		Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%
Low habitat quality	<0.25	615.63	8.12	1237.70	16.32	2067.30	27.27
Relatively low habitat quality	0.25~0.5	6021.31	79.39	5360.43	70.68	4620.15	60.94
Relatively high habitat quality	0.5~0.75	52.40	0.69	54.37	0.72	69.81	0.92
High habitat quality	>0.75	895.17	11.80	932.00	12.29	824.75	10.88

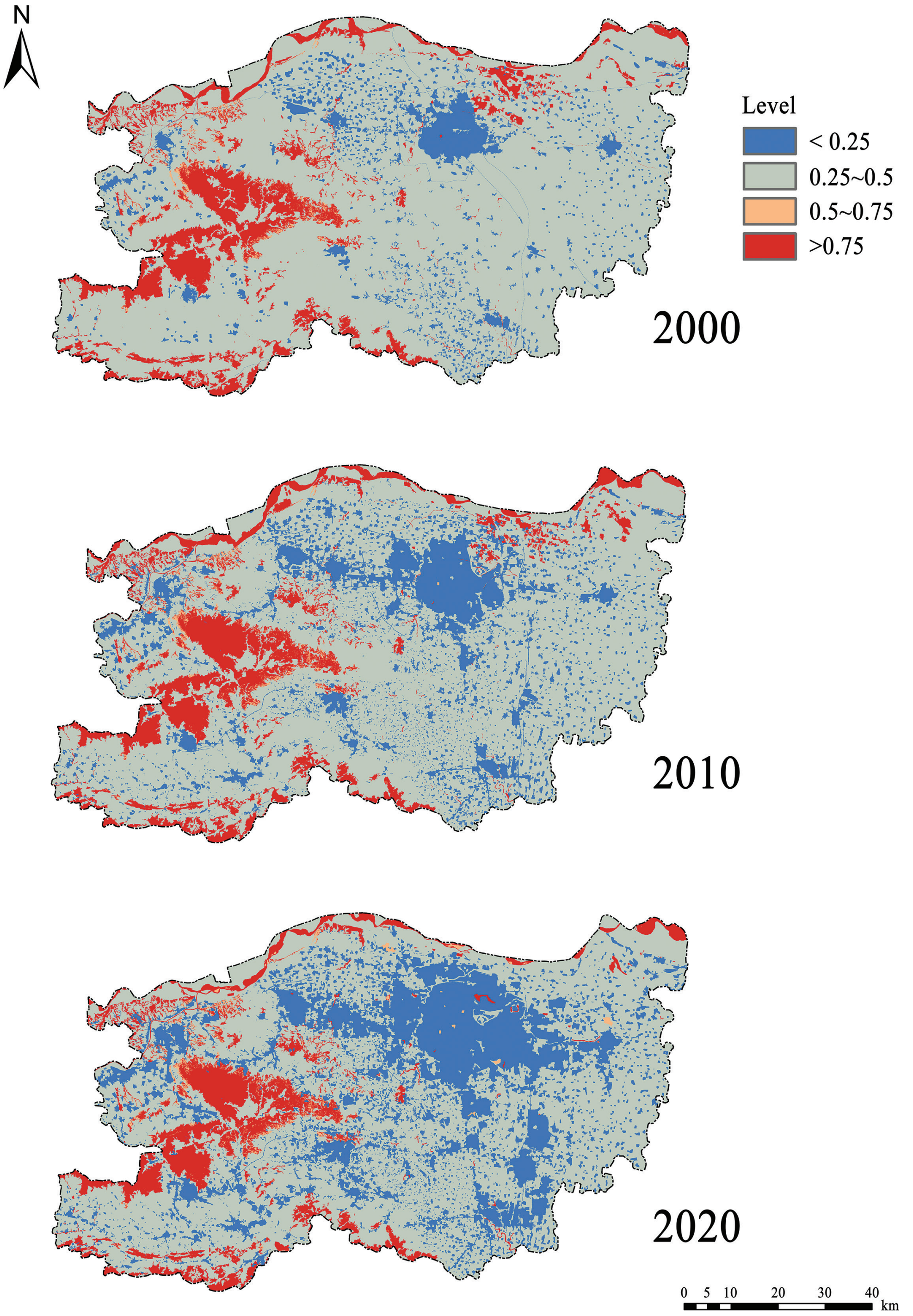

Figure 2. Spatial pattern of HQ.

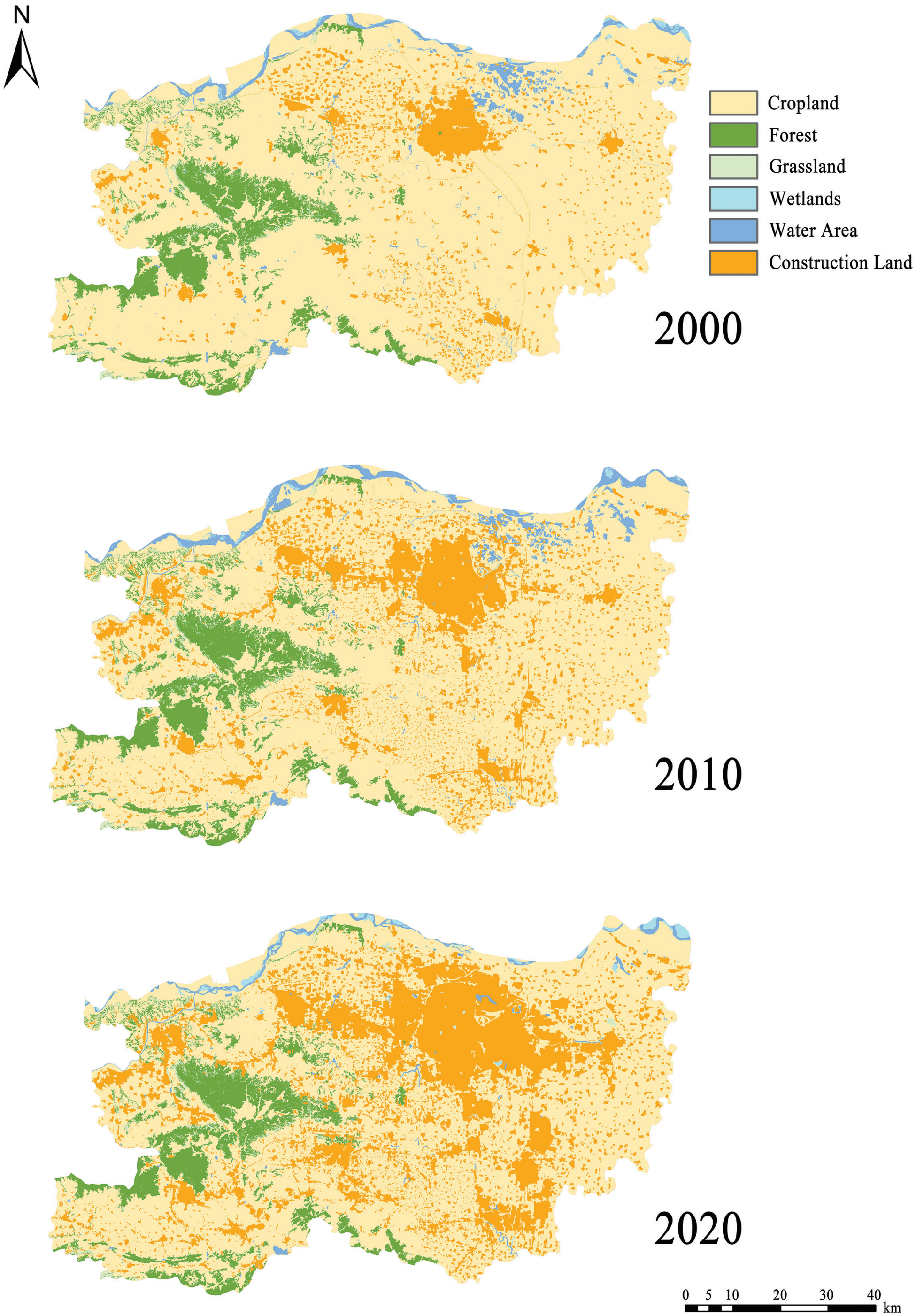

Figure 3. Landscape classification map of Zhengzhou City.

HQ changes in Zhengzhou City from 2000 to 2020 were calculated by using the ArcGIS software, through the natural break method the results were classified into five categories: significant decrease, slight decrease, no significant change, slight increase, and significant increase (Fig. 4). The northeastern part of the main urban area, where the urban construction activities are most concentrated, has significantly reduced HQ. The area centered on the urban to the distant suburbs with a slight decrease in HQ. The quality of habitats in places adjacent to natural woodlands and rivers improved slightly. The mountainous zone in the west and the Yellow River basin in the north have high HQ themselves, with little overall change and significant improvement in some areas.

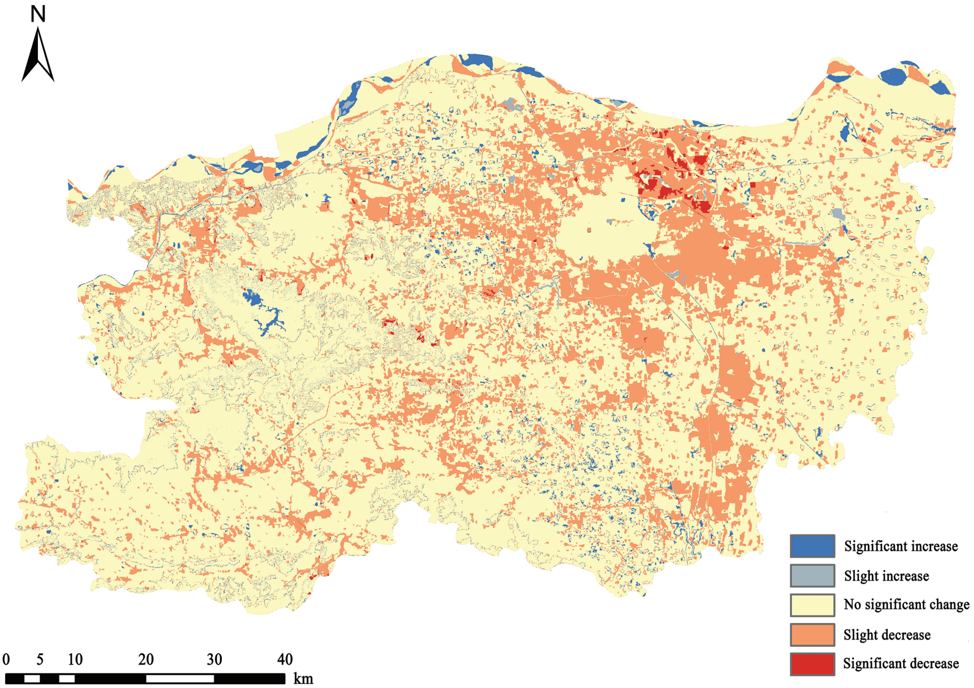

Figure 4. The variation of HQ.

3.2. Spatial autocorrelation analysis of HQ and different impact factors

3.2.1. Global autocorrelation

Moran's *I* indices for seven sets of bivariate variables were obtained using GeoDA software, after 999 random permutations, all of them passed the z-test ($p = 0.001$), indicating a significant spatial autocorrelation between the bivariate variables at the 99.9% confidence level.

As shown in Table 5, the Moran's *I* indices of three socioeconomic indices, POP, NTL, and LUR, and HQ are negative, indicating negative spatial correlations; the Moran's *I* indices of four landscape pattern indices, PD, CONTAG, SHDI, and ED, and HQ are positive, indicating positive spatial correlations. Comparing the Moran's *I* indices of each year, it can be found that the absolute values of NTL, POP, LUR, and PD are all higher, indicating that the spatial aggregation of NTL, POP, LUR, PD and HQ in the study area is strong. The Moran's *I* indices of NTL, LUR, and PD showed an increasing trend, except POP which showed a decreasing trend. In 2020, LUR and NTL are strongly negative (-0.518, -0.513) impact factors, and PD is a strongly positive (0.320) impact factor.

Table 5. Moran's *I* indices of HQ and impact factors.

Year	ED	CONTAG	SHDI	PD	POP	NTL	LUR
2000	0.246	0.151	0.184	0.302	-0.347	-0.320	-0.300
2010	0.218	0.180	0.127	0.279	-0.366	-0.428	-0.439
2020	0.272	0.277	0.176	0.320	-0.324	-0.513	-0.518

3.2.2. Local autocorrelation

From Fig. 5, it can be obtained that the spatial aggregation effects of different impact factors and HQ are significantly different. The landscape pattern indices mainly showed H-H cluster and L-L cluster, and the socio-economic factors mainly showed H-L outlier and L-H outlier.

Among the landscape pattern factors, the distribution and development trend of PD and ED are similar, the H-H cluster is mainly in the western mountainous area, the H-H cluster is surrounded by the H-L outlier in 2000, the H-H cluster gradually expands and the H-L outlier gradually decreases in 2010, and the H-H cluster has been distributed in a continuous pattern in the western part of Zhengzhou City in 2020. There were also many similarities between CONTAG and SHDI. CONTAG and SHDI were dominated by H-L outlier in 2000, which were scattered in the study area, and H-H cluster appeared in the western and northeastern parts of the study area, and then turned out to be dominated by H-H cluster. H-H cluster of CONTAG developing to the southwest and H-H cluster of SHDI clustering steadily in the west, the H-L and L-H outlier scattered at their edges. The L-L cluster of all four landscape pattern indices are increasing in size with the direction of urban expansion and moving to the southeast.

Among the socio-economic factors, the NTL and LUR aggregation area development is more consistent. In 2000, their L-H outlier was mainly distributed in the central part of the study area to the north, and in 2010, they expanded to the south, and in 2020, they were concentrated in the study area in a south-central direction, and a small number of H-H clusters appeared in the suburban areas at the edge of the city. The H-L outlier was distributed around the L-H outlier in 2000, gradually decreasing in size in 2010, then becoming concentrated in the western and northern parts of the study area in 2020. There is less variation in POP, with the L-H outlier mainly in the

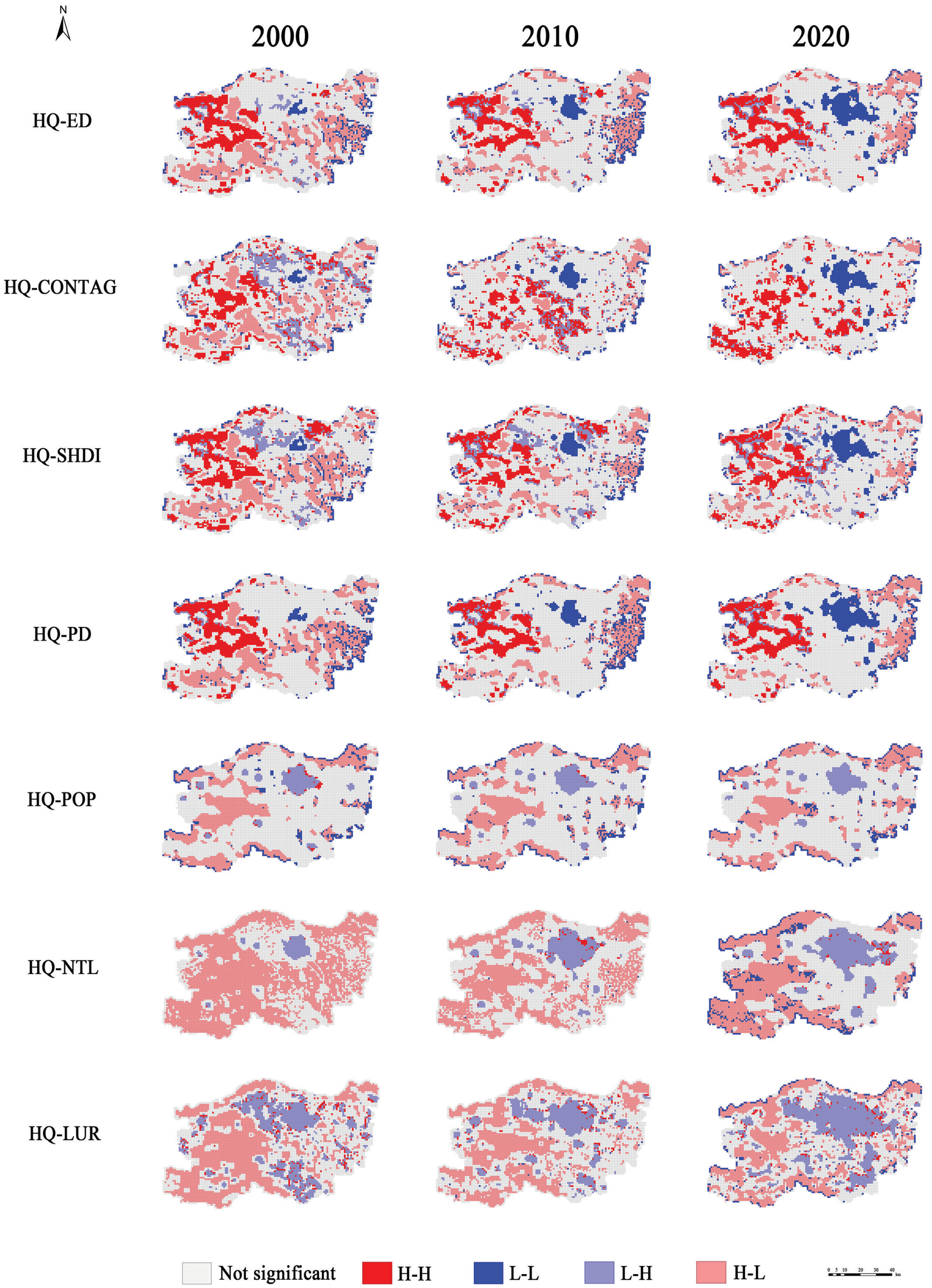

Figure 5. LISA clustering map of HQ with different impact factors.

central part of the study area to the north and the H-L outlier mainly in the western, southwestern and northern parts of the study area, with a significant decrease in the H-H cluster and a small expansion in the other agglomerations over the 20-year period.

The above shows that from 2000 to 2020 the development intensity of the landscape pattern factor, which is positively correlated with HQ, is lower than that of the socioeconomic factor, which is negatively correlated. Besides, the influence of socioeconomic and landscape pattern on HQ has different development direction and magnitude in space and time. The west and the north are the main sites for HQ protection, while the southeast is the key area for urban expansion and intensive development. In the future, metropolitan construction requires zoning plans for the development direction of different areas.

3.3. Driving force analysis of different impact factors

According to the results of the factor detector in the Geodetector, the average deterministic powers (q-value) of the seven driving factors were ranked in descending order: NTL > LUR > PD > POP > ED > SHDI > CONTAG.

In Fig. 6, except for POP, the explanatory power of the other six drivers is increasing over the period 2000–2020. From 2000 to 2010, SHDI and ED are relatively stable, the explanatory power of NTL, LUR, and CONTAG is growing, with increases of 20.49%, 40.78%, and 38.00%, while the determining power of POP and PD is decreasing, with declines of 25.33% and 22.79%. From 2010 to 2020, the influence of all factors except POP has increased, NTL and CONTAG have increased significantly, 45.36% and 69.55% respectively. The average determinant q values of NTL, LUR and PD were above 0.1 as the main drivers. The average decision force q values of POP, ED, and SHDI ranged from 0.05 to 0.1 for the secondary drivers. The mean q-value of CONTAG was below 0.05, with a small explanatory power. This suggests that NTL, LUR and PD have the greatest influence on HQ in the study area during 2000 to 2020.

Overall, the mutual gap between NTL and LUR is narrowing, and the growth trend of landscape pattern indices is similar. During the 20-year period, the determinants of NTL and LUR respectively increased by 0.21 and 0.20, the determinants of the four landscape pattern indices increased by less than 0.05, and the determinants of

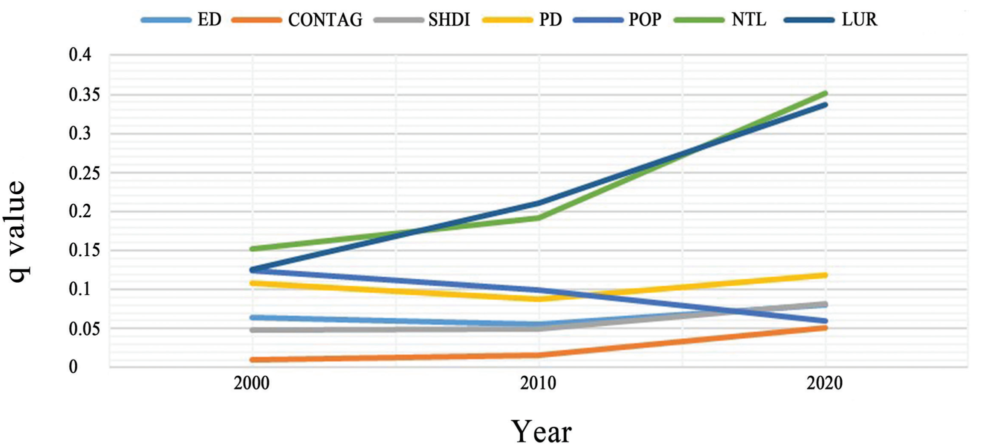

Figure 6. Changes of q-value during 2000–2020.

POP decreased by 0.06. The overall influence of the socio-economic factors was greater than the landscape pattern factors, denoting that the socio-economic factors have a more prominent influence on HQ.

The results of the ecological detector and interaction detector are shown in Table 6. By examining the differences in the effects of the seven drivers on the spatial distribution of HQ through the ecological detector, combined with the results of the factor detector, it can be confirmed that LUR, NTL, and PD have the greatest influence on HQ, and the other factors have a weaker influence. The joint effect between the seven drivers was detected by the interaction detector, and Table 6 shows that all drivers two-by-two showed a non-linearly enhanced or bi-factorially enhanced effect on the HQ distribution, indicating that the joint effect of each two drivers was stronger than the effect of the individual factors. The strongest joint effect is NTL ∩ PD in 2000 (0.2621), in 2010 the strongest is LUR ∩ PD (0.2885), and in 2020 the strongest is NTL ∩ LUR (0.4315). The nonlinear enhancement effect is greater than the two-factor enhancement. In 2000 and 2010, the co-action of the five factors CONTAG, SHDI, LUR, POP, and NTL with other factors is basically nonlinear enhancement, and only the co-action of CONTAG with other factors is nonlinear enhancement in 2020, denoting that although the co-action has been shown to be enhanced, the enhancement effect is weakening.

Table 6. Ecodetector and interaction detector results.

Year		ED	CONTAG	SHDI	PD	POP	LUR	NTL
2000	ED							
	CONTAG	N†						
	SHDI	N	Y†					
	PD	Y	Y†	Y				
	POP	Y†	Y†	Y†	N			
	LUR	Y†	Y†	Y†	N	N		
	NTL	Y†	Y†	Y†	Y†	Y	Y	
2010	ED							
	CONTAG	N†						
	SHDI	N	Y†					
	PD	Y	Y†	Y				
	POP	Y†	Y†	Y†	N			
	LUR	Y†	Y†	Y†	Y	Y		
	NTL	Y†	Y†	Y†	Y	Y	N	
2020	ED							
	CONTAG	N†						
	SHDI	N	Y†					
	PD	Y	Y†	Y				
	POP	N	N	N	N			
	LUR	Y	Y†	Y	Y	Y		
	NTL	Y	Y	Y	Y	Y	N	

† indicates that the interaction of the two factors is nonlinearly enhanced and blank indicates the interaction of the two factors is bilinearly enhanced (Appendix 3)(Wang and Xu 2017). Y means that the influence of the vertical column factor is stronger than the horizontal column factor in the ecological detector and N means that the vertical column factor is weaker than the horizontal column.

In summary, the spatial and temporal distribution of HQ in Zhengzhou City is influenced by a combination of socioeconomic and landscape pattern factors, and the influence of most factors is increasing year by year, but the influence of socioeconomic factors is dominant.

4. Discussion

4.1. Mechanisms influencing changes in HQ distribution

4.1.1.The variation of HQ

HQ in the study area showed a distribution as "high in the northwest and low in the southeast". With the expansion and construction of Zhengzhou metropolitan area, the urban land gradually evolved from point distribution to continuous distribution in patches, and the agricultural land and forest land at the edge of the city were transformed into construction land. The suburban area is also the main area of reduced HQ, as the flat topography of the central to southeastern part of the study area facilitates the laying and upgrading of traffic routes (Wang et al. 2021) which accelerates the fragmentation of the landscape. The western mountainous areas are gradually surrounded by successive towns, the degree of threat to pristine habitats has increased, and fragmentation of marginal habitats has occurred, therefore the HQ has been reduced. HQ at the northern edge of the study area showed an interwoven distribution of enhanced and degraded areas, indicating that the Yellow River basin is highly sensitive, with low ecosystem stability and HQ prone to fluctuating changes. In recent years, Zhengzhou City has focused on ecological protection and has drawn ecological red lines, which have seen an improvement in HQ in natural mountains, woodlands and rivers. In the process of building garden city and sponge city, the ecological environment of river networks and urban green areas has been maintained and improved, the new blue and green patches have been added, and hence patches of improved HQ appear within the main city. This is consistent with related studies showing that rapid urbanization significantly affects the distribution of HQ (Haddad et al. 2015), that topographic and protected area constraints can inhibit the negative effects of human activities (Huang et al. 2020a), and that increasing landscape richness and ecosystem complexity has a facilitative effect on HQ (Bai et al. 2019).

4.1.2. Changes in the correlation between different indicators and HQ

The results showed that the socio-economic factors in the study area had a negative relationship with HQ, and the landscape pattern factors had a positive relationship with HQ. Besides, the deterministic power and spatial aggregation of all influencing factors was increasing year by year, with the strongest explanatory power of NTL, LUR, and PD. The NTL represents the degree of gathering of human activities, and the LUR represents the urbanization ratio per unit area. The higher the NTL and LUR, the more intensive the human activities, the larger the artificial surface area, the more homogeneous the habitat type and the lower the HQ, and vice versa. PD represents the number of patches, the more blue and green patches per unit area indicates the proximity to the natural habitat gathering area, low urban development, high ecological land preservation and good HQ, while the more impervious patches indicate the proximity to the main urban area, high urban development, high ecological land destruction and low HQ, the larger total number of patches the more complex the landscape composition and the higher HQ. CONTAG represents the connectivity of patches, and in the study area CONTAG in combination with either factors showed an effect of increased explanatory power, indicating that blue-green landscape connectivity has an important contribution to HQ.

In a similar study, four landscape pattern indices, including ED and SHDI, also showed significant positive correlations with HQ in the Beijing-Tianjin-Hebei region of China, although the strength of the correlations was weakening year by year (Chang et al. 2021). In Changchun City, the most significant negative correlation was found between POP and HQ (Bai et al. 2019). These denote that the coupling relationship between socioeconomic and HQ, landscape patterns and HQ is complex and variable in different regions. Vega and Küffer (Vega and Küffer 2021) found that for dense urban green infrastructure patches, connectivity is associated with a beneficial effect on species richness, which is an important expression of HQ and ecosystem service value, which, combined with this study, suggests that increasing blue-green landscape connectivity is beneficial in weakening the negative effects of urbanization on ecosystems.

4.2. Policy's driver and suggestions for urban planning

Changes in socioeconomic indicators and landscape pattern indices mainly originate from policy formulation and implementation, and reasonable policy planning can balance regional development and ecological environment protection (Le Roux et al. 2014; Huang et al. 2020b). Ruan et al (Ruan et al. 2016) found that the ecological condition of Chongming Island was improved, and ecosystem services were enhanced under the intervention of ecological conservation policies. Waylen et al (Waylen et al. 2019) found that in Europe the ecological enhancement of agricultural land due to the support of rural development programs (AES) had a positive impact on wildlife on farmland. Françoso et al (Françoso et al. 2015) noted that the establishment of protected areas has been effective in protecting habitats and biodiversity.

The response of HQ to urbanization in the study area also corresponds to the content of policy implementation during the same period. After the approval and implementation of the General Land Use Plan of Zhengzhou City (1997~2010), the government has increased the protection of nature reserves, forest parks, wetland parks and water source protection areas based on the existing Songshan Mountain National Forest Park and Yellow River Wetland, and has improved the level of watershed management based on the Yellow River and Huaihe River water system. It has been vigorously promoting the integration process of counties (cities) and districts such as Zhongmou County, Xingyang City, Shangjie District and Xinzheng City with the central city, and accelerating the development of Zhengdongxinqu (it is an independent economic zone) to the east (Wang et al. 2021). Therefore, from 2000 to 2010, small areas of low HQ were evident in Shangjie District, Xingyang City and Zhongmu County, and the area of high HQ areas increased in northern Zhongmu County. The H-H aggregation area of landscape pattern indices and HQ gradually formed a convergence pattern in the western and northern parts of the study area, and the H-L outlier of socioeconomic indices and HQ increased in size. Later, the General Plan of Zhengzhou City (2010~2020), the Ecological Construction Plan of Zhengzhou National Central City (2016~2025), and the Spatial Plan of Zhengzhou Metropolitan Area (2018~2035) (The People's Government of Zhengzhou Municipality http://www.zhengzhou.gov.cn/) were issued one after another, the goal of regional centralized development in Zhengzhou City is clarified, and the spatial structure of "one core, four axes, three belts and multiple points" is proposed, while the integration of Zhengzhou-Kaifeng, Zhengzhou-Xinzheng, Zhengzhou-Jiaozuo and Zhengzhou-Xuchang is deeply integrated. Therefore, the low HQ areas in the study area from 2010 to 2020 are interconnected into pieces and expanded toward Zhongmou County on the basis of the original ones, and new low HQ blocks have also appeared in Xinzheng City. The high HQ of the northeastern part of the main city in Zhengzhou City has been internalized as large urban green areas, and the increased intensity of development has led to a decrease in HQ. Due to the effective implementation of the ecological protection plan, there has been an improvement in HQ in both the western mountains and the northern water system. The H-H cluster of landscape pattern indices and HQ basically formed a continuous cluster in the northwestern part of the study area, and the H-L outlier of socio-economic indices and HQ showed a clear trend of expansion to the southeast.

Excessive resource exploitation and economic growth will inevitably lead to an ecological crisis, which will in turn lead to the collapse of human society (Daly 1968; Qi and Wang 2016). To ensure the harmonious development of people and nature, from the perspective of urban planning, the adjustment of policies and plans should be based on ecological arguments (Peterson et al. 2005; Fisher et al. 2008). HQ, as an ecosystem service, can influence multiple dimensions of human well-being through its merits and demerits (Hattam et al. 2015). Combined with the analysis results of this study, it is recommended to implement diverse spatial regulation and management to gradually improve the quality of multiple habitats and provide help to enhance the integrated carrying capacity (Kiss and Kiss 2018) and sustainability of ecosystems.

(1) For habitats dominated by natural mountains, woodlands and water bodies, focus on protecting the integrity of the natural landscape and ecological stability, and ecological buffer zones can be installed in bordering areas to reduce ecological sensitivity.

(2) For the main urban areas where the population gathers, the connection and combination of similar patches should be improved. Increasing blue-green space while satisfying socio-economic development, such as the combination of urban greenways

and commercial streets, the connection of medium and large parks, the intensive layout of living space, etc., to avoid the fragmented distribution of landscape patches and gradually improve the quality of urban habitats.

(3) Preserving large blue-green patches at the junction of urban and rural development. Focus on the production red line delineation and ecological protection of farmland, develop field complexes, and flexibly regulate the Sansheng Spaces (production, living and ecological space) in response to changes in landscape patterns and HQ.

(4) Actively play the role of landscape pattern indicators to promote HQ, especially to enhance blue-green landscape diversity and connectivity, and to improve urban habitats with diverse management measures that maintain natural succession combined with human intervention, thereby increasing ecosystem service functions and enriching biodiversity.

4.3. Limitation

Since the choice of research scale affects the development of urban planning schemes (Guo et al. 2012; Yue and Liu 2017), follow-up analyses at multiple grid scales can be conducted by applying high spatial resolution data sources to improve the accuracy of habitat assessment results while investigating in depth the scale effects of the relationship between urbanization and HQ.

5. Conclusions

This paper assesses the change of HQ in Zhengzhou City from 2000 to 2020, analyzes the spatial correlation between HQ and different influencing factors, and compares the magnitude of the explanatory power and the strength of the joint effect of the influencing factors, finally obtaining the following conclusions:

(1) HQ in Zhengzhou City shows a spatial condition of "high in the west and low in the southeast", and the overall HQ shows a decreasing trend from 2000 to 2020. According to the evaluation results of the InVEST model, the average HQ index decreased from .51 to .41, and the low-HQ area increased by 1451.68 km^2, the proportion increased by 19.15%, mainly from the fragmentation and disappearance of agricultural and forest land in peri-urban.

(2) The high value areas of HQ are stably distributed in natural habitats, such as western mountains, southern woodlands, and northern waters. The low value areas are distributed in the main urban area of Zhengzhou City, and have a tendency to spread to the southeast.

(3) The influence of socio-economic and landscape patterns on HQ from 2000 to 2020 has different directions and magnitudes in space and time. The relationship between landscape pattern indices and HQ mainly shows H-H cluster and L-L cluster, the relationship between socio-economic factors and HQ mainly shows H-L outlier

and L-H outlier. Besides, the intensity of the influence of the landscape pattern factors is weaker than those of the socio-economic factors.

(4) Based on the value of the average influence, NTL (0.23), LUR (0.22), and PD (0.11) are the main determinants. The more intensive human activities, the larger the artificial surface area, the more homogeneous the habitat type, and the lower the HQ. The richer the landscape type, the more complex the landscape composition, and the higher the HQ. Analysis of the joint effects of the influencing factors revealed that blue-green landscape connectivity has a strong promoting effect on HQ.

This study provides a clearer picture of the differences in landscape patterns and socioeconomic development on HQ, and denotes that the synergistic construction of construction land and blue-green space driven by policies will contribute to the improvement of HQ, which has important implications for the planning and design of urban regionalization and the sustainable development of ecosystems.

(1) It is recommended that the planning of habitat is not limited to cities, and that a combination of natural maintenance and artificial intervention is implemented depending on the composition of the ecosystem type.

(2) In the ecological protection areas, the original landscape composition should play a role in promoting HQ, and a buffer zone should be established at the junction with the main urban area to reduce the risk of habitat fragmentation.

(3) At the boundary of urban sprawl development, there is a need to plan construction land intensively, enrich landscape diversity, protect large blue-green patches, such as natural habitats, wilderness and so on, enhance the connectivity of high-quality patches, guarantee the ecological stability of farmland, and thus avoid habitat degradation and loss.

(4) In cities with mainly impervious surfaces, blue-green patches with richer species diversity should ensure their integrity, avoid over-artificialization of blue-green spaces, and re-wild the habitats according to the habitat needs of plants and animals to gradually enrich the ecosystem service functions within the city.

Data availability statement

The data presented in this study are available on request from the first author.

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Appendix 1

Table A1. Description of landscape classification in Zhengzhou City.

Code	Classification	Description
10	Cropland	Land used for growing crops, including paddy fields, irrigated dry land, rain-fed dry land, vegetable land, pasture land, greenhouse land, land with fruit trees and other economic trees between mainly planted crops, as well as tea plantations, coffee plantations and other shrubs for cash crops.
20	Forest	Land covered by trees with more than 30% canopy cover, including deciduous broadleaf forest, evergreen broadleaf forest, deciduous coniferous forest, evergreen coniferous forest, mixed forest, and open forest land with a canopy cover of 10–30%.
30	Grassland	Land covered by natural herbaceous vegetation with a cover greater than 10%, including grasslands, meadows, savannas, desert grasslands, and urban artificial grasslands, etc.
50	Wetlands	Land located in the border zone between land and water, with shallow standing water or excessively wet soil, mostly with boggy or wet plants growing. Includes inland bogs, lake bogs, river floodplain wetlands, forest/shrub wetlands, peat bogs, mangroves, salt marshes, etc.
60	Water area	The area covered by liquid water in the land area, including rivers, lakes, reservoirs, ponds, etc.
80	Construction land	The surface formed by artificial construction activities, including towns and other types of residential land, industrial and mining, transportation facilities, etc., excluding continuous green areas and water bodies within the construction site.

Appendix 2

Table A2. Calculation formula of impact factors.

<table>
<tr><th>Abbreviation</th><th>Metrics</th><th>Calculation formula</th><th>Notes</th></tr>
<tr><td>ED</td><td>Edge density</td><td>$ED = \frac{E}{A}$</td><td rowspan="4">E is the total edge length of the patches within the landscape; A is the total area of the landscape. P_i is the percentage of area occupied by type i patches; g_{ik} is the number of type i patches and type k patches adjacent to each other; m is the total number of landscape patch types. NP is the number of patches.</td></tr>
<tr><td>CONTAG</td><td>Contagion index</td><td>$CONTAG = \left[1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right]\left[\ln(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right]}{2\ln(m)} \right]$</td></tr>
<tr><td>SHDI</td><td>Shannon's diversity index</td><td>$SHDI = -\sum_{i=1}^{m} (P_j)(\log_2 P_j)$</td></tr>
<tr><td>PD</td><td>Patch density</td><td>$PD = \frac{NP}{A}$</td></tr>
<tr><td>POP</td><td>Population density</td><td>$POP = \frac{r}{S}$</td><td>r is the population size; S is the area.</td></tr>
<tr><td>LUR</td><td>Land urbanization rate</td><td>$LUR = \frac{ul + il + tl}{ul + il + tl + rl}$</td><td>ul is the scale of urban land use; il is the scale of industrial and mining land use; tl is the scale of transportation land use; rl is the scale of rural settlement land use.</td></tr>
</table>

Appendix 3

Table A3. The interactive types of two factors and the description.

Interactive Types	Description
$q(x_1 \cap x_2) > q(x_1) + q(x_2)$	Nonlinearly enhanced
$q(x_1 \cap x_2) = q(x_1) + q(x_2)$	Independent
$q(x_1 \cap x_2) > Max(q(x_1), q(x_2))$	Bilinearly enhanced
$Min(q(x_1), q(x_2)) < q(x_1 \cap x_2) < Max(q(x_1), q(x_2))$	Unique nonlinearly weakened
$q(x_1 \cap x_2) < Min(q(x_1), q(x_2))$	Nonlinearly weakened

Supplementary material 1

Notes on the data

Authors: Mengqi Zhao

Data type: pdf. file

Explanation note: This file contains link to download the datas used in the paper and the description of the datas.

Link: https://doi.org/10.3897/natureconservation.48.85179.suppl1