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Original Research

Identifying the Drivers of Habitat Quality in Beizhen with Consider Arable Land Protection Based on the PLUS-InVEST Model

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Abstract

Rapid economic development and implementation of environmental policies have greatly changed land-use/ land-cover (LULC) at different periods, and effective evaluation of spatiotemporal progression about habitat quality (HQ) influenced by LULC changes at a finer spatial scale is meaningful for sustainable development. This study coupled the PLUS and InVEST models to analyze the influence of various factors on LULC, and then obtain the influence of these changes on HQ from 2000 to 2020. Based on this analysis, that scenario has been simulated for 2040: the arable land protection scenario (APS) and the natural increase scenario (NIS). The results showed that: (1) LULC between 2000-2020 was dominated by arable and garden land. (2) HQ improved steadily, particularly between 2011-2020. The main natural factors influencing HQ were elevation and distance to water, whereas the important anthropogenic factors were GDP and distance to secondary roads. (3) The simulated HQ indices of APS and NIS in 2040 were 0.501 and 0.525; the largest differences were in forestland and dryland. The urban expansion area in the APS was 1.62 km^2 less than NIS. These results indicate the need for government to adopt reasonable approaches to managing areas of different HQ.

Keywords: InVEST model, PLUS model, habitat quality, influencing factors, arable land protection

Introduction

Land-use/land-cover (LULC) has changed substantially at a global scale as a result of a rapid growth in productivity and economic activities [1, 2], thereby posing a risk to terrestrial ecosystem services (ES) about structures, processes, and functions of ecosystems [3, 4]. Findings show that from 2000 to 2015, China's ESI levels underwent a continuous downward trend. Furthermore, the relationship between ESI and LULC change showed obvious spatial dependence and heterogeneity, which had statistically significant negative associations [5, 6]. Moreover, some changes to LULC have been triggered by common natural and intensive anthropogenic activities [6, 7]. Past studies have identified anthropogenic activities as core drivers of dynamic changes in the trade-offs and synergies of ecosystem services [8]. Urbanization, agricultural expansion, and the establishment of policies, such as

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the establishment of nature reserves, have intensified the rate and pattern of land use change [9]. Some inappropriate actions have triggered the introduction of exotic species or even the loss of species, which in turn have had negative impacts on the quality of human life [10, 11].

Planning for conservation can be facilitated by the use of alternative environmental indicators to forecast the relationship between anthropogenic influences and ES [12, 13]. Some previous studies have shown that the InVEST model is an ideal tool for supporting landscape management and conservation planning worldwide, which mainly includes water yield,carbon storage, soil conservation, habitat quality and so on to quantify ES [14, 15]. Among them, HQ is a desirable indicator of the potential to maintain biodiversity in an area [16-18]. Habitat quality (HQ) refers to the ability of an ecosystem to provide basic survival conditions for resident wildlife or an entire population of species [9, 17]. HQ represents ecosystem service functions and ecological security [18].

Evaluation models widely used in previous studies include the SoLVES, SDM, and InVEST-HQ models. In comparison, the advantage of this model is the most mature ability to rapidly evaluate the potential influences of changes in LULC on biodiversity [19]. Therefore, the InVEST-HQ model is frequently used to assess the health of ecosystems [20, 21]. Remote sensing images allow large-scale study of the spatial and temporal changes in LULC [22, 23]. Improvements in remote-sensing-based tools have greatly increased the practicality of model assessment methods [24]. For example, Gong integrated the InVEST-HQ, landscape pattern index, and NPP to examine spatial and temporal fluctuations in plant biodiversity at the raster scale [25]. Bai examined the spatiotemporal evolutionary features of habitats in Changchun and their drivers, and further investigated the impact of urbanization on HQ [26]. Wang applied the FLUS and InVEST models to six future LULC scenarios to analyze staple food production, sustainable stocking, and HQ, following which an integrated trade-off method was applied to measure overall development quality [27]. However, few studies have explored HQ across both temporal and spatial scales, the drivers of change to each land type, and their relative impacts.

Understanding potential future changes to LULC is essential for anticipating impacts on HQ [28]. Modelling tools that can help predict future changes to LULC include the Cellular Automata (CA)-Markov model [29], the Conversion of Land Use and its Effects (CLUE)-S model [28], the Future Land Use Simulation (FLUS) model [30], and the Patch-generating Land Use Simulation (PLUS) model [31]. Liu compared the simulations of these models to land use data from 2000 to 2010 and found that the FLUS model performed better than the CLUE-S and CA models [32]. The application of the FLUS model to four development scenarios for 2050 showed that the model can effectively simulate future LUCC. The PLUS model was developed by adapting the FLUS model [31, 33] to describe the forces regulating the dynamics of each land type conversion and their relative strengths [33-35]. The PLUS model also has the most sound scientific foundation among the traditional tools [31].

The city of Beizhen (BZ) was chosen as the study area for this study which experienced a general shift in the environment from rapid growth to high-quality growth. This transformation in BZ has involved three major stages (1) primary industry acting as the main economy; (2) the transition period during which there was equal emphasis among primary, secondary, and tertiary industry; (3) the continuous development of the primary and tertiary industries by 2020. Clear features of transformation in the economic structure are evident in BZ, which has rich mineral and farmland resources.

The present study aimed to explore the effects of various factors' intensity on LULC change and then obtains the influence of LULC change on habitat quality in BZ from 2000 to 2020, making use of PLUS and InVEST models with the geographical information system (GIS). Moreover, HQ in 2040 was simulated under different scenarios. The present study had the following objectives: (1) characterize changes to land use from 2000 to 2020 and explore the weights of each factor driver of land use change; (2) reveal the spatial and temporal characteristics of HQ over 20 years; (3) simulate HQ in 2040 under a natural increase scenario (NIS) and an arable land protection scenario (APS).

Study Area and Methods

Study Site

The study area includes 14 townships and 5 streets and has a length of 53.9 km from north to south and a width of 53.1 km from east to west, covering an area of 1.69×10^3 km^2. The study area has a diverse physiographic unit, with almost equal areas of mountains, plains, and depressions. The study region falls within a temperate semi-humid continental monsoon climate with simultaneous rain and heat, characterized by short, rainy summers and long, poor winters. The study area also contains the Lv Mountain national reserve and the Xin Li Lake Wetland national wetland park. The nine major rivers in the study area with a total length of 306 km fall within the Liao River Basin, which is part of the Yangtze River system. These rivers provide good ecological background conditions. The population of the study area has been declining since 2000, with 422,000 people living in the city by the end of 2020 and the regional GDP has reached 10.85 billion yuan.

Data Preparation

The present study utilized six methods of collecting data:

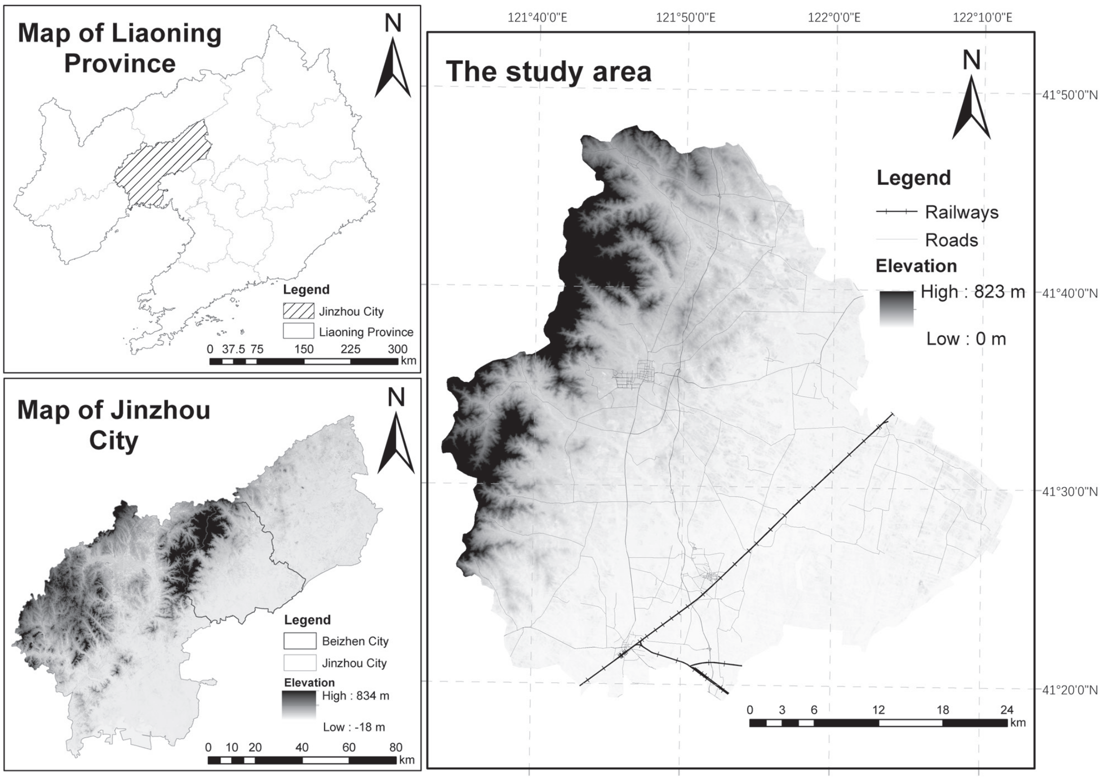

Fig. 1. Location and topography of the study area.

(1) Remote sensing image data (Table 1) and digital elevation model (DEM) data were obtained from the China Geospatial Data Cloud Platform (http://www.gscloud.cn). Elevation and slope images were taken from the 30-m resolution DEM data. The present study selected remote sensing images from September to October to avoid the effects of clouds.

(2) The traffic database used in the present study were obtained from the Open Street Map (OSM) platform (http://www.openstreetmap.org). Railroads, highways, primary roads, secondary roads, and tertiary roads were selected as risk factors within the InVEST model.

(3) GDP and population (POP) data were obtained from the Global Change Research Data Publish & Repository platform (http://www.geodoi.ac.cn/WebCn/Default.aspx).

(4) Annual average temperature and precipitation data were obtained from the WorldClim platform (https://www.worldclim.org/).

(5) Soil class data were obtained from the Resource and Environment Science and Data Center, Chinese Academy of Sciences (RESDC) (https://www.resdc.cn/Default.aspx).

(6) Information for farmland and statistical yearbook data for the research area were obtained from the Department of Natural Resources in Liaoning Province.

The present study used ENVI5.3 and ArcGIS10.6 software to process and analyze vector and raster data. The PLUS model was then used to simulate future HQ within BZ, and HQ was observed and compared at various periods using InVEST-HQ.

Statistical Analyses

Supervised Classification of the Random Forest Algorithm

The Random Forest (RF) classifier algorithm is flexible and easy-to-use, with a selection tree as a primary unit. The RF classifier makes use of more than one trunk to instruct and predict samples. The RF is increasingly used for supervised classification and interpretation of remote sensing images. The multi-feature RF does not overfit, is less sensitive to outliers and noise, is less computationally intensive, and achieves higher classification accuracy compared with traditional supervised classification methods, such as the maximum likelihood analysis algorithm and K-nearest neighbor method [27]. The present study used the ENVI remote sensing image processing software for RF classification. Samples were selected based on land-use categories, and the number of trees was set to 200. Square Root was selected as the number of features, the Gini Coefficient was selected as the impulse function, and other settings were set to default values. Eight and 14 major categories and sub categories of land use were integrated in the present study (Table 2).

Table 1. A summary of Landsat data used within the present study.

Year	Satellite	Sensors	Acquisition time	Line/Column number
2000	Landsat 5	TM	2000-09-08	120/31
2011	Landsat 5	TM	2011-09-23	120/31
2020	Landsat 8	OLI	2020-10-17	120/31

Table 2. Land-use typology system of Beizhen City.

Primary land use types	Secondary land use types	Primary land use types	Secondary land use types
Cultivated land	Paddy field	Residential land	Urban area
	Watered land		Rural settlement
	Dryland		Other construction
Forest land	Forest land	Wetland	River
	Shrub land		Lake
Garden land	Orchard	Industrial and mining land	Industrial and mining land
Grassland	Grassland	Idle land	Bare land

Simulation of Habitat Quality by the InVEST Model

The HQ was obtained based on the InVEST model, which considers the intensities of threats as well as habitat sensitivity to produce a habitat degradation layer and a HQ layer. The habitat threat level D_{xj} in the raster cells in the land use type is calculated as:

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

where D_{xj} shows a level of habitat degradation, denoting the depth of habitat degradation of LULC category j in lattice x; ω_r is the strength of each risk element; r_y is the thickness of the risk factors; $ß_x$ shows the tolerance of the habitat to interference; S_{jr} is the sensitivity of sites to each risk item; r and y denote the target threat factor and the lattice size in r.

The habitat quality (Q_{xj}) was obtained by:

$$Q_{Xj} = H_j \left[1 - \left(\frac{D_{xj}^2}{D_{xj}^2 + K^2}\right)\right] \tag{2}$$

where Q_{xj} shows the level of HQ in grid x in LULC category j; H_j is the habitat suitability of grid x in LULC type j, and K shows the semi-saturation constant.

The index in the habitat degradation layer lies between 0–1, with the value proportional to the degree of habitat degradation. The HQ is also in the range of 0 to 1 and is proportional to habitat suitability. The sources of threats identified in the present study included paddy field, dryland, watered land, industrial and mining land, urban areas, rural settlements and traffic data (Table 3).

Table 3. Attributes of threats to habitat quality.

Threat factor	Maximum distance /km	Weight	Spatial decay type
Paddy field	0.3	0.2	Linear
Dryland/ Watered land	0.5	0.5	Linear
Industrial and mining land	2.4	1.0	Exponential
Urban area	2.0	1.0	Exponential
Rural settlement	1.0	0.8	Exponential
Primary road	1.5	1.0	Linear
Secondary road	1.0	0.7	Linear
Tertiary road	0.5	0.4	Linear
Railroad	0.8	0.7	Exponential
Highway	0.5	0.5	Exponential

Table 4. The habitat suitability and sensitivity of land-use type to each threat factor.

Land-use type	Habitat suitability	Threat factor									
		Paddy field	Dryland/ Watered land	Industrial and mining land	Urban area	Rural settlement	Primary road	Secondary road	Tertiary road	Railroad	Highway
Paddy field	0.5	0.0	0.3	0.5	0.5	0.5	0.25	0.15	0.1	0.35	0.35
Watered land	0.3	0.2	0.0	0.5	0.5	0.5	0.25	0.15	0.1	0.35	0.35
Dryland	0.3	0.2	0.0	0.5	0.5	0.5	0.25	0.15	0.1	0.35	0.35
Forest land	1.0	0.6	0.8	0.7	0.7	0.7	0.5	0.4	0.3	0.55	0.55
Shrub land	1.0	0.8	0.8	0.7	0.7	0.7	0.5	0.4	0.3	0.55	0.55
Orchard	0.7	0.3	0.3	0.5	0.5	0.5	0.3	0.2	0.1	0.35	0.35
Bare land	0.4	0.0	0.0	0.3	0.5	0.5	0.1	0.0	0.0	0.10	0.10
Grassland	1.0	0.3	0.3	0.4	0.5	0.5	0.3	0.2	0.1	0.35	0.25
Lake	0.9	0.7	0.6	0.9	0.9	0.9	0.7	0.6	0.5	0.65	0.65
River	1.0	0.7	0.5	0.9	0.9	0.9	0.7	0.6	0.5	0.65	0.65
Industrial and mining land	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Urban area	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Rural settlement	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other construction	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Road data were extracted according to the road classification system of mainland China, and different weights were assigned to railroads, highways, primary roads, secondary roads, and tertiary roads according to threat. The weights assigned to HQ for each threat in the parameter settings ranged from 1 (maximum threat) to 0 (no threat). The settings of key factors (Table 4), such as maximum effective range habitat suitability, habitat susceptibility to stressful actors, and half-saturation constants were assigned with full reference to the software operation manual and examples in combination with local basic conditions, and referred to relevant studies combining similar study areas such as Tang [1, 17] and He [36]. The spatial decay type describing the decay of threat over distance was chosen as a linear or exponential type:

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\,max}}\right) if\ linear \tag{3}$$

$$i_{rxy} = exp\left[-\left(\frac{2.99}{d_{r\,max}}\right) d_{xy}\right] if\ exponential \tag{4}$$

where d_{xy} denotes the existence as a linear range of grid cells x & y and $d_{r\ max}$ is the largest feature range under which t threat r propagates in space.

The present study used secondary land-use types for a more accurate and detailed estimation of the interaction between land-use types and HQ (Table 2).

Simulation of Land-Use by the PLUS Model

Further development of the FLUS model resulted in the Patch Generated Land Use Simulation (PLUS) model, which combines the CA model based on various random patch seeds with a land broadening strategy for analysis [33]. Liang [31] concluded that the PLUS model generated landscape pattern metrics that were closer to the actual landscape than that produced by CA. Furthermore, combining the PLUS model with the Land Expansion Analysis Strategy (LEAS) allows a more rigorous evaluation of the drivers of land use change than prior lookups.

The present study selected basic LULC figures from 2000 to 2020 for the analysis of LULC scenarios in 2040. Also, 14 natural and socio-economic drivers were considered in the analysis, covering POP (2011), GDP (2011), soil type, DEM, slope, year temperature, year rainfall, and proximity to towns, railroads, roads, primary roads, secondary roads, tertiary roads, and open water. There are many uncertainties associated with future environmental changes in BZ. Therefore, the present study explored the significance of cropland conservation policies on future land-use variations and HQ by simulating land use changes in 2040 under two scenarios, namely the natural increase scenario (NIS) and arable land protection scenario (APS).

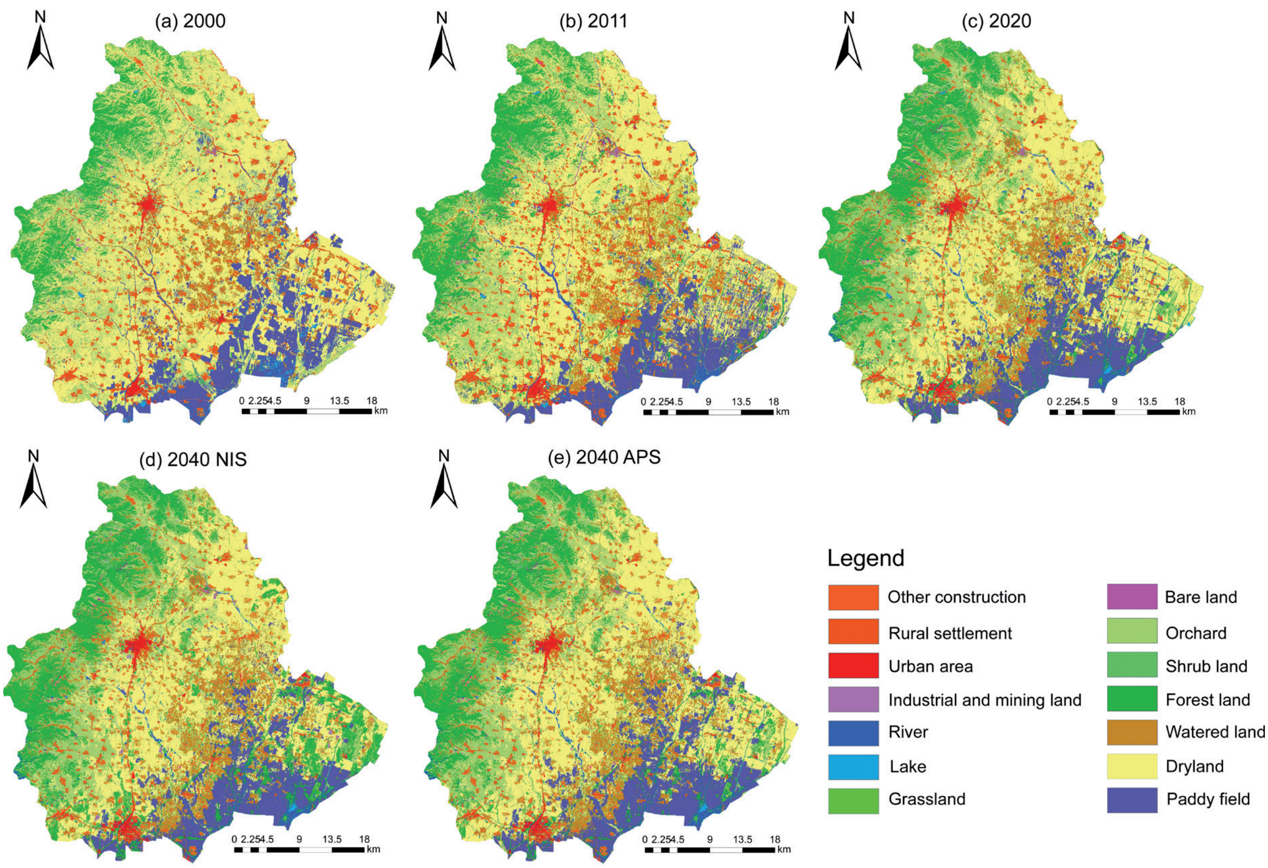

Fig. 2. Land use/land cover (LULC) status of Beizhen between 2000-2040.

Results

Analysis of Land-Use Evolution

Land-Use Trends during 2000 to 2020

The study area experienced a typical period of development from 2000 to 2020, incorporating a phase of economic change transitioning from a significant rise to slow development. The main land-use type in BZ in 2000 was arable land, followed by garden land and forest land, accounting for 67.1%, 11.3%, and 10.7%, respectively. While there was a significant change in LULC by 2020, the main land-uses remained cropland, garden land, and forest land. Although arable land retained its dominance in the study area, it decreased to 56.3%, with an area of 954.03 km^2, whereas garden land and forest land increased to 18.984% and 15.116%, respectively.

Fig. 2 shows the distribution of LULC in the study area, showing the wide-ranging change in LULC from 2000 to 2020, which can be attributed to the influences of anthropogenic activities, with the most obvious driver being the change in the area of arable land. The present study was divided into two phases to facilitate a comparative analysis: (1) 2000 to 2011 and; (2) 2011 to 2020. The proportion of arable land area peaked in 2000, after which it decreased to 54.952 km^2 in 2011. There was a more dramatic reduction in arable land in the second phase, decreasing by 126.582 km^2. The reduction in arable land was mainly due to conversion to garden land and forest land, particularly at higher altitude areas, and there was also a significant increase in forest cover near roads and rivers. Secondly, there were wide-ranging changes to the areas of garden land and forest land. The area of garden land decreased slightly during the first phase but increased dramatically in the second phase. The area of forest land increased steadily by 3.039% and 1.339% in the first and second phases, respectively, collectively adding an area of 74.242 km^2.

There were slight increases in the areas of other land-use types, like grassland and idle land, which increased by 0.165% and 0.341% respectively. There were rapid increases in the areas of industrial and mining land by 0.365%, equating to an area of 6.174 km^2. The areas of built-up land and wetlands first increased and then decreased, but overall showed a slight reduction in area by 1.649% and 0.173%, respectively.

Analysis of Critical Regional Drivers

The present study used the simulations of the PLUS model to generate a table of the drivers of each land use type conversion and their intensity. Among them, there presents the results of the importance analysis of fourteen drivers for drylands, urban lands, and forests for the period from 2000 to 2020 in Fig. 3, considering the area proportion and influence status of each type. As shown in Fig. 3: (1) distance from the city center was an important factor within the influence of cities on land use. The large area of arable land near BZ along with the proximity of the western side of the city to the Lv Mountain national reserve limit future urban expansion. Primary roads and highways also play a crucial role in the growth of urban areas. (2) Arable land comprises a large proportion of the study area, of which the area of dryland is the largest. As shown in Fig. 3, elevation was the most important factor influencing dryland, with dryland mainly distributed at an elevation of 4 to 130 m in the central and eastern parts of the study area. Another factor influencing dryland is water sources. By the way, railroads and primary highways were more likely to be built around arable land, reducing the impact on the residential environment. (3) The vegetation of BZ experienced recovery during the study period. The main factor influencing this recovery was elevation, with the area of vegetation growing rapidly in the mountainous area in conjunction with the enforcement of the policy of restoring farmland to forests. Moreover, the areas along the railroad and near open water sources experienced increases in vegetation cover.

Land Use Simulation for 2040 in Two Scenarios

The present study provided a description of LULC in 2040 by using PLUS to profile the spatial allocation of future LULC under two scenarios. The results showed a dramatic change in LULC by 2040 compared to that in 2020.

Both scenarios showed similar trends in changes in different land-use types. There were decreasing trends in the areas of rural settlement land, dry land, and garden land. As shown in Fig. 4, among these changes, rural settlement land mainly shifted to urban land, dryland, irrigated land, and forest land; dryland mainly shifted to forest land and irrigated land; garden land mainly shifted to forest land and irrigated land; and there were small declines in the areas of other land-use types, such as waterbodies, grassland, and bare land. The land-use type experiencing the largest growth under both scenarios was forest land, followed by irrigated land.

As shown in Fig. 4c), the largest differences between the two scenarios were for forest land and dryland. There were increases and decreases in the areas of forest land and dryland of 4.78% and 3.38% compared to 2020 under the natural increase scenario, respectively, whereas those under the cropland protection scenario increased and decreased by 1.34% and 0.38%, respectively. The area of urban expansion under the natural growth scenario also exceeded that under the cropland protection scenario by 1.62 km^2.

Habitat Quality Evaluation

The habitat quality depicts the state and evolution of habitats over time in a study region and is proportional to habitat environmental quality. The present study

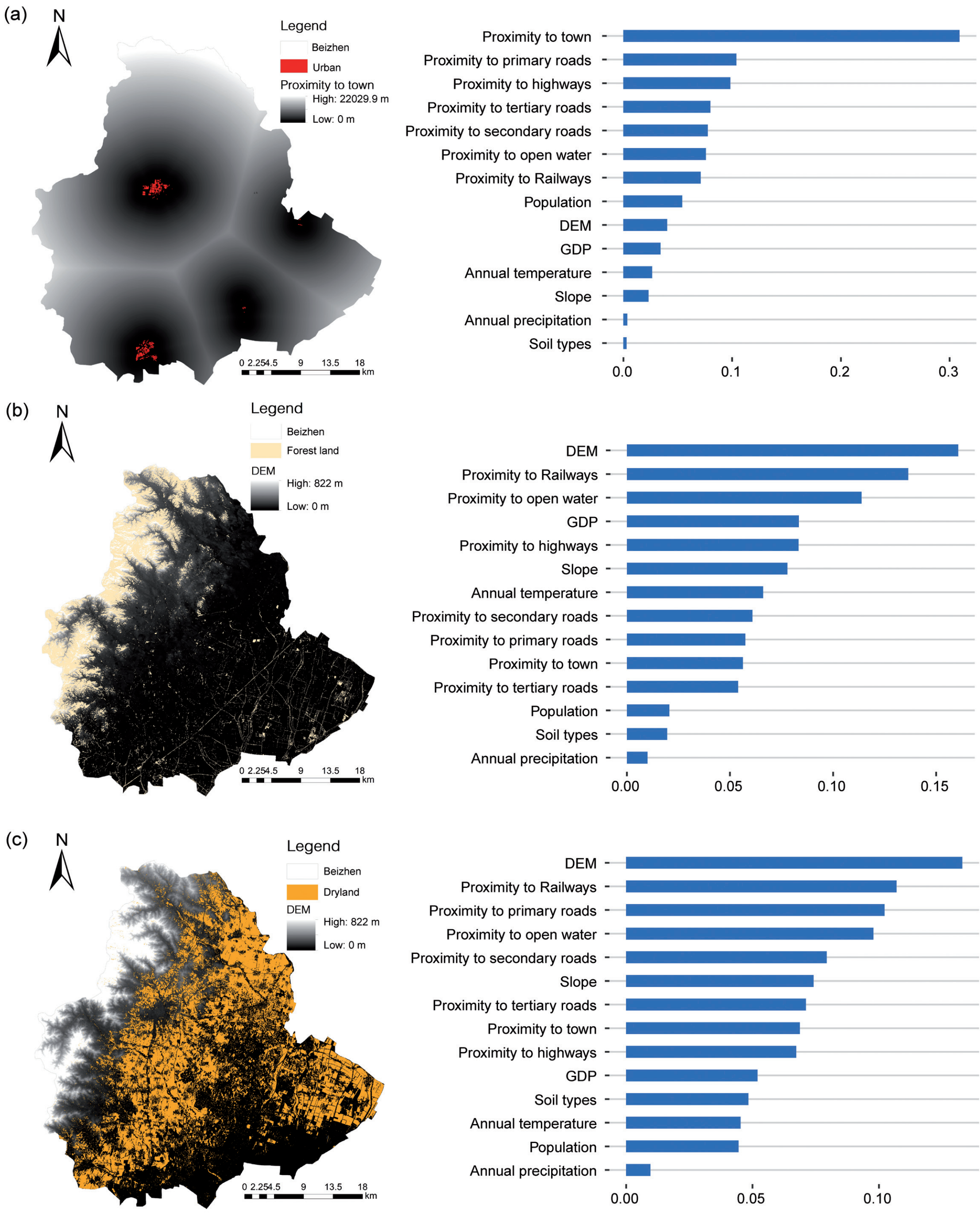

Fig. 3. The relative value of each variable to the response of the three land-use patterns.

refers to the relevant literature [1,7] to divide the HQ into five classes: (1) 0 equating to a low HQ area; (2) 0-0.3 equating to a relatively low HQ area; (3) 0.3-0.5 representing the medium HQ area; (4) 0.5-0.7 representing a relatively high HQ area, and; (5) 0.7-1 equating to a high HQ area. The InVEST simulations showed a steady overall trend of increasing HQ. The mean HQ values were 0.434, 0.445, and 0.496 in 2000, 2011, and 2020, respectively, with a clear greater increase between 2011 and 2020.

As shown in Fig. 5 below, there were steady increases in HQ in the western hills, whereas areas of poor HQ in the southeastern hilly area gradually transitioned to high and medium HQ areas. The results indicated a possible correlation between the geographical distribution of HQ and landscape features. From HQ grading statistics, the proportion of areas with medium HQ changed slightly from 2000 to 2020. In contrast, low and relatively low HQ areas gradually decrease, while high and relatively high HQ areas increase significantly. In general, there was a trend of increasing HQ in the study area.

Additionally, the PLUS digitally driven strengths identified the top-ranked HQ influences as DEM, distance to open water, GDP, distance to a second road,

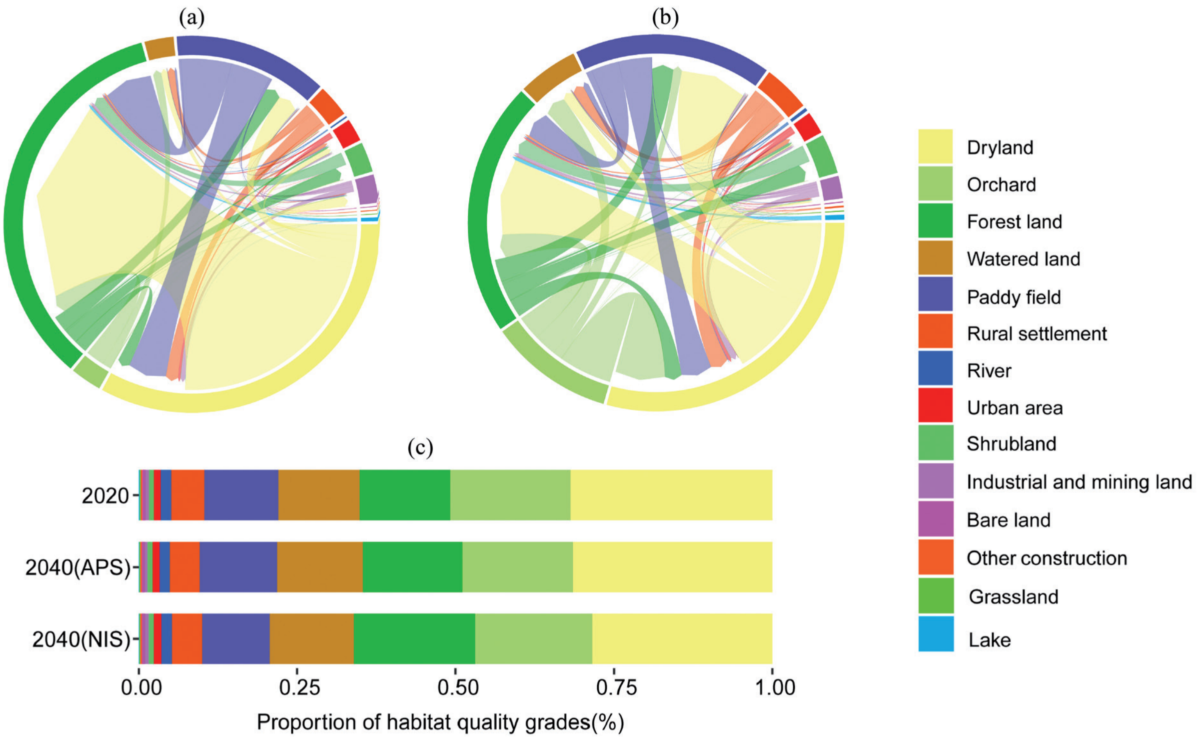

Fig. 4. The land use transfer map from 2020 to 2040 under the a) natural increase scenario b) arable land protection scenario; c) the proportions of the area occupied in different LULC

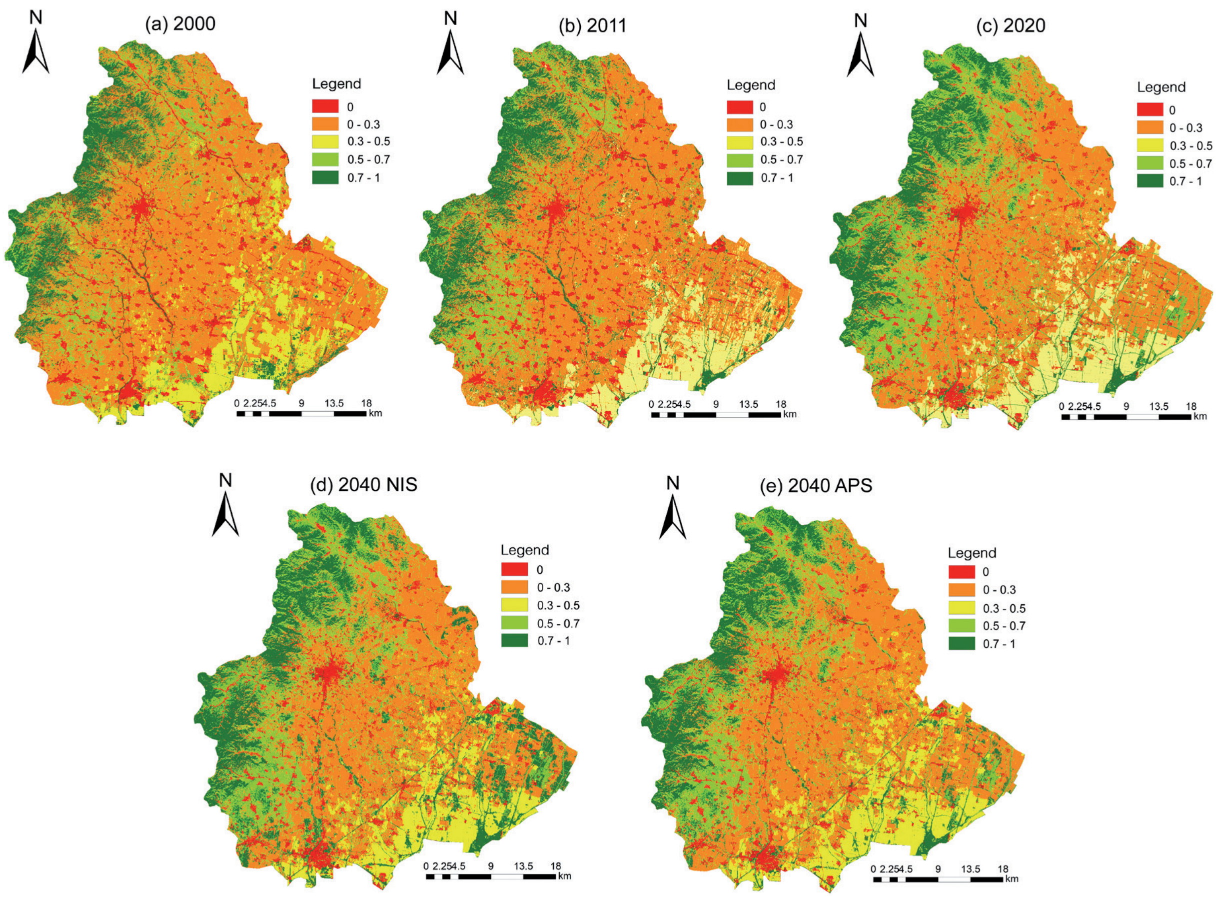

Fig.5. The proportions of area occupied by different categories of land use/land cover (LULC) in 2020 and 2040 as estimated by the Patch-generating Land Use Simulation (PLUS) model.

and distance to town. The factors can be summarized as natural factors including DEM and distance to open water source, social factors GDP, and distance to second highway. Furthermore, the influence degree of natural factors is greater than that of social factors in BZ.

The simulations for 2040 showed more intensive land use with a threshold in HQ change exceeded. The average HQ under the NIS and APS were 0.525 and 0.501, respectively. Forest land is characterized by an integrated ecosystem with high HQ. The increases and decreases in arboreal forest land and dryland, respectively under the natural growth model resulted in significantly higher HQ than that under the arable land conservation scenario.

Discussion

Spatiotemporal Variation in HQ

The main upward trend in HQ in BZ since 2000 to 2020, with steady rises in the areas of relatively high and high HQ, is different to trends observed in other study areas in China [5]. This result can mainly be attributed to the implementation of the policy of returning farmland to forests and wetlands in over-cultivated areas of the mountains and also to a growing service industry under which patterns of income of the local population are sufficiently diversified to reduce the destruction of habitats. The results of the present study are consistent with those of Mengist et al. [9].

Identification of areas with HQ can assist in the establishment and adjustment of relevant conservation strategies. Habitat conservation during the study period was concentrated in peri-urban and industrial and mining sites, consistent with the findings of Sun et al. [37] and Li et al. [38]. In particular, there was a rapid increase in the area of the city in 2011 along with drastic development of the industrial and mining industries. These land use types occupied a large area of arable land, which resulted in the destruction of biological habitats and contributed to a low HQ. The government can assist in preventing habitat deterioration and in achieving sustainable development by strengthening risk monitoring and assessment in these areas.

Factors Influencing Habitat Quality

Most countries globally are facing the challenge of environmental threats as the bio-physical nature of the environment changes [39]. This study combines the PLUS and InVEST models to quantitatively analyze HQ in BZ. Fourteen drivers that may influence land use change were considered in conjunction with the actual situation and by referring to other papers [40-42], which can be classified overall as natural and human drivers. Consistent with the findings of Zhang [18], the most clearly characterized natural factors were DEM and water sources. There is a positive correlation between vegetation cover and elevation, while dryland area and anthropogenic activity are inversely related. Around open water sources in the study area, the original vegetation was retained or trees were planted to reduce water pollution and consolidate the soil. Wilderness reserves have been established along bird migration routes, thus providing high-quality biological habitats. Irrigated land has been placed close to water sources, which poses a threat to open water sources. The most influential anthropogenic factors are GDP and distance from secondary roads, in contrast to the drivers (population) derived from the Weihe River Basin survey by Wu et al. [42] and Zhang [7]. Higher areas of GDP in BZ are associated with the intensity of human activity and natural resource exploitation, which is inversely related to HQ. Secondary road construction on HQ is the finding of this study, which linking administrative and commercial points or large industrial areas promotes a greater impact of built-up land, industrial areas, and irrigated land on LULC changes with a greater impact on HQ along the route in BZ.

Policy Implications for Habitat Quality

The ecological development of the western mountainous and southeastern hilly areas of the study area is particularly evident under policy interventions. This development is mainly reflected in: (1) A more reasonable land use structure in the western mountainous areas. There has been a decrease in the area of arable land near rural residences, whereas the areas of forest land, shrub woodland, and garden land have increased. The development of special tourism has been actively promoted, and the challenges of indiscriminate logging and excessive reclamation have been effectively curbed while the efficiency of economic production has been improved. (2) Migratory birds are passing through the Xinli Lake wetland in the southeastern part of the study area. This can be attributed to the implementation of a series of measures, such as returning farmland to wetlands, returning wasteland to wetlands, and restoring wetland plant diversity.

There has been the construction of high-quality farmland, implementation of modern agriculture, and improvements to the capacity of agricultural production in the study area to strengthen the restructuring of the agricultural industry. The government actively cooperates with the national policy of "three regions (urban space, agricultural space, and ecological space) and three lines (urban development boundary, permanent basic agricultural land, and ecological protection red line)" to reasonably plan the delineation of the area. This policy will lead to a reduction in habitat fragmentation and an improvement in HQ. The survey conducted in the present study has provided a scientific reference for future development by establishing two scenarios, the arable land protection scenario and the natural development scenario.

Limitations and Outlook

Analyzing the coordination of the interaction between various elements and habitat quality on a finer spatial scale can allow a more in-depth consideration of the relationship between arable land protection and habitat quality. The coupled PLUS and Invest analysis model used in the study tends to be highly operational, with a low limit on the scale of the study area, and easy to combine with other methods for integrated assessment. There also had some limitations. On the one hand, the present study showed a greater consideration of changes in land-use types such as vegetation, water bodies, build-up land, and cropland for calculations of HQ, whereas less attention was paid to biological information, such as animal and plant distributions. On the other hand, the inherent disadvantage of the PLUS model is that the provided HQ data fall between 0 and 1 and can only be used for relative analysis within a region. The present study obtained some parameter settings, such as threat factors, by combining local conditions and references to previous studies, which is an approach that is both flexible and subjective.

Conclusions

The present study simulated the spatiotemporal transition of HQ under LULC change in Beizhen during 2000 to 2020 by combining ArcGIS and InVEST software. The present study further discussed the drivers of land use conversion and their intensities by utilizing PLUS to generate the spatial allocation of land-use in 2040. The conclusions can be summarised as follows.

(1) HQ in 2000, 2011, and 2020 were 0.434, 0.445, and 0.496, respectively. The widespread change in LULC of BZ can be attributed to the influence of human activities, among which the most obvious factor is the transformation of dryland. In particular, through the implementation of plantations and increased garden areas in suitable places during 2011-2020, the vegetation cover in BZ has increased clearly, which indicates the effectiveness of the established nature reserves and the eco-red lines in habitat protection. The main natural factors influencing HQ were elevation and distance to water, whereas the main anthropogenic factors were GDP and distance to secondary roads.

(2) Considering the apparent change in dryland area in BZ and the significant impact on HQ, the study set up two scenarios for analysis. The HQ under the arable land protection and the natural increase scenarios were 0.501 and 0.525 in 2040, respectively, which show the same overall trends in LULC change. The increase in forest land and the decrease in dryland resulted in a significantly higher HQ in the NIS than in the APS. The APS achieved the food security conservation goal to a greater extent. Moreover, the APS had an impact on urban expansion, with the area of urban expansion of 1.62 km^2 less than that under the natural growth scenario. These results emphasize the need for future sustainable development through the implementation of a high-standard farmland policy to improve the quality of arable land and conditions of agricultural production.

Overall, the designation of conservation red lines based on original ecological zones is necessary to reduce indiscriminate deforestation. The Government will continue to explore pathways in the future to achieve planning and protection of core ecological function areas and promote quality development in all regions.

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Conflict of Interest

The authors declare there are no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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