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Optimization of Land Use Patterns in a Typical Coal Resource-Based City Based on the Ecosystem Service Relationships of 'Food–Carbon–Recreation'

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Abstract: Imbalanced supplies and demands of ecosystem services (ESSD) can negatively affect human well-being. Optimizing land use patterns in cities and regions is, in fact, essential to mitigate this challenge and ensure sustainable development. In this context, the present study aims to analyze the supply and demand of food production services (FPs), carbon sequestration services (CSs), and recreation services (RSs) in a typical coal resource-based city (Huainan) in China. In addition, the main influencing factors and their driving mechanisms were further explored using the geographical detector (Geo-Detector) and multi-scale geographic weighted regression (MGWR) models. Future land use changes were also predicted under traditional and constrained development scenarios using the GeoSOS-FLUS model. The obtained results indicated that: (1) the comprehensive ecosystem service (ES) supply index decreased from 1.42 to 0.84, while the comprehensive demand index increased from 0.74 to 0.95 during the 2010–2020 period; (2) the urban and rural areas had spatial disparities; (3) changes in the construction, ecological, and cultivated land strongly impacted ES; (4) implementing constrained development scenarios can effectively protect the ecological land, control urban expansion, and improve the ESSD relationships in Huainan City. This study provides a valuable theoretical foundation and a methodological framework for future urban and land use optimization efforts, as well as for enhancing the sustainability of ecosystem services and mitigating the imbalance between the supplies and demands of ecosystem services.

Keywords: ecosystem services; residents' welfare; InVEST model; Geo-Detector; MGWR model; driving factors; coal resource-based cities

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1. Introduction

There has been continuous overexploitation and utilization of natural resources through rapid industrialization, urbanization, and socio-economic development. However, the imbalance between natural resource supplies and human demands has resulted in the deterioration of the environment, posing serious threats to the sustainability of socioeconomic and human health [1–3]. Indeed, researchers have devoted great attention to the relationships between supplies and demands in ecosystem services (ESSD) and effective ecosystem management in recent years.

Early research on ESSD relationships has focused mainly on conceptual definitions. Wackernagel proposed the ecological carrying capacity concept, defining the maximum level of resource provision that ecosystems can sustainably maintain [4]. Burkhard (2012) suggests the need to consider humans' actual capacity in ecosystem service (ES) demands [5], while other researchers have defined ES demands based on societal and individual preferences [6,7]. In addition to conceptual delineation, various scholars have employed different methods to quantitatively assess ESSD. Burkhard (2012) [5] proposed the supply and demand matrix method to quantitatively assess ESSD based on land use types and expert ratings. However, although this semi-quantitative and semi-qualitative method is convenient and widely applicable, it is subject to significant subjectivity, making its accuracy influenceable by the expertise of assessors [5]. Costanza (1997) utilized economic value estimation methods to assess the global ESs [8]. Villamagna (2013) assessed ES demands using the willingness to pay (WTP) method [6]. This method is, in fact, based on extensive economic and social data, mitigating the effects of subjectivity on calculation results to some extent. However, it remains challenging to comprehensively assess ESSD based on economic value due to the complexity of ESs. Furthermore, some researchers have employed various models to evaluate ESSD, such as InVEST [9], ARIES [10], RUSLE [11], and FRESF [12]. In recent years, numerous quantitative studies have explored the influencing factors of ESSD, as well as their relationships and spatial heterogeneity, to propose scientific strategies for effective ecological management and planning [13]. Other, related studies have focused on ESSD on both large scales, including watersheds [14] and urban agglomerations [15], and small scales (cities) [16–18]. However, previous related studies have paid insufficient attention to coal resource-based cities, where the relationships between ecological environments and social demands are particularly complex.

Coal resource-based cities are often densely populated, with abundant coal deposits and frequent environmental issues, resulting in obvious changes in their ecological and socio-economic features through their development [19]. Intensive coal-mining activities have resulted in the expansion of land subsidence areas, leading to severe damage to farmland, residential areas, and infrastructure [20]. The construction of mining areas and the relocation of villages have expanded construction land, leading to drastic changes in regional land use patterns [21]. Furthermore, coal mining operations can generate great amounts of coal gangue on cultivated and ecological land, resulting in reduced crop yields and disturbed ecological landscapes [22]. Due to the combined negative effects of coal mining activities and urbanization, coal resource-based cities have been facing distinct and different ecological challenges compared to other urban areas. Therefore, it is crucial to explore the ESSD relationships in these cities and identify key influencing factors to provide guidance for ecosystem management. As one of China's 14 major coal-producing bases, Huainan City possesses abundant coal reserves that have long driven regional economic growth. However, prolonged extensive mining has resulted in a series of environmental challenges, including land degradation and ecosystem disruption. The rapid urbanization process has additionally intensified environmental resource deprivation effects. Moreover, Huainan City has mining areas at different stages, such as closed and active mining zones, making it a representative case study for coal resource-based cities.

In this context, the present study aims to quantitatively assess ecosystem services (ESs) in a representative coal resource-based city (Huainan City), including food production services (FPs), carbon sequestration services (CSs), and recreational services (RSs), as well as their supply–demand relationships, taking into account the specific urban characteristics, ecological environment, government priorities, and residents' welfare needs. In addition, the key factors and the mechanisms underlying their impacts on changes in FP, CS, and RS relationships were further identified and explained in this study. The changes in the land

use types of the study area were also explored using the GeoSOS-FLUS (V. 2.4.0) under various scenarios to provide a useful reference for ensuring effective management and regulation of ESs.

2. Materials and Methods

2.1. Study Area

Huainan City is situated in the north-central part of Anhui Province (116°21′5″ E–117°12′30″ E; 31°54′8″ N–33°00′26″ N), covering both banks of the Huai River (Figure 1). In 2020, the urban population of Huainan City was 1.85 million, accounting for 61.08% of the total population, while the rural population was 1.18 million, accounting for 38.92%. The terrain of Huainan City is flat, with distinct seasons and abundant rainfall, making it an important production base for rice and wheat. In terms of mineral resources, as an important coal-fired power and coal chemical base in East China and Anhui Province, its coal consumption accounts for 22% of the province's total, and its carbon emission intensity is 2.4 times the provincial average, with carbon dioxide emissions from electricity generation accounting for 79.1%. Due to intensive coal mining activities, the region has experienced large-scale land subsidence, vegetation destruction, housing damage, and loss of arable land. Furthermore, the extensive land development pattern in Huainan City induced damage to the local ecosystem, explaining the selection of Huainan City as a case study for this research. The administrative divisions of Huainan City include Tianjia'an, Datong, Xiejiaji, Bagongshan, Panji, Fengtai, and Shouxian. It is worth noting that Shouxian was not considered in this study as there was a lack of coal mining activities, as part of the 2016 administrative jurisdiction.

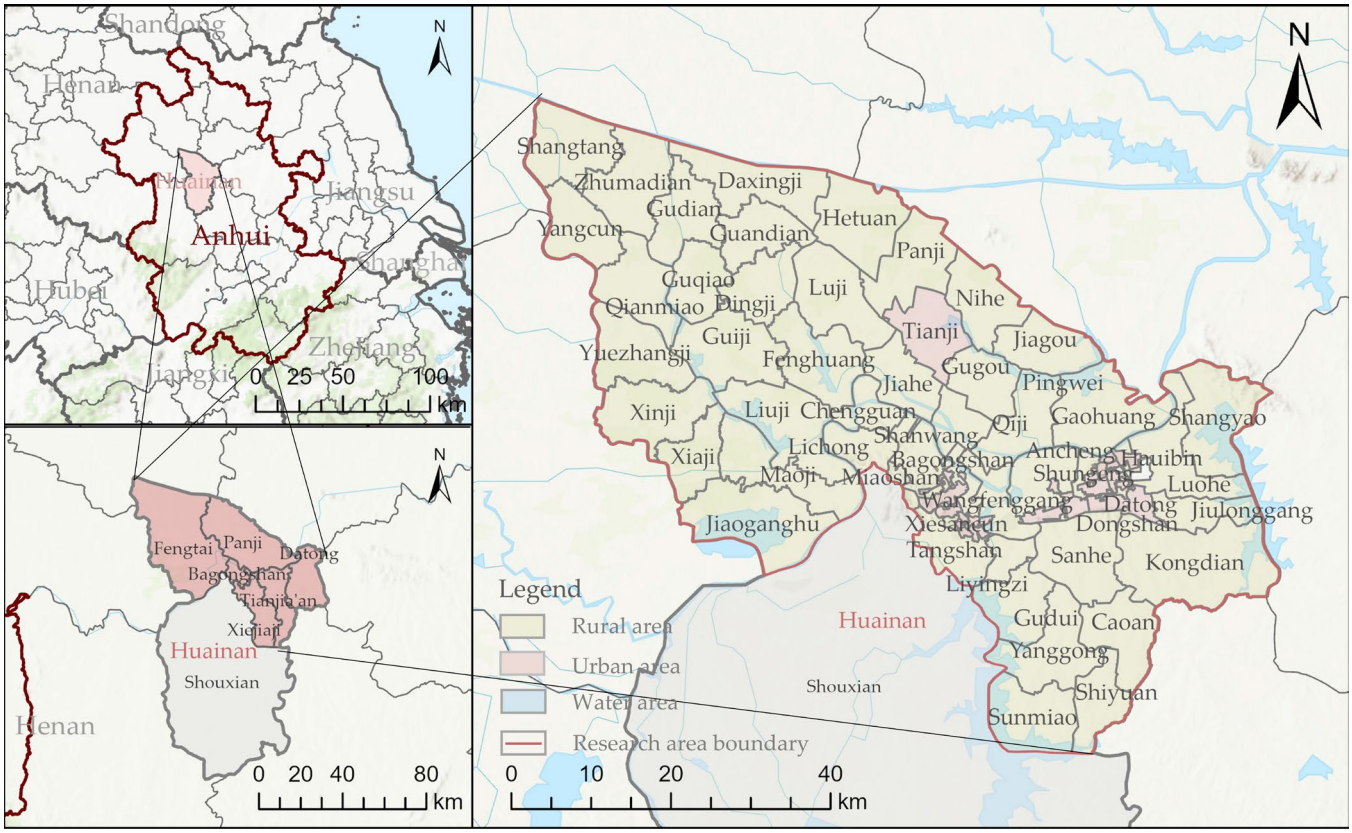


Figure 1. Geographic location of the research area.

2.2. Data Sources

As shown in Table 1, the Normalized Difference Vegetation Index (NDVI) is an indicator of vegetation growth. It is calculated based on the difference in reflectance of red (Red) and near-infrared (Near-Infrared, NIR) light by plants. The value of NDVI typically ranges from −1 to 1. Through this index, it is possible to distinguish between vegetation and non-vegetation areas as well as the growth condition. In this study, the maximum NDVI value dataset of China over the 2000–2020 period, with a 30 m spatial resolution, was supplied by the National Ecosystem Science Data Center (http://www.nesdc.org.cn/, accessed on 2 August 2024) to determine the FP supplies. The land use data of the study area were extracted from the China Multi-Temporal Land Use Remote Sensing Monitoring Dataset provided by the Resource and Environmental Science Data Platform (http://www.resdc.cn/DOI, accessed on 3 August 2024). In this study, further corrections were performed using remote-sensing images to enhance the accuracy of the collected data. Land use data were employed to calculate the CSs and RSs of the study area. The nighttime light data were obtained from the China Annual Nighttime Lights Dataset, provided by the Resource and Environmental Science Data Platform (http://www.resdc.cn/DOI, accessed on 3 August 2024), to determine CS demands. Digital Elevation Model (DEM) elevation data were sourced from the 30 m resolution ASTER GDEM provided by the Geospatial Data Cloud (http://www.gscloud.cn/, accessed on 6 August 2024). The DEM data were first preprocessed using different techniques, including the mosaic creation tool, projection transformation, and mask-based extraction before generating the DEM map of Huainan City. These data were used to extract the slope and aspect features of the study area. The economic and social data of Huainan City were collected from the "China County Statistical Yearbook" and the "Huainan Statistical Yearbook" provided by the China National Knowledge Infrastructure (https://data.cnki.net/, accessed on 11 July 2024). Additionally, the "Bulletin of National Economic and Social Development Statistics" of the municipality, district, and county, as well as the "Sixth National Population Census Bulletin" and "Seventh National Population Census Bulletin", were provided by the Huainan Government (https://www.huainan.gov.cn/, accessed on 11 July 2024).

Table 1. Data Sources and Resolution.

Data	Source	Time	Spatial Resolution
NDVI	National Ecosystem Science Data Center (http://www.nesdc.org.cn/, accessed on 2 August2024)	2010 and 2020	30 m
Land use	Resource and Environmental Science Data Platform (http://www.resdc.cn/DOI, accessed on 3 August 2024)	2010 and 2020	30 m
DEM	Geospatial Data Cloud (http://www.gscloud.cn/, accessed on 6 August 2024)	2009	30 m
Nighttime light data	Resource and Environmental Science Data Platform (http://www.resdc.cn/DOI, accessed on 3 August 2024)	2010 and 2020	0.008 degree and 0.004 degree
Economic and social data	China County Statistical Yearbook and Huainan Statistical Yearbook (https://data.cnki.net/, accessed on 11 July 2024) Bulletin of National Economic and Social Development Statistics and Seventh National Population Census Bulletin (https://www.huainan.gov.cn/, accessed on 11 July 2024)	2010 and 2020	/

2.3. Methods

(1) Quantification of FP supply and demand

Belmahi (2023) [23] revealed a significant linear relationship between FP and the NDVI. The NDVI has also been widely applied in studies focused on rice and wheat yield estima-

tion [24–26]. Therefore, the ratio total for FP-to-NDVI ratios was calculated in this study to characterize the FP supply capacity of each cultivated land grid (Equation (1)). Given that rice and wheat planting areas account for 93.22% of cultivated land in Huainan City, this study primarily considers these two crops as the main FP sources in the region. Based on the planting patterns for rice and wheat, NDVI data from April and September were selected for analysis. Using the Extract by Mask function in ArcGIS 10.5, we extracted NDVI values for cultivated land and used a raster calculator to determine the maximum NDVI values between the two months, thereby characterizing the FP capacity of cultivated land.

$$\text{Food_supply} = \sum \frac{\text{NDVI}_i}{\text{NDVI}_{sum}} \times \text{Food_supply}_{sum} \quad (1)$$

Food_supply represents the allocated FP of the grid i; Food_supply_{sum} represents the total FP of the study area; NDVI_i denotes the NDVI of the grid i; and NDVI_{sum} denotes the sum of the NDVI values over the cultivated land grids.

The FP demand was estimated in this study by multiplying the per capita grain demand by the total population. The per capita grain demand was determined based on the grain demand standard published by the National Bureau of Statistics of Anhui Province according to the following formula (Equation (2)):

$$\text{Food_demand} = \text{Food_consumption}_p \times \rho_{pop} \quad (2)$$

Food_demand represents the grain demand; $\text{Food_consumption}_p$ represents the per capita grain demand; and ρ_{pop} represents the total population in the study area.

(2) Quantification of the CS supply and demand

In this study, the InVEST software model (V. 3.9.0) [27] was employed to evaluate the CS supply in Huainan City. InVEST, a tool designed to explore how changes in ecosystems may lead to changes in the benefits flowing to people, typically employs a production function approach to quantify and assess ES [28,29]. The model calculates carbon stocks by considering four primary carbon pools, namely, aboveground biomass (C_{above}), belowground biomass (C_{below}), soil (C_{soil}), and dead (C_{dead}) organic matter. The calculation formula was obtained from carbon sequestration studies, in areas surrounding Huainan City [30], as follows (Equation (3)) [31]:

$$C_{tot} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (3)$$

Numerous studies have demonstrated that nighttime light data can reflect the intensity of human activities and exhibit a significant linear relationship with regional carbon emissions [32–34]. Therefore, this study allocated carbon emission data based on the ratio of the nighttime light index for each grid to the total nighttime light index. The calculation formula is as follows (Equation (4)):

$$C_{demand} = \sum \frac{NL_i}{NL_{sum}} \times C_{emission} \quad (4)$$

C_{demand} denotes the CS demand; NL_i denotes the nighttime light index of the grid i; NL_{sum} denotes the total nighttime light index; and $C_{emission}$ denotes the total carbon emissions.

(3) Quantification of the RS supply and demand

Recreational services (RSs) are closely related to human subjective cognition. In this study, a matrix was established to quantitatively assess the RS supply and demand [5].

Specifically, six experts with extensive knowledge of natural and social environments in Huainan City were invited to evaluate the RS supply and demand under five land use types (Table 2).

Table 2. Supply and Demand Matrix of the RS in Huainan City.

	Cultivated Land	Forest Land	Grassland	Water Bodies	Construction Land
Supply	1	5	4	5	0
Demand	2	0	0	0	4

The rating values indicate the levels of the RS supply and demand. Rating values of 0, 1, 2, 3, 4, and 5 indicate no, low, relevant, medium-relevant, highly relevant, and very highly relevant capacities, respectively [5]. A higher score implies a higher level of supply or demand [35].

(4) Supply–Demand Index of the ESs

The matching degrees of the ESSD were calculated using the Supply–Demand Index (SDI) according to the following formula (Equation (5)):

$$SDI = \frac{ES_s - ES_D}{ES_D} \quad (5)$$

The SDI denotes the matching degree of the ESSD; ES_s denotes the supply of the ESs; and ES_D denotes the demand of the ESs. $SDI > 0$, $SDI = 0$, and $SDI < 0$ indicate surplus, balanced, and deficit statuses, where the supply is greater than, equal to, and less than the demand, respectively.

(5) Influencing factors analysis

In this study, the factor detection module of the Geo-Detector was used to identify the main factors influencing the ESSD, including both natural and socio-economic factors.

$$q = 1 - \frac{1}{N_0^2} \sum_{i=1}^{m} n_{0i}^2 \quad (6)$$

where q denotes the explanatory power of the factors on the SDI, ranging from 0 to 1. The highest q value indicates stronger explanatory power of the factors [36]. N_0 denotes the total number of samples; n denotes the number of samples for each subcategory or region. $\sum_{i=1}^{m} n_{0i}^2$ denotes the sum of the squares of the sample sizes for all subcategories which were first obtained. This sum is then normalized by dividing it by N_0^2. Finally, subtracting this ratio from 1 yields q.

Although the Geo-Detector can be used to explore influencing factors, it cannot effectively explore spatial heterogeneity and reveal the main mechanisms underlying the effects of influencing factors [37]. Therefore, multi-scale geographic weighted regression (MGWR) was used to explore the relationships between dependent and explanatory variables, taking into account spatial heterogeneity according to the following Equation (7) [38]:

$$y_i = \sum_{j=1}^{n} a_j x_{ij} + \sum_{j=n+1}^{m} \beta_j(x_i, y_i) x_{ij} + \varepsilon_i \quad (7)$$

The bandwidth search method, model type, and bandwidth selection optimization method considered in this study are the golden section search, Gaussian, and the Akaike information criterion (AIC), respectively.

(6) Prediction of future land use types

Predicting future land use types is essential for developing effective land management and development strategies, thereby ensuring rational utilization of resources. This is crucial for promoting sustainable development and improving the ecological environment. The GeoSOS-FLUS model combines the advantages of System Dynamics (SD) and Cellular Automata (CA) models, incorporating the Artificial Neural Networks (ANNs) algorithm and a roulette selection mechanism [39]. This comprehensive approach was considered to predict land use changes with high precision, taking into account multiple influencing factors of land use dynamics, such as natural, social, and economic factors [40].

3. Results

3.1. Spatial Distribution of the ES Supplies and Demands

The results revealed similar spatial distributions of the FP and CS supplies in Huainan City (Figure 2). The strongest supply capacities were found in the northwestern and southeastern rural areas, while the lowest supply capacities were observed in the central urban areas. In contrast, the spatial distribution of the RSs was different from those of the FPs and CSs. Specifically, scattered high RS values were found due to the impacts of natural resource endowment. On the other hand, similar spatial distributions of the FP, CS, and RS demands were observed, showing high values in the eastern and western urban districts of Huainan City.

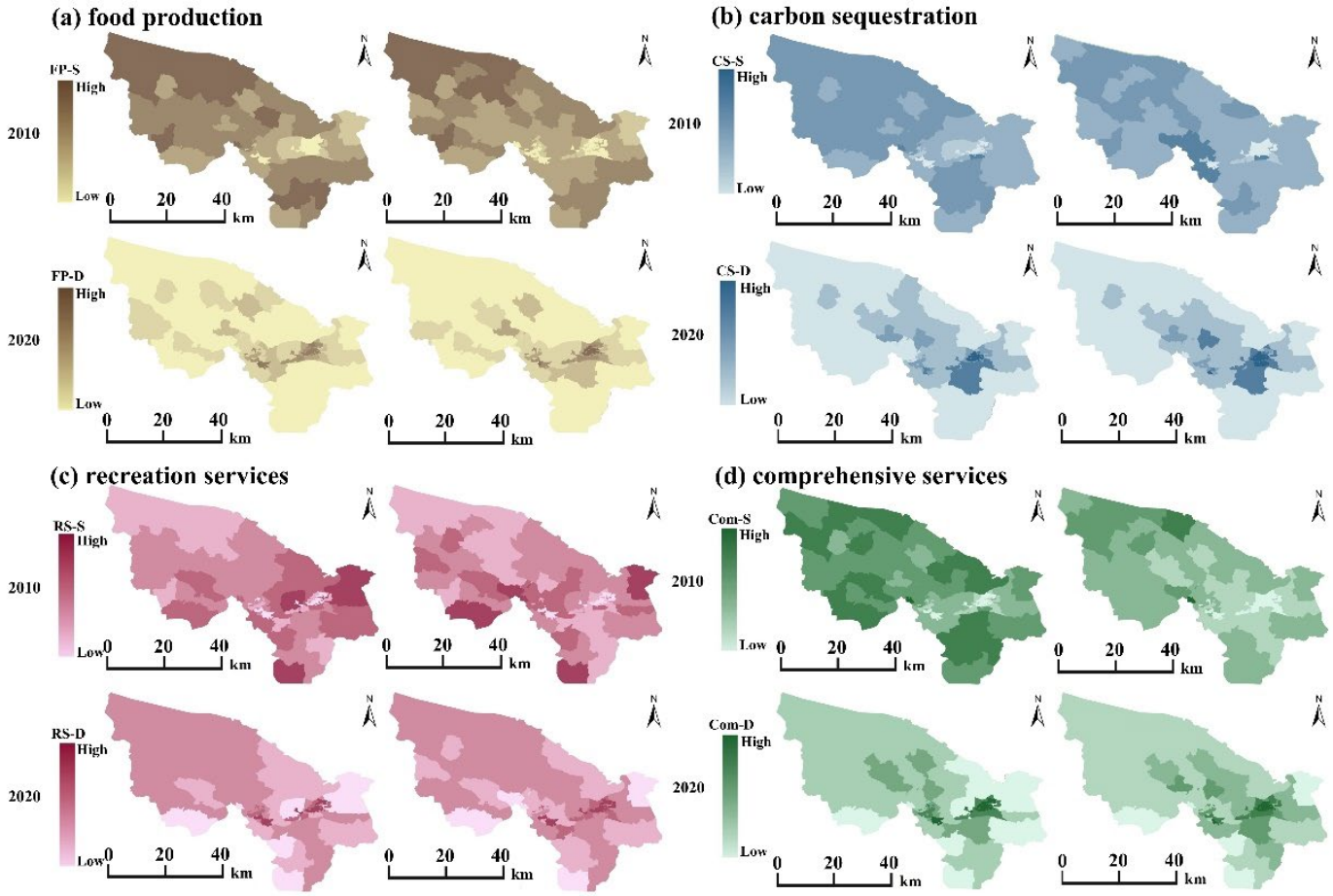


Figure 2. Spatiotemporal distributions of the ESSD in Huainan City (FP-S: Food production services supply; FP-D: Food production services demand; CS-S: Carbon sequestration services supply; CS-D: Carbon sequestration services demand; RS-S: Recreation services supply; RS-D: Recreation services demand; Com-S: Comprehensive supply; Com-D: Comprehensive demand).

In this study, the FPs, CSs, and RSs were considered equally important for human well-being. Therefore, the min–max normalization method was applied to standardize the service data, followed by summation to obtain comprehensive supply and demand indices. The average comprehensive ES supply indices in Huainan City were 1.42 and 0.84 in 2010 and 2020, respectively. On the other hand, the average comprehensive ES demand indices were 0.74 and 0.95 in 2010 and 2020, respectively (Figure 2). In addition, the comprehensive ES supply and demand indices showed decreasing and increasing trends, respectively. These indices exhibited similar spatial variation characteristics to the supply of FPs, CSs, and RSs, characterized by urban–rural differentiations.

The spatial distribution of the ESs in Huainan City exhibited urban–rural differentiation due to the high population density and large impervious surfaces in the urban areas, which reduce the availability of ecological areas and, consequently, result in weak supply capacities and high demands for the ESs [41]. In contrast, rural areas are characterized by comparatively lower population densities and larger ecological areas, enhancing the supply capacities and decreasing the demands for the ESs. However, urban expansion and rural development in Huainan City significantly impacted ecological areas [42]. These impacts resulted in slight declines in the ES supply and increased demand in the rural areas over the 2010–2020 period.

3.2. Spatial Distribution of the SDI

The results showed surpluses in the supply–demand relationship of FPs in Huainan City. The surplus and deficit units in 2010 accounted for 68.66 and 31.34%, respectively. The deficit and surplus areas were primarily concentrated in the central urban district and rural townships away, respectively. Similar spatial surplus and deficit characteristics were found in 2020 to some extent (Figure 3).

According to the obtained results, CSs exhibited significant supply–demand mismatches, with deficit rates reaching 61.19% in 2010 and increasing to 70.15% by 2020. The overall supply–demand relationship of RSs was also in deficit. Specifically, 83.58 and 88.05% of the RS values were in deficit in 2010 and 2020, respectively. The CS and RS surpluses were scattered variation patterns in the study area, particularly in areas rich in natural resources. The CS and RS deficit concentrated spatial distributions near the eastern and western urban districts.

The comprehensive supply–demand deficit rates in 2010 and 2020 were 26.87 and 34.32%, respectively. Although the deficit proportions were moderate, they exhibited increasing trends. The ESSD relationships in Huainan City exhibited a spatial distribution characteristic of urban–rural duality. In urban areas, the supply–demand relationship was in deficit, while in towns and villages, it was predominantly in surplus. In addition, the results showed an expansion trend of the deficit areas from the central urban area to the surrounding towns and villages.

3.3. Factors Influencing the ESSD Relationships

Previous studies on ESSD-influencing factors have predominantly focused on natural and social drivers [43–46]. In this study, we systematically reviewed the factors identified in existing literature and selected nine key determinants by considering data availability and the natural, economic, and social conditions of Huainan City (Table 3). Geo-Detector was employed to identify the main factors influencing the spatiotemporal variations in the ESSD relationships.

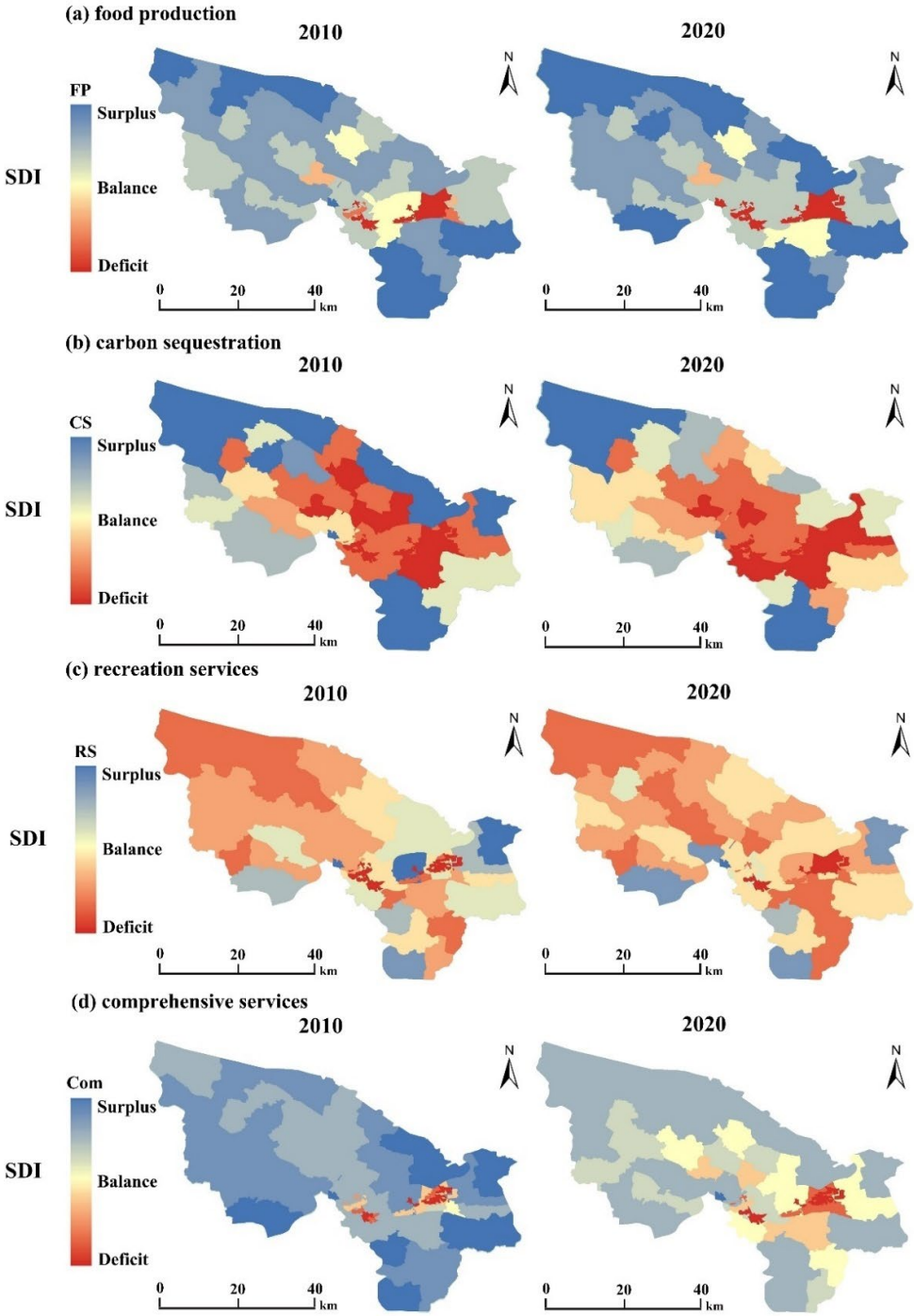


Figure 3. Spatiotemporal distribution of the SDI in Huainan City (FPs: food production services; CSs: carbon sequestration services; RSs: recreation services; Com: comprehensive).

Table 3. Factors driving the ESSD relationships.

Categories		Factors	Significance
Natural Factors	x_1	Elevation	Height of the ground above the sea level
	x_2	Slope	The steepness of the terrain
	x_3	Precipitation	Mean annual rainfall amounts
	x_4	Temperature	Mean annual temperatures
Social Factors	x_5	Population	The number of permanent residents within the units
	x_6	Gross domestic product (GDP)	The economic development status of the units
	x_7	Cultivated land area	The scale of the cultivated land within the units
	x_8	Construction land area	The scale of the construction land within the units
	x_9	Ecological land area	The scale of ecological land within the units

The Geo-Detector results demonstrated the influences of the social and natural factors on the ESSD relationships in Huainan City (Figure 4). The q-values of the construction and ecological land areas were relatively higher than those of the other social factors. Among the natural factors, on the other hand, the precipitation and temperature data had relatively higher q-values. However, the contribution rates of the social factors were higher than those of the natural factors, demonstrating the strong controlling effects of the social factors on the ESSD relationships.

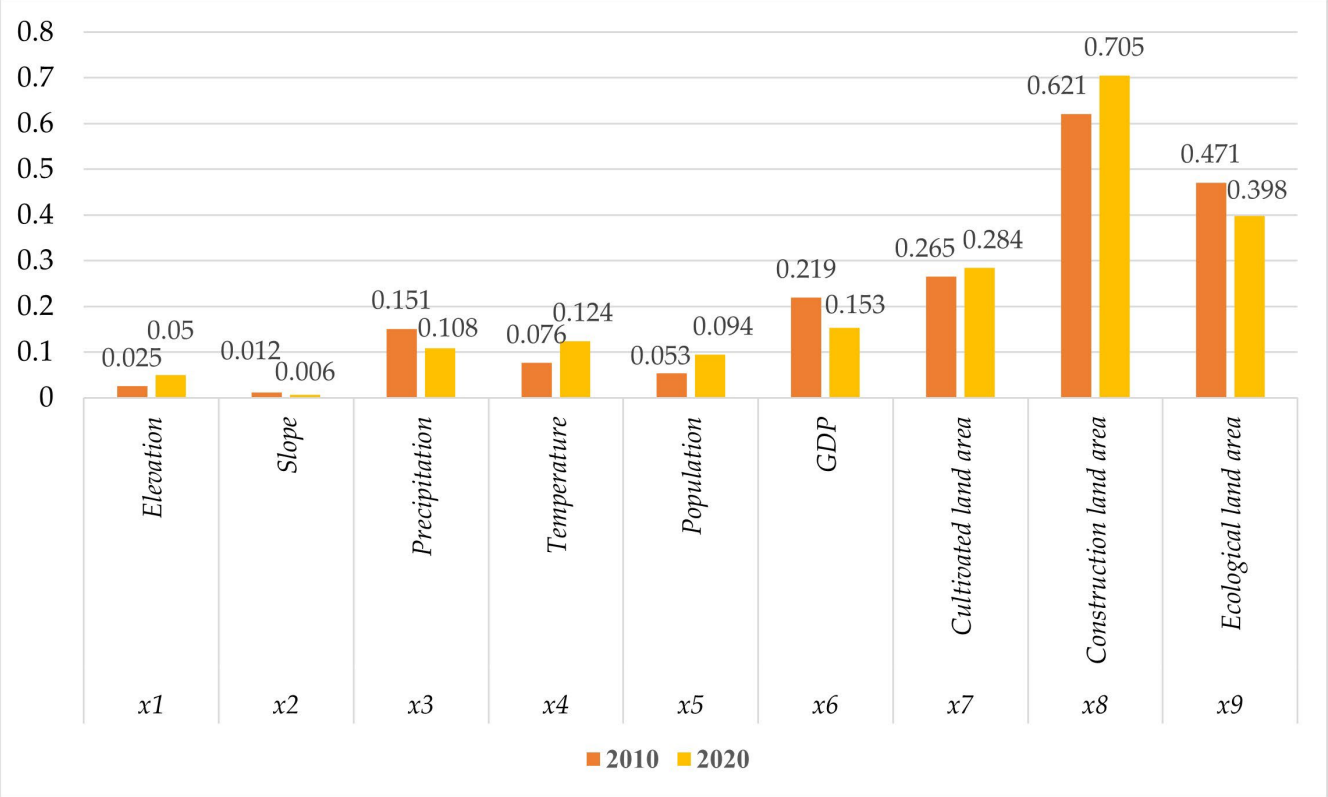


Figure 4. Geo-Detector analysis results.

The Geo-Detector method accurately identified the main factors influencing the ESSD relationships in Huainan City without revealing the main mechanisms underlying the impacts of the selected factors within each unit. Therefore, factors with explanatory power values greater than 0.25 in the Geo-Detector results were selected and considered as input variables into the MGWR model to determine the directions, intensities, and spatiotemporal variations in the impacts exerted by the factors on the ESSD relationships.

The regression coefficients of the construction land areas in 2010 and 2020 were negative, indicating the negative impacts of increased construction land areas on the ESSD relationships. The negative impacts of the increased construction land on the supply–demand relationship were, in fact, more pronounced in the western region when compared with those in the eastern region. On the other hand, the regression coefficients of the ecological and cultivated land areas in 2010 and 2020 were positive, demonstrating the positive impacts of these factors on the ESSD relationships. The regression coefficients of these factors were higher in the central region than those in the eastern and western regions (Figure 5).

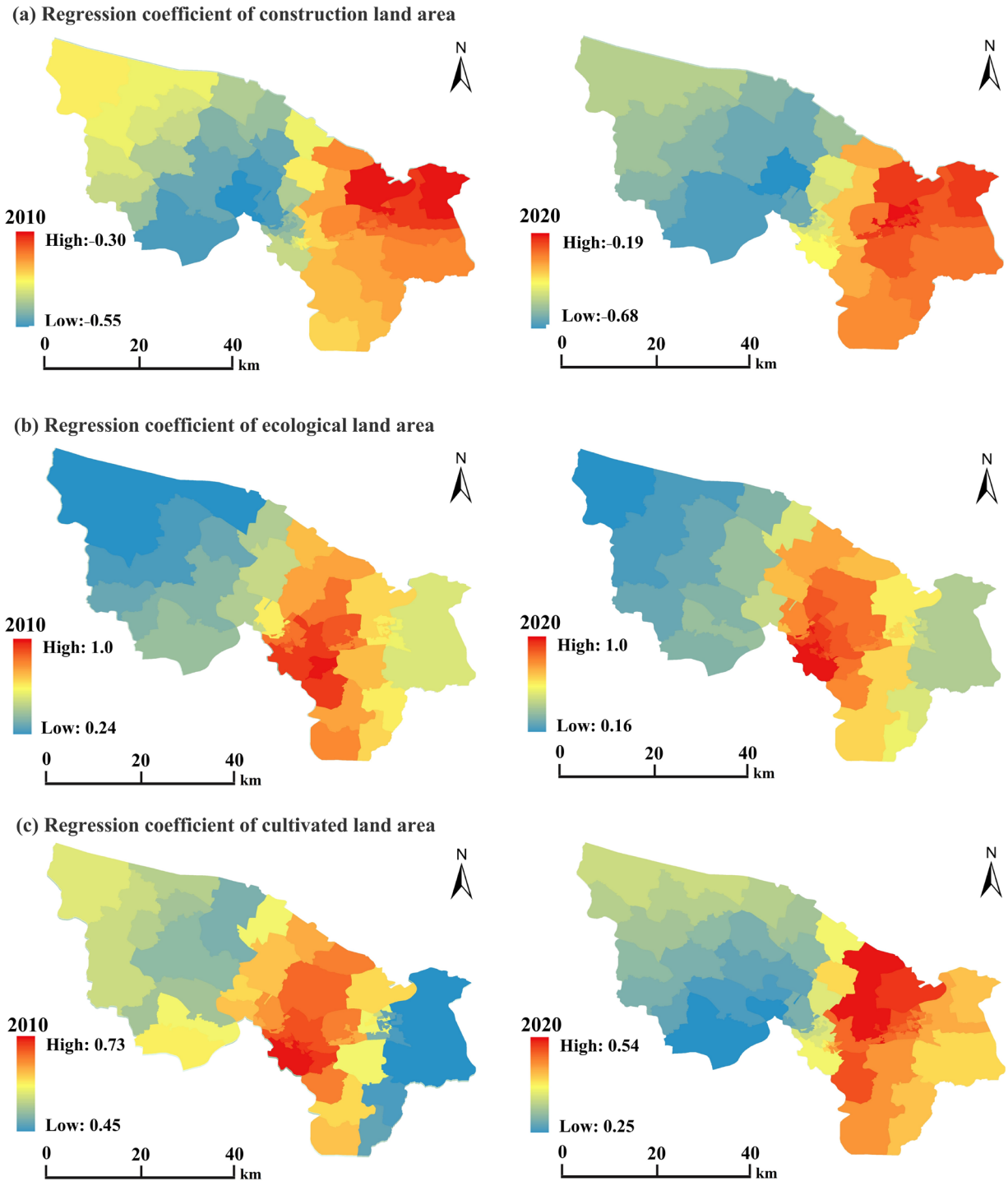


Figure 5. MGWR Analysis results.

3.4. Future Land Use in Huainan City

The analysis results indicated strong impacts of land use patterns on the ESSD relationships in Huainan City. The increased construction land negatively affected the balance between the ES supplies and demands. In contrast, the ecological and cultivated land areas were beneficial for maintaining the stability of supply–demand relationships. Therefore, land development patterns can influence future ESSD relationships in Huainan City. To ensure comprehensive risk assessments and resource allocation strategy formulations, it is essential to predict and analyze future development scenarios. In this study, a land use transition probability matrix was further established based on the collected historical

land use data and various related factors (Figure 6), taking into account the MGWR-based regression coefficients of the MGWR. This matrix was employed to predict land use patterns in Huainan City for 2030 under the traditional and constrained development scenarios (Figure 7).

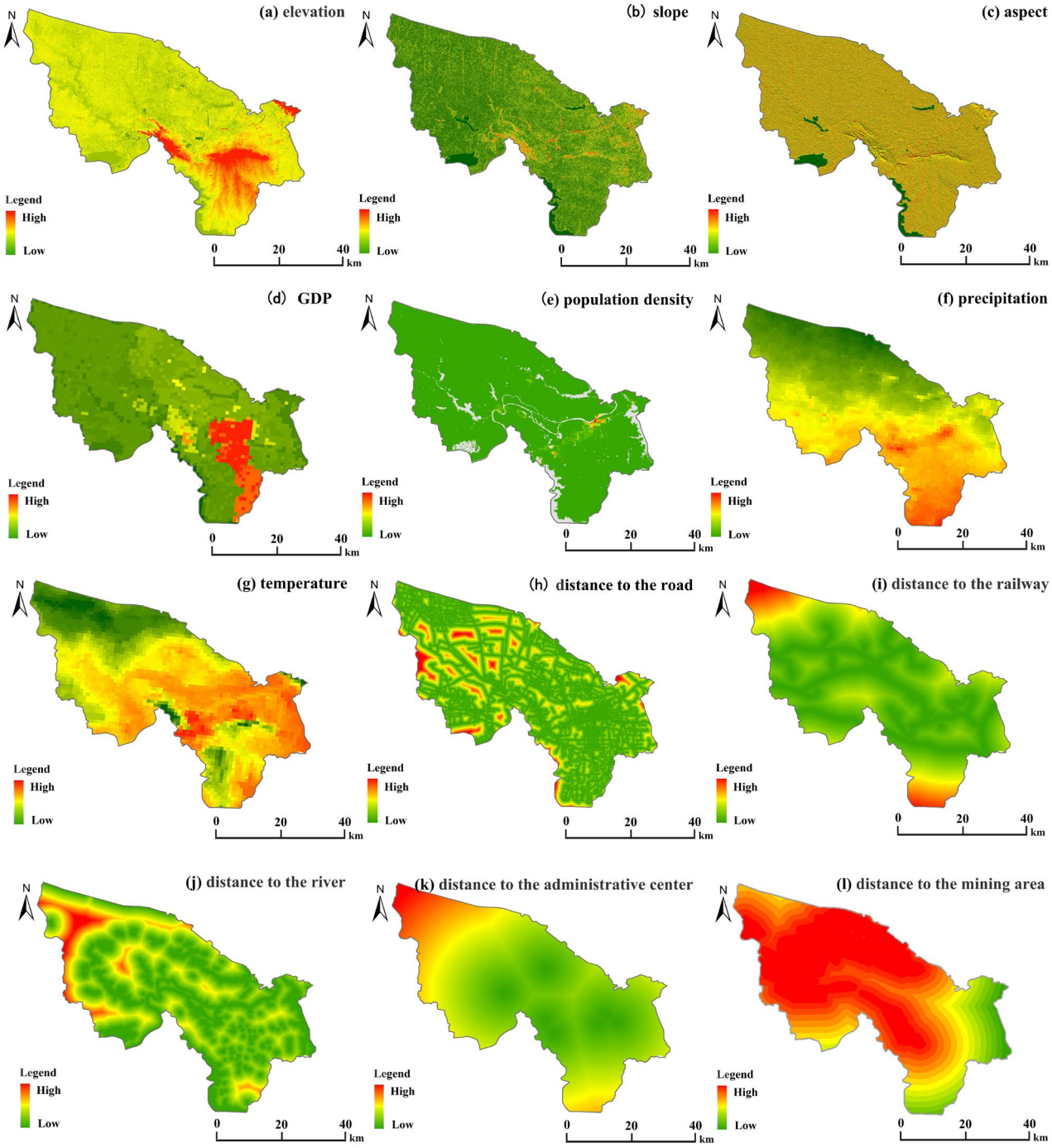


Figure 6. Spatial distributions of the driving factors in the study area.

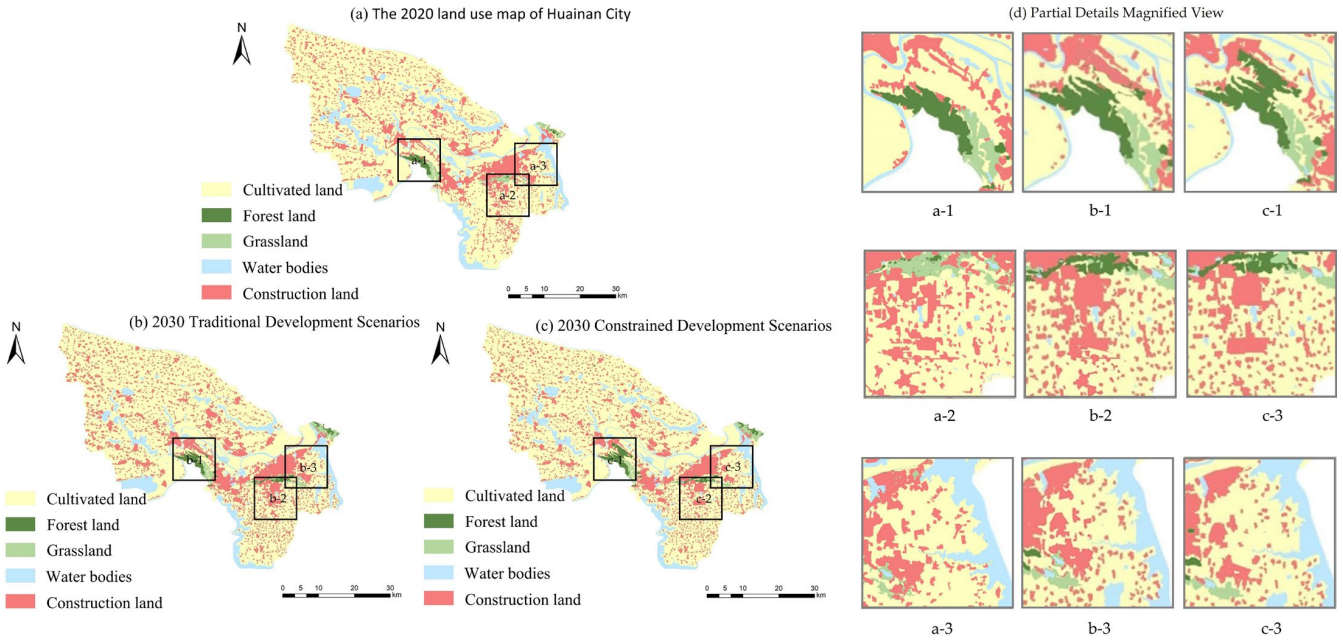


Figure 7. Land use map of Huainan City.(Figures a-1, b-1, c-1, a-2, b-2, c-2, a-3, b-3, and c-3 are the detail magnification images of Figures (**a**), (**b**), and (**c**), respectively.)

The land use types in the study area were unaffected by the national agroecology policies under the traditional development scenario. They were influenced mainly by the historical changing trends, as well as by other influencing factors, such as terrain, natural conditions, socio-economic factors, and location conditions. Under the constrained development scenario, on the other hand, ecological priorities are emphasized for maintaining sufficient cultivated land areas. Indeed, the protection measures for the ecological function zones were strengthened. Moreover, strict control measures were implemented to restrict obvious conversions of ecologically valuable forests, grasslands, and water bodies to construction land areas in the study area.

The predicted expansion rate of the construction land under the traditional development scenario was substantially greater than that under the constrained development scenario, resulting in reduced ecological areas. Under the constrained development scenario, on the other hand, the expansion rate of the construction land was restricted without a substantial difference to that revealed in 2020. The ecological areas under this scenario were well protected with no significant reductions. Furthermore, areas with good ecological resources exhibited an expansion trend towards the urban areas.

The results showed a significant expansion of the eastern urban construction land area towards Shungengshan under the traditional development scenario, resulting in reduced ecological and farmland areas. These construction land areas had a continuous expansion trend in the southern mountain areas, substantially reducing the farmland areas. Comparatively higher expansion rates were found in the eastern part of the study area. In addition, construction land patches in the Huainan Economic Development Zone showed an increasing trend towards the eastern main urban area.

The expansion of urban construction land in Huainan City was restricted under the constrained development scenario, resulting in more intensive land construction. The spatial distribution of land use types in the northern part of Shungengshan in 2030 was relatively similar to those observed in 2020, showing a lack of significant expansion toward the mountain areas under the traditional development scenario. On the other hand, some ecological areas were found in the urban areas under the constrained development scenario. However, the observed expansion rates of the urban area in the southern parts of the

Shungeng Mountain and the Eastern Economic Development Zone were limited. Therefore, the overall urban development in the east-central area was within a reasonable range, which could ensure effective ecological protection.

4. Discussion

4.1. Comparison of the Results with Relevant Research Findings

Ecosystem services (ESs) are crucial for human society's survival and development. It is, therefore, important to comprehensively explore the relationship and mechanisms of factors influencing the ESSD [47,48]. This study evaluated the distribution, evolution, and influencing factors of ESSD under the combined impacts of coal mining activities and urbanization on land use changes to elucidate the relationships between human activities, land use dynamics, and ecosystems. In addition, this study explained the processes and driving mechanisms associated with social and ecological transformations. This study revealed a significant spatial mismatch in the supply and demand pattern of ES in Huainan City. Urban areas exhibited high ES demand coupled with low supply, while rural areas demonstrated the inverse pattern of high supply but low demand. This phenomenon is mainly due to the combined effect of natural and social factors, among which the roles of construction land area and ecological land area are particularly significant. Regulating the ESSD in Huainan City through land use patterns is actively effective. By comparing two land use scenarios, it is found that the traditional development scenario will continue to lead to the expansion of construction land and reductions in ecological land, which will further deteriorate the ESSD. On the contrary, if a constrained land use development model is adopted, it will reduce the degree of construction land expansion and increase the area of ecological land in important ecological nodes, which is conducive to regulating ESSD. This provides new perspectives and methods for future research on ESs and land use optimization, as well as a scientific basis for exploring the main mechanisms underlying social-ecological interactions and guiding the management and planning of ESs in coal resource-based urban areas.

Contrary to previous related studies on ESs at city [49], county [50], and grid [51] scales, this study considered townships as fundamental research units. This approach can provide accurate measurements of the ESs and facilitates administrative actions by local authorities to improve the efficiency of ES protection and restoration [52]. Most related studies have, typically, conducted time series analyses at intervals of 5 or 10 years [53,54]. In this study, we have conducted the time series analysis with 10-year intervals, taking into account administrative adjustments and the extent of changes in ESs. The combination of the Geo-Detector and MGWR models was effective in exploring the main mechanisms underlying the effects on the ESSD [37]. Furthermore, the different input variables into the MGWR have different bandwidths, effectively capturing the heterogeneity in the spatial data [55,56].

The analysis results of the influencing factors were consistent with those revealed in previous related studies, highlighting the combined impacts of social and natural factors on the ESSD relationships [57]. The natural and social factors predominantly affected the ES supplies and demands, respectively. The endowments and levels of economic and social development can vary between different research regions, resulting in varied intensities of their effects [58]. In Huainan City, where natural conditions were relatively stable, significant changes in the economic and social characteristics were found, including increased construction land and population growth. These changes, consequently, increased the ES demands [59]. Therefore, the ESSD relationships were mainly driven by the social factors over the 2010–2020 period. Among these factors, changes in the land use types

notably affected the ESSD relationships, which is in line with the findings revealed in previous related studies [60–62].

Some scholars have further explored the impacts of land use changes on the ESSD relationships using predictive models [63,64]. According to their findings, economic growth or uncontrolled development can exacerbate the imbalance between the ESSD relationships. In contrast, ecological conservation or controlled development can effectively enhance ESs [65,66]. These findings are in line with those revealed in the present study, highlighting the need for balanced economic growth and enhanced ecological benefits in Huainan City to achieve sustainable development that harmonizes human needs and environmental conservation.

4.2. Policy Directions

Regarding policy directions for ESSD optimization, scholars have conducted extensive discussions, such as establishing ecological protection zones [67,68], strengthening the construction of green infrastructure [69,70], and improving ecological compensation mechanisms [71,72]. By drawing on relevant strategies and combining the analytical results, this study puts forward targeted policy direction suggestions. Huainan City is suggested to ensure optimal economic growth, effectively allocate existing resources, restrict urban expansion, reduce construction land areas, and increase farmland/ecological land areas in Huainan City to achieve the constrained development scenario. Underused or unused construction land areas can be converted into street corner gardens and parks, thereby increasing ecological land areas and promoting the restoration and enhancement of the urban ecosystems. It is suggested that great efforts be devoted to ecological restoration and management in the mining regions by the government to mitigate environmental issues caused by coal mining activities. In addition, sustainable economic growth and ecological protection can be achieved by replacing governance indicators with development indicators.

Comprehensive planning strategies, strengthened urban–rural linkage, and orderly distributions of ecological resources need to be implemented in the study area in response to the existing disparities in the ESSD between the rural and urban areas. Additionally, ecological corridors can be established through water systems and transportation networks to enhance ecological connectivity between the urban and rural areas.

4.3. Limitations of This Study

This study focused only on three components of the ESSD impacting the well-being of residents in Huainan due to the lack of comprehensive related data. These components were ESs—those of food, carbon, and recreation. Hence, it is suggested that in the future, related studies be conducted while taking into account a broader range of ESs, such as water conservation, soil preservation, and water/air purification, to provide more comprehensive assessments of the ESSD in Huainan City. It is also suggested that meteorological and climate models be considered to accurately predict future natural, economic, and social development, thereby providing further insights into the evolution of ESSD under various future scenarios. Such studies can guide the formulation of effective environmental protection policies and sustainable development plans, optimize resource allocation, and promote ecosystem stability.

5. Conclusions

The present study aimed to assess the ESSD relationships in a coal resource-based city (Huainan) using multi-source data from 2010 to 2020. The Geo-Detector and MGWR models were employed to identify the main influencing factors and their mechanisms, as well as to predict future land use changes.

The following conclusions were drawn in this study:

(1) Compared to 2010, FP supplies in 2020 increased while demand decreased; in contrast, both CSs and RSs experienced a decline in supply alongside a rise in demand during the same period. Overall, the comprehensive supply–demand relationship showed a surplus. However, the surplus degrees and their spatial distributions exhibited decreasing trends.

(2) Spatially, the ESSD relationships showed a clear urban–rural dichotomy. In urban areas, ES demands were high, while supplies were low. The ESSD deficits were mainly concentrated in urban areas and extended to surrounding areas.

(3) The ESSD relationships were mainly influenced by the selected social factors. The construction land areas negatively impacted the ESSD across the study region, while the increased ecological land and cultivated land had positive effects.

(4) The urban expansion in Huainan City can be effectively controlled under the constrained development scenario. In addition, this scenario is of great importance for reducing the impact of urban encroachment on ecological land, thereby promoting ecological expansion in areas with good ecological resources.

(5) The government of Huainan should focus on limiting incremental growth, restoring existing natural resources, and implementing effective measures to restore mining and ecological areas. Additionally, it is crucial to consider urban–rural coordination and resource allocation optimization to achieve sustainable urban development.

(6) This study provides a replicable framework for the sustainable development of coal resource-based cities through the optimization of land use based on ESSD. By analyzing the influencing factors, it was found that the control of land use patterns plays a crucial role in ESSD. In the development process, coal resource-based cities should curb excessive development activities and adopt scientific land use patterns to ensure sustainable development.

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Abbreviations

The following abbreviations are used in this manuscript:

ESSD	supplies and demands of ecosystem services
FPs	food production services
CSs	carbon sequestration services
RSs	recreation services

MGWR	multi-scale geographic weighted regression
ES	ecosystem service
WTP	willingness to pay
NDVI	The Normalized Difference Vegetation Index
SD	System Dynamics
CA	Cellular Automata
ANN	Artificial Neural Networks

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