Pol. J. Environ. Stud. Vol. 34, No. 1 (2025), 801-813
DOI: *10.15244/pjoes/186582* ONLINE PUBLICATION DATE: 2024-06-18

Original Research

Identification and Driving Effects of Land Use Conflicts in Mega-City in Northeast China: A Case Study of Shenyang City

Ruiqing Su[1], Ge Song[1, 2, 3*], Quanxi Wang[1]

[1]School of Humanities and Law, Northeastern University, Shenyang 110169, China
[2]Research Base for Land Use and Protection in Liaoning Province, Shenyang 110169, China
[3]Key Laboratory of Land Protection and Use, Department of Natural Resources of Liaoning Province, Shenyang 110169, China

Received: 5 February 2024
Accepted: 27 March 2024

Abstract

Land use conflicts (LUCs) are the spatial manifestation of contradictions in human-land relations. The scientific identification of LUCs and the revelation of their spatial and temporal evolution mechanisms are of great significance for effectively alleviating human-land conflicts, strengthening the control of territorial spatial planning, and promoting coordinated regional development. This study took place in Shenyang, the only megacity in Northeast China, which faces multiple pressures, such as agricultural production, urban construction, and ecological protection. The study adopted the LUCs intensity model and the GTWR model to identify the LUCs, clarify the evolution pattern, and reveal the spatial and temporal heterogeneity of driving factors. The study results showed that (1) from 1986 to 2020, the intensity of LUCs in Shenyang decreased and then increased. The conflict intensity in the core urban area was lower, whereas the conflict intensity in other areas was higher. (2) The influence of different driving factors on LUC intensity in Shenyang showed apparent spatial differentiation. Socio-economic factors significantly impacted the core urban area and suburban areas, whereas natural environmental factors significantly impacted the exurban areas. (3) Population density was central to triggering LUCs in Shenyang from 1986 to 1997. Urbanization levels were central in triggering LUCs in Shenyang from 1997 to 2020. In the future, Shenyang should give full play to the comparative advantages of different functional zones, strengthen land use control, optimize land resource allocation, alleviate LUCs, and improve the stability of the spatial pattern of national territory. The indicators and models used in this study can effectively reflect the LUC situation and provide scientific references for the planning and regional layout of Shenyang City.

Keywords: Land use conflicts, spatial-temporal evolution, driving factors, GTWR model, Shenyang City

*e-mail: songge@wfxy.neu.edu.cn

Introduction

Rapid urbanization and industrialization have exacerbated human demand for land, leading to frequent changes in land use types and intensified land use conflicts (LUCs) [1]. Serious LUCs may affect socio-economic development and destabilize the natural ecological environment system [2]. Therefore, LUCs have become a hot issue of global concern and research. China is the world's largest developing country, and its level of urbanization has grown from 17.9% at the time of reform and will open up to 65.22% in 2022 [3]. The rough and inefficient use of land resources has accompanied the rapid development of urbanization and industrialization. The large-scale and disorderly expansion of urban and rural settlements has led to the fragmentation of arable land, a decline in the stability of the ecological environment system, and the frequent occurrence of the phenomenon of LUCs [4-6]. This further threatens regional agricultural production, urban development, and ecological security [7]. In order to effectively address LUCs resulting from frequent changes in land use structures, the government has developed relevant policy documents. In 1986, China promulgated the Land Management Law, which called for strengthening planning management, preparing overall land use plans, and the protection of land resources. The concept of land use control was first proposed in 1997. In 2008, the Outline of the National Overall Land-Use Plan (2006-2020) extended the scope of land use control from cultivated land to land used for construction. In 2017, the 19th National Congress of the Communist Party of China (CPC) presented a new expression of high-quality development for the first time [8]. In 2018, China formed the Ministry of Natural Resources (MNR), responsible for managing the land use system. The MNR was formed to uniformly exercise responsibility for the land use control of all land space. At the same time, China has changed its original development model from rough development to high-quality development. In 2020, the CPC made high-quality development the theme of China's economic and social development in the next five years. It can be seen that China has always attached great importance to the control of land use. At the same time, China will enter a new phase of socio-economic transformation, which will inevitably involve an increase in demand for land use, and intensify competition for spatial resources, thus affecting the stability of the spatial dynamics of land landscapes, exacerbating their perturbations, and triggering LUCs. As the growth pole of regional development, how do we realize the comprehensive and efficient utilization of land resources when coordinating the goals of urban construction, agricultural production, and ecological protection [9, 10]? Therefore, it is necessary to scientifically identify LUCs, reveal the characteristics of spatial and temporal evolution, and explore the spatial and temporal heterogeneity of the role of their driving factors.

LUCs cut across stages of socio-economic development. The identification, spatial and temporal evolution, and driver research of LUCs have been a topic of great academic interest. There were scholars based on sociology, ecology, economics, and geography perspectives, the comprehensive use of game theory, landscape ecological risk index, land use suitability evaluation, and other methods to identify LUCs. Related research had significant reference value. Our study focused on LUCs caused by changes in land use structure, which were closely linked to land use patterns, so the landscape pattern and ecological risk effect index model constructed based on landscape vulnerability, complexity, and stability were selected to carry out the study to identify the conflict areas and evaluate the intensity of conflicts (Fig. 1). The logical implication of the research was that when the land elements were disturbed by the external environment, they caused pressure on their ecosystem. The difference in ecosystem structure and spatial distribution characteristics jointly determined the vulnerability of their ecosystems. Under pressure and its vulnerability, the stability of land elements decreases, and finally, the phenomenon of LUCs appears. The primary conceptual framework of logical implication was founded upon the dynamic process of LUCs, and it provided a theoretical description of the geographical and temporal patterns of conflicts [11]. Researching the spatial and temporal evolution characteristics of LUCs can help to comprehensively grasp the dynamic changes in regional socio-economic development conditions [12]. Existing studies have revealed the spatiotemporal evolution characteristics of LUCs through land use type conversion [13], the process of dynamic changes in land landscape patterns [14], land suitability evaluation, and integrated land use intensity [15]. However, it is regrettable that the current research has a short time series, making it challenging to accurately capture the long-term trends and dynamics of LUCs. The spatial and temporal evolution process analysis needs more depth and understanding. Therefore, studying the spatial and temporal evolution characteristics of LUCs in long time series under critical time nodes is necessary. When studying the driving factors of LUCs, researchers used various analytical models, such as multilevel linear regression models [16], cross-wavelet methods [17], and decision laboratory analysis [18]. These methods aimed to research the drivers of LUCs at specific points in time or over more extended periods at different scales. However, traditional analytical methods often require more attention to the characteristics of non-stationary change processes in LUCs. It leads to a lack of exploration and exploitation of the spatiotemporal heterogeneity of the driving factors. The Geographically and Temporally Weighted Regression Model (GTWR) incorporated the spatiotemporal variables into the traditional multiple regression model, thus addressing the limitation of insufficient consideration of the spatiotemporal changes in the impacts of the drivers.

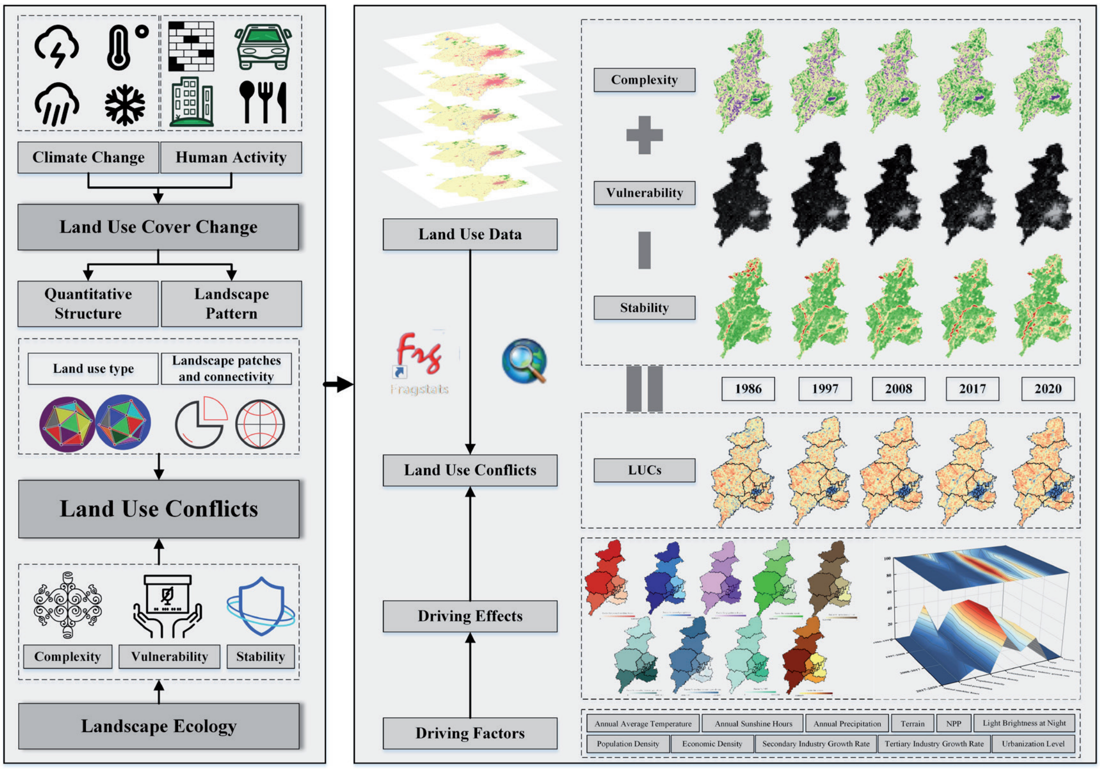

Fig. 1. Logical framework of the study.

The formation mechanisms of LUCs differed across time, as did the temporal imbalances [19]. Therefore, the GTWR model can provide more insights into the scientific rationale for generating LUCs at different stages.

Shenyang is the only megacity in the main grain-producing area of Northeast China [20]. It is also the city with the highest intensity of land development, undertaking multiple tasks of agricultural production, urban development, and ecological protection, and LUCs are occurring. Therefore, it is representative and typical to carry out LUC research with Shenyang City as the study area. This paper mainly addresses the following questions: (1) Under the critical nodes of policies, how was the intensity of LUCs in Shenyang, what were the changing trends, and was there any difference in the spatial pattern? (2) What factors drove LUC, what were the dominant factors, and did they show spatial heterogeneity?

Material and Methods

Study Area

Shenyang City (122°25'9"-123°48'24"E, 41°12'51"-43°02'13"N) is located in the southern part of Northeast China, in the center of Liaoning Province, and is an essential hub for political, economic, cultural, and commercial activities in Northeast China. Shenyang is located in the middle of the Liaohe Plain, connected to the Liaodong Peninsula in the south and the foothills of the Changbai Mountains in the north [21]. The terrain slopes gently from east to west, and the terrain is flat and open, with a temperate, humid continental climate. It is 115 km wide from east to west and 205 km long from north to south, with a total area of 12,860 square kilometers, of which 63% is cultivated land. The region is an essential grain-producing area, and the eastern part is located in the remnants of Changbai Mountain, which bears the critical task of protecting the ecological environment. Shenyang City has ten districts, two counties, and one city under its jurisdiction. Heping District, Shenhe District, Dadong District, Huanggu District, and Tiexi District are located in the core urban area. Sujiatun District, Hunnan District, Shenbei New District, and Yuhong District are located in the suburban area. Liaozhong District, Kangping County, Faku County, and Xinmin City are located in the exurban area (Fig. 2). In 2020, the city's resident population was 9.073 million, with an urban population of 7.668 million, an urbanization rate of about 85%, and a large scale of land development.

Driving Factors

The emergence of LUCs can be attributed to endogenous factors inherent to the natural environment and exogenous factors influenced by human activities. The interconnected confluence of multiple factors collectively affects the alteration of land use structure and types, resulting in LUCs. Natural environmental

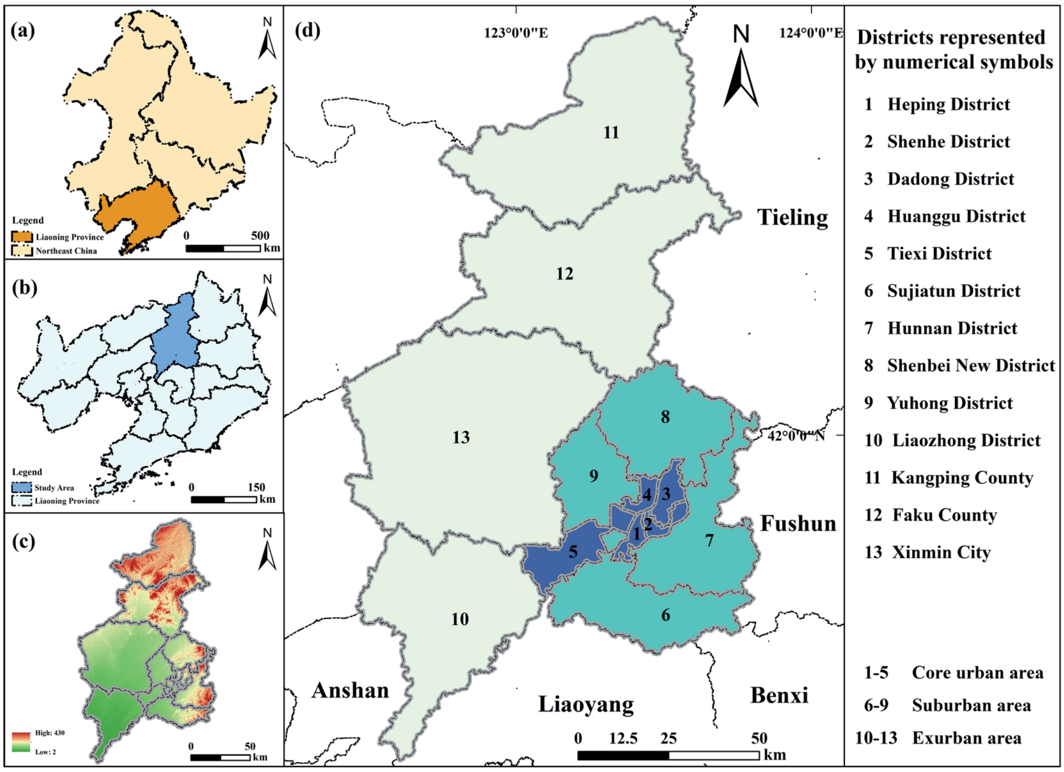

Fig. 2. The geographical location of Shenyang is in Northeast China

factors play a significant role in establishing the primary conditions for LUCs. The topographical feature would affect the direction of change in LUCs. Moreover, various climatic factors such as temperature, precipitation, and sunshine significantly influence urban development, industrial distribution, living conditions, agricultural practices, and agricultural productivity. External variables that contribute to LUCs include social and economic factors. Population density, economic density, urbanization level, the growth rate of the secondary sector, the growth rate of the tertiary industry, and night-time light levels reflect the urban sphere of influence and indirectly reflect the rate of change in land use structure and the intensity of LUCs. Therefore, this study has chosen eleven indicators from the natural and socioeconomic domains to examine and discuss the impact of these factors on LUCs in Shenyang (Table 1).

Data Source

The data used in this study mainly included land use data, socio-economic statistics data, and basic geographic information data. Land use data from 1986 came from Landsat images, and land use data from 1997 to 2020 came from the China annual land cover data set that Wuhan University provided, with an image accuracy of more than 80% that can meet the research requirements (http://doi.org/10.5281/zenodo.4417809). Using ArcGIS, we classified the land use types into cultivated land, forest land, grassland, water bodies, construction land, and unused land to calculate the LUCs each year. The social and economic data mainly came from the statistical data of the Liaoning Provincial Statistical Yearbook and the Shenyang Municipal Statistical Yearbook from 1986 to 2021. Basic geographic information data included temperature, precipitation, sunshine, terrain, NPP, and night light. We got the temperature data from the 1-km monthly mean temperature dataset for China (1901-2021) (https://doi.org/10.11888/Meteoro.tpdc.270961). We got the precipitation data from the 1-km monthly precipitation dataset for China (1901-2021) (https://doi.org/10.5281/zenodo.3185722). The National Tibetan Plateau Scientific Data Center provided these datasets. We also got data on sunshine from meteorological

Table 1. Driving factors of LUCs in the study area.

Indicator type	Specific indicators
Natural and environmental factors	Annual average temperature, annual sunshine hours, annual precipitation, terrain, NPP
Socio-economic factors	Population density, economic density, urbanization level, secondary industry growth rate, tertiary industry growth rate, light brightness at night

weather stations and topographical data from the geospatial data cloud. NPP was obtained from the terrestrial ecosystem monthly Net Primary productivity 1 km Grid data set for China (1985-2015) and the MODIS MOD17A3HGF NPP dataset. Night light data is obtained from a prolonged Artificial Nighttime-light Dataset of China (1984-2020).

Methods

Model for Measuring the Intensity of LUCs

Landscape patterns can reflect LUCs in the spatial structure [16] based on the relevant landscape ecological risk assessment methods and the pressure-vulnerability-stability process of LUCs. In this study, the complexity index, vulnerability index, and stability index were employed to measure the intensity of LUCs.

$$LUCs = C + V - S \quad (1)$$

Where C is the complexity index, V is the vulnerability index, and S is the stability index.

(1) Complexity index (C). This study assessed the complexity of landscape patches using the area-weighted mean patch fractal dimension (AWMPFD), which indicated the intensity of external pressures on landscape patterns [22]. It can effectively characterize the impacts of neighboring landscapes on current land use disturbances. AWMPFD was positively correlated with the complexity of the boundaries of landscape patches. The higher the value of AWMPFD, the more complex the landscape patch boundary and the higher the risk to land resources. The study results were linearly normalized in the range [0, 1] for further measurements.

$$AWMPFD = \sum\sum\left\{\left[\frac{2ln(0.25P_{ij})}{ln(a_{ij})}\right] \times \left(\frac{a_{ij}}{A}\right)\right\} \quad (2)$$

P_{ij} is the patch perimeter, a_{ij} is the patch area, and A is the total landscape area.

(2) Vulnerability index (V). It elucidated the exposure status of land patches. Based on variations in susceptibility among distinct land use categories as risk receptors and in conjunction with the developmental attributes of the study region, this investigation established vulnerability indices for construction land, forest land, grassland, cultivated land, water bodies, and unused land as 1, 2, 3, 4, 5, and 6.

$$V_i = \sum_{i=1}^{n} f_i \times \frac{a_i}{Z} \quad (3)$$

V_i is the vulnerability index of the i th land use landscape type, f_i is the vulnerability index of different landscape types, a_i is the area of the i th land use type within the spatial unit, and Z is the total area of the spatial unit.

(3) Stability index (S). Patch density is a quantitative measure of the degree of landscape fragmentation in a given area. Higher densities indicated more significant fragmentation within a given spatial unit and reduced regional biodiversity and cohesion. It implied decreased stability and increased the likelihood of ecological hazards to land resources. Therefore, patch density can indicate the stability of regional landscapes [23], providing valuable information for understanding the threats they may face. Finally, each spatial unit was standardized over a range of [0, 1].

$$S = 1 - \frac{PD - PD_{min}}{PD_{max} - PD_{min}} \quad (4)$$

$$PD = \frac{n_i}{A} \quad (5)$$

PD is the patch density index within a spatial landscape unit, PD_{max} and PD_{min} represent the maximum and minimum values of the patch density index of the spatial landscape units, and n_i is the number of patches in the i th land use type within the spatial unit.

The landscape index was calculated using the moving window method, with a research granularity of 90 meters and a window size of 3 km * 3 km.

Geographically and Temporally Weighted Regression Model

The GTWR model expanded the GWR model that couples time to space factors, constituting the space-temporal three-dimensional coordinates. It accurately represented the temporal changes in variable data [24]. In the present study, the model considered the non-stationary characteristics of both time and space, enabling an accurate estimation of the factor parameter.

$$Y_m = \beta_0(x_m, y_m, t_m) + \partial_n \beta_n(x_m, y_m, t_m) X_{mn} + \theta_m \quad (6)$$

Where Y_m, is the response variable on the study unit m; x_m, y_m, t_m is the longitude, latitude, and the time coordinate of m; $\beta_0(x_m, y_m, t_m)$ is the regression intercept of m, X_{mn} is the data of the n-th explanatory variable on the study unit m; θ_m is the residual; $\beta_n(x_m, y_m, t_m)$ is the regression coefficient of the n th explanatory variable on the study unit m, which is estimated as

$$\hat{\beta}(x_m, y_m, t_m) = [X^t W(x_m, y_m, t_m) X]^{-1} X^T W(x_m, y_m, t_m) Y \quad (7)$$

Where $\hat{\beta}(x_m, y_m, t_m)$ is the estimated values of $\beta_n(x_m, y_m, t_m)$, X is the matrix of independent variables, X^t is the transposition of the matrix X, Y is the matrix of samples, $W(x_m, y_m, t_m)$ is the spatio-temporal weight matrix, and the spatio-temporal distance between the sample m and n is:

$$d_{mn} = \sqrt{\delta\left[\left(U_i - u_j\right)^2 + \left(y_i - y_j\right)^2 + x\left(t_i - t_j\right)^2\right]} \quad (8)$$

In this study, the Akaike information criterion (AIC) was used for adaptive bandwidth.

Results

Spatio-Temporal Characteristics of LUC Intensity

Regarding the time dimension, there was a notable decline in the magnitude of LUCs in Shenyang over the period spanning from 1986 to 2020, as shown in Fig. 3. The intensity of LUCs in the central cities of Heping, Shenhe, Dadong, Huanggu, and Tiexi has consistently decreased. The intensity of suburban LUCs in Sujiatun, Hunnan, Shenbei, and Yuhong at the beginning of the study was similar to the final results. The intensity of LUCs in the exurban regions of Liaozhong, Kangping, Faku, and Xinmin has experienced a notable increase. With spatial distribution, it can be observed that the intensity of LUCs in Shenyang between 1986 and 2020 was relatively low inside the central urban area, while it exhibited a higher intensity in other regions (Figs. 3, 4). The regions characterized by lower levels of conflict intensity were primarily centered inside the core urban areas, where human activities and urbanization were more active. The stability of construction land in the central urban area of Shenyang presents difficulties with its conversion to other land types, resulting in a low-value area characterized by LUCs. Furthermore, as the urban built-up area continued to expand, there was a concurrent increase in the construction land area [25]. This growth resulted in a decrease in landscape vulnerability and a reduction in the intensity of land use space conflict inside the central urban area. The distribution of high-conflict land use areas within districts and counties was concentrated near towns. The frequent changes in land use around cities contributed to the distinct diffusion effect of LUCs regarding spatial distribution.

In 1986, the average intensity of LUCs in Shenyang was 0.9814, spatially in a clustered distribution. The intensity of conflict in the central city was low, and the intensity of LUCs was lower than average in the research area. However, in Xinmin, Yuhong, Hunnan, and Sujiatun, the conflict intensity was higher and more significant, with values exceeding 1.05. In 1997, the LUC intensity in Shenyang was 0.9411, indicating a decrease compared to the conflict intensity observed in 1986. However, it is essential to note that conflict intensity remained relatively high in Xinmin City, eastern Hunnan District, and east of Sujiatun District. The central city experienced reduced LUC intensity, accompanied by a diffusion trend. In 2008, the mean intensity of LUCs in Shenyang was 0.9521. The spatial distribution had undergone substantial alterations. A notable expansion was observed in the geographical extent of regions characterized by minimal levels of conflict. Moreover, the intensity of LUCs in peripheral districts had escalated. In 2017, the average intensity of LUCs in Shenyang was 0.8661. The spatial pattern analysis revealed that the LUC intensity was relatively low in the city center and the riverside, while other areas had higher levels of LUC intensity. Shenyang is a city with a water shortage, and the high-value area of LUCs was distributed along the river at this stage. In 2020, the intensity of LUCs in Shenyang significantly improved, with an average value of 0.9348. The city center had remained relatively stable, experiencing minimal changes in land use and consequently exhibiting low conflict intensity. However, the conflict intensity in

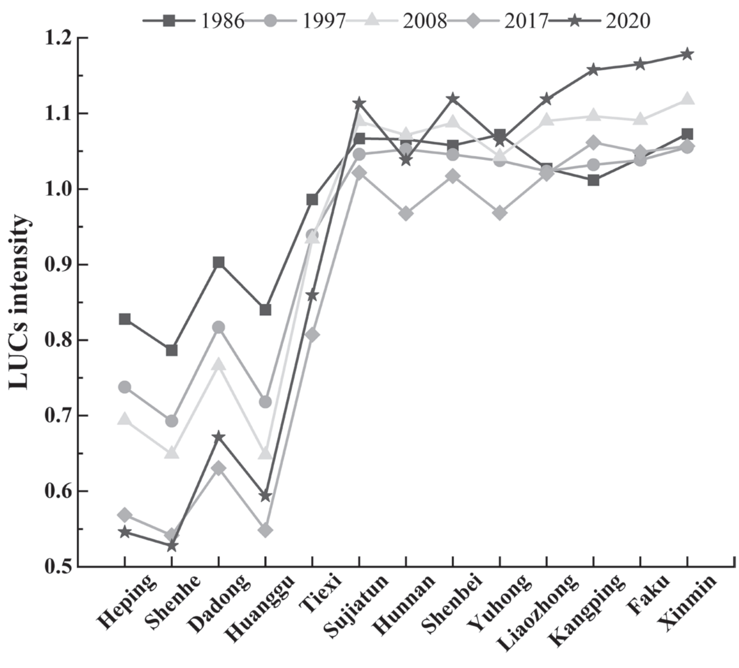

Fig. 3. Time change trend of LUCs intensity from 1986 to 2020.

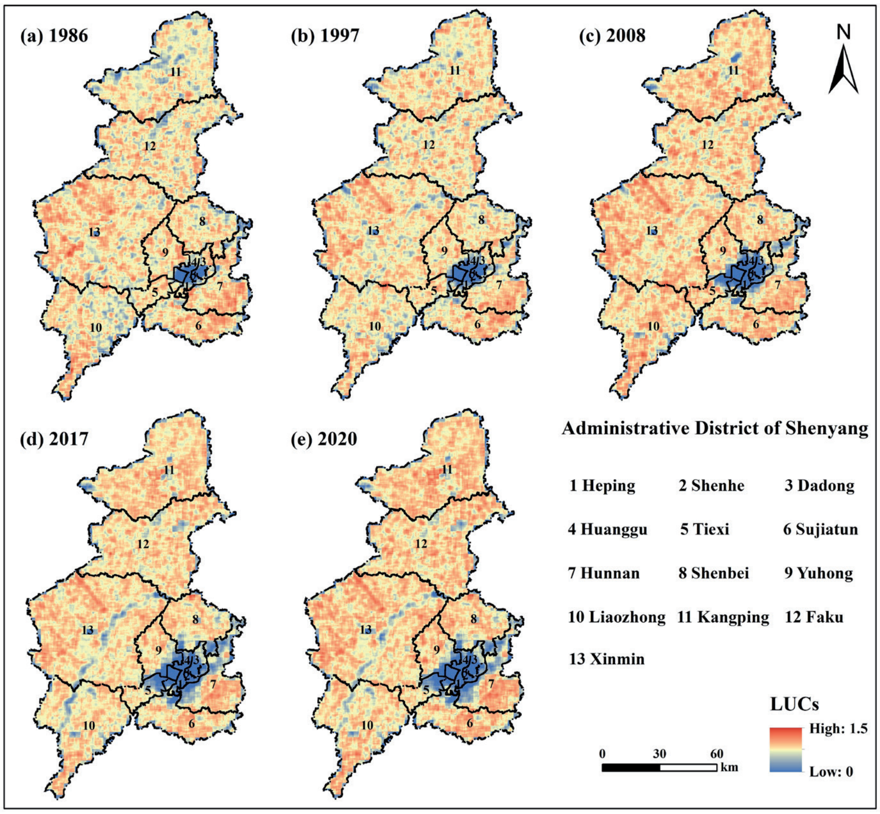

Fig. 4. The spatial distribution of LUCs intensity from 1986 to 2020.

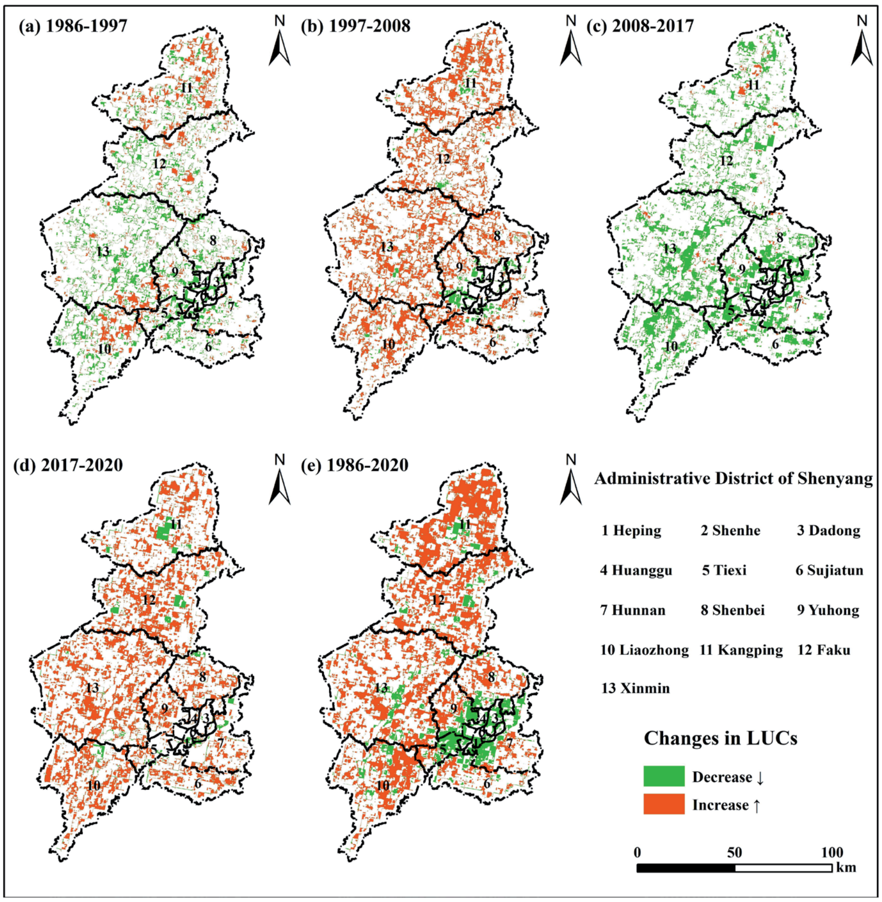

Fig. 5. Spatial pattern changes in LUCs from 1986 to 2020.

Table 2. Global regression results for the GTWR model.

Evaluation indicators	Values
Goodness of fit (R^2)	0.928
Correction (adjust the R^2)	0.913
Akaike information criterion	-124.830
Residuals	0.386

the remaining counties had increased significantly. These areas displayed a spatial pattern with low conflict intensity near rivers and high conflict intensity elsewhere (Fig. 5).

Role Effects of LUC Drivers

Data Inspection and Accuracy Evaluation

Before building the GTWR model, all variables need to be standardized. It is necessary to do a multiple collinearity test on all variables after standardization to avoid spurious regression in the study. The findings indicated that nine indicators exhibit a variance inflation factor below 10. Regarding the adequate number of parameters, the global regression findings (Table 2) showed a goodness of fit (R^2) of 0.928 and an adjusted R^2 of 0.913. The F test was conducted on the model, yielding a significant result ($F = 61.802$, $p = 0.000<0.05$). The results indicated that the GTWR model demonstrates a superior ability to identify the linear association between nine driving indicators and LUCs at the spatial-temporal scale.

Effect Analysis of Driving Factors

The descriptive statistics and spatial distribution of the coefficients of the GTWR model are shown in Table 3 and Fig. 6. Annual sunshine hours, annual precipitation, the growth rate of the secondary industry, and NPP showed significant positive correlations with the intensity of LUCs. Moreover, a higher coefficient corresponded to a more significant driving effect (Table 4). The regression coefficients for the four indicators are $7.41×10^{-5}$, $2.07×10^{-4}$, $5.15×10^{-2}$, $4.37×10^{-2}$, and $1.21×10^{-3}$. Among these coefficients, it is observed that the growth rate of the secondary industry has the most significant positive influence on the intensity of LUCs in Shenyang.

Concerning spatial distribution, the regions exhibiting elevated coefficients of annual sunshine hours were predominantly situated in the exurban areas of Shenyang. Specifically, Kangping, Faku, and Xinmin demonstrate average annual sunshine time coefficients of $1.49×10^{-4}$, $8.61×10^{-5}$, and $8.75×10^{-5}$. Similarly, the areas characterized by higher coefficients of annual precipitation were primarily found in Kangping, Xinmin, and Liaozhong. These regions exhibited average annual precipitation coefficients of $2.36×10^{-4}$, $2.34×10^{-4}$, and $2.48×10^{-4}$.

The impact of climate factors on LUCs in the exurban areas of Shenyang was relatively apparent. Suburban and core urban areas were not significantly affected by climatic factors. The areas exhibiting a high growth coefficient in the secondary industry were primarily concentrated in the core urban area, Hunnan, Sujiatun, and other adjacent suburbs. These locations had an annual average growth rate of over 0.04 in the secondary industry. The NPP coefficient differences among counties were minor, with coefficient values ranging from 0.0011 to 0.0013. The NPP coefficients in eastern Shenyang City, specifically in Shenbei, Hunnan, and Sujiatun, were relatively high.

A notable inverse relationship existed between the intensity of LUCs and various factors, including population density, economic density, urbanization level, growth rate of the tertiary industry, and terrain. Larger coefficients indicate a less significant driving effect. The regression coefficients of the five indicators were $-5.15×10^{-2}$, $-3.08×10^{-6}$, $-2.01×10^{-1}$, and $-6.38×10^{-4}$. The higher the population density, economic density, urbanization level, and growth rate of the tertiary

Table 3. Global fit coefficients for the GTWR model.

Driving factors	Average	Minimum	Maximum
Annual sunshine hours	$7.41×10^{-5}$	$5.63×10^{-5}$	$1.49×10^{-4}$
Annual precipitation	$2.07×10^{-4}$	$1.85×10^{-4}$	$2.48×10^{-4}$
Population density	$-5.15×10^{-2}$	$-5.61×10^{-2}$	$-4.75×10^{-2}$
Economic density	$-3.08×10^{-6}$	$-3.12×10^{-6}$	$-3.01×10^{-6}$
Urbanization level	$-2.01×10^{-1}$	$-2.07×10^{-1}$	$-1.92×10^{-1}$
Secondary industry growth rate	$4.37×10^{-2}$	$1.91×10^{-2}$	$5.29×10^{-2}$
Tertiary industry growth rate	$-2.54×10^{-2}$	$-4.27×10^{-2}$	$1.35×10^{-2}$
NPP	$1.21×10^{-3}$	$1.12×10^{-3}$	$1.27×10^{-3}$
Terrain	$-6.38×10^{-4}$	$-6.98×10^{-4}$	$-5.42×10^{-4}$

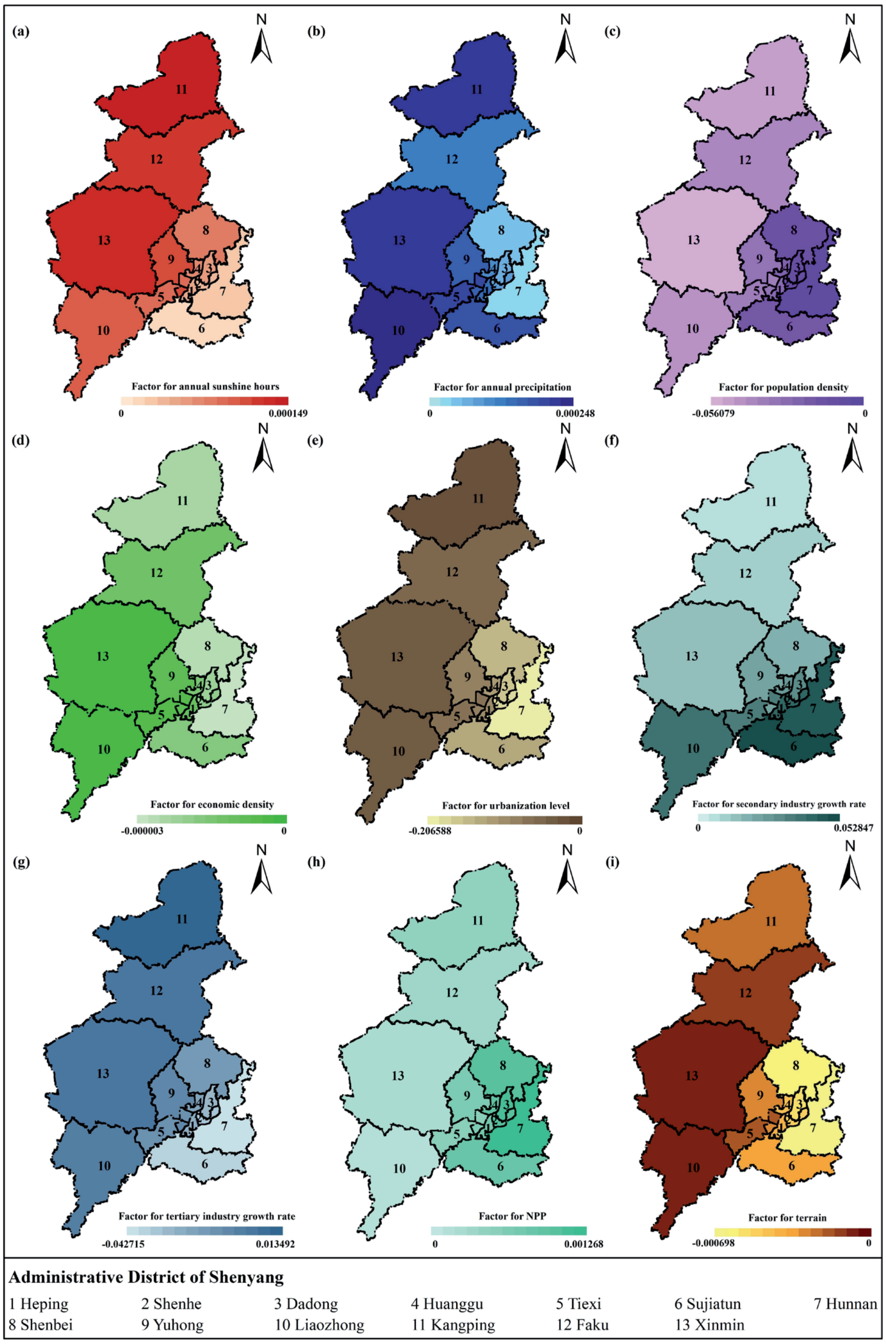

Fig. 6. Spatial distribution of the local regression coefficients of the GTWR model

industry, the higher the regional urban development level, the more stable the construction land, the lower the probability of transforming into other land types, and the lower the LUC intensity. The higher absolute value of the coefficients in the spatial pattern analysis indicated that the above factors significantly impacted Shenyang's core urban and suburban areas. The eastern part of Shenyang, notably the Changbai Mountain, exhibited high vegetation coverage and a larger ecological land area. Nevertheless, the contradiction between urban development and ecological protection was prominent in the suburban areas, which were crucial for urbanization development, and the possibility of LUCs was high.

The Importance of the Driving Factors Changes

The study evaluated the significance of each driving factor in the following periods: 1986-1997, 1997-2008, 2008-2017, and 2017-2020 (Table 4, Fig. 7), to clarify the principal driving factors behind LUCs. The results showed that social and economic factors caused LUCs in Shenyang throughout the study period. From 1986 to 1997, population density had the most influence over other factors, placing it at the top of the list. From 1997 to 2020, the rate of urbanization had a decisive influence on the LUCs. Meanwhile, the results indicated that

Table 4. Importance of each driving factor for different periods from 1986 to 2020.

Importance of each driving factor (%)	1986-1997	1997-2008	2008-2017	2017-2020
Annual sunshine hours	0.0308	0.0090	0.0140	0.0235
Annual precipitation	0.0617	0.0605	0.0532	0.0262
Population density	37.3933	11.3818	2.5949	10.3139
Economic density	0.0027	0.0003	0.0003	0.0002
Urbanization level	30.9032	52.7098	57.1783	39.6701
Secondary industry growth rate	19.1559	8.1259	7.8853	18.3612
Tertiary industry growth rate	11.8328	27.5012	31.9846	31.2179
NPP	0.5052	0.1233	0.1753	0.2380
Terrain	0.1146	0.0881	0.1142	0.1491

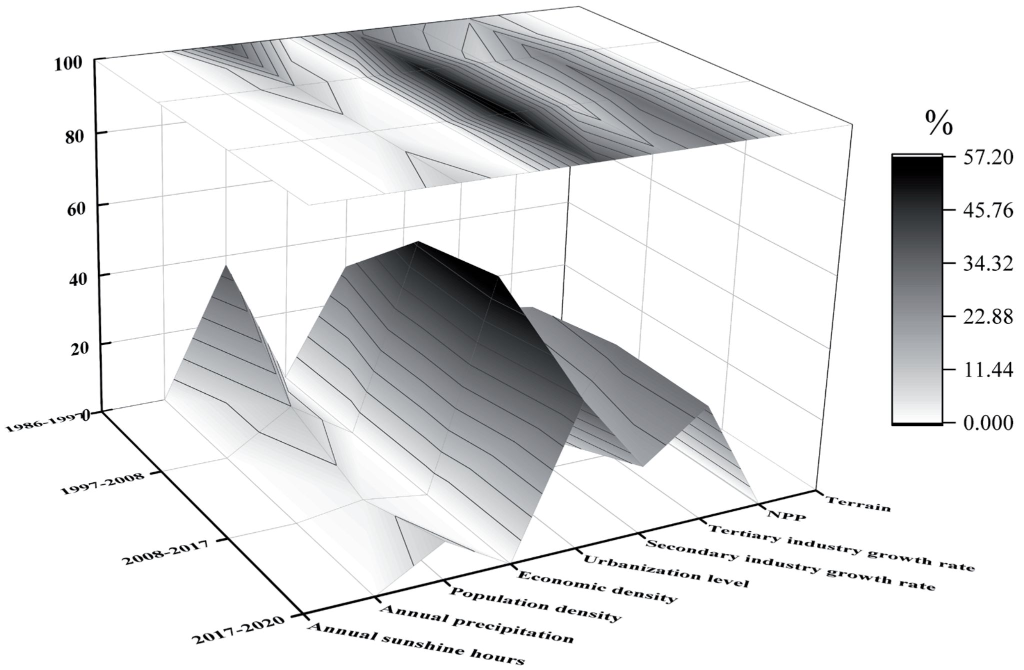

Fig. 7. The importance of LUCs driving factors over time.

the impact of natural environmental factors on LUCs was insignificant. Specifically, the significance of natural and environmental factors, such as annual sunshine hours, annual precipitation, NPP, and terrain variables, was low at all stages, less than 1%.

Population density was the primary factor driving LUCs in Shenyang City from 1986 to 1997, accounting for 37.39% of the total importance. From 1997 to 2020, LUCs were mainly caused by the urbanization level, accounting for 52.71%, 57.18%, and 39.67% of the total importance. In Shenyang, the urbanization rate played a significant role in LUCs, contributing more than 30% of the total significance in all the stages. Economic density was not an important factor driving LUCs in Shenyang at all stages, as seen by its low importance. From 1986 to 2020, the impact of the secondary industry growth rate on LUCs fluctuated, first declining and then increasing, and the strength of action at the start and finish of the research period was the same. The growth rate of the tertiary industry was increasingly driving LUCs, which increased to 31.22% from 11.83%.

Discussion

Changes in LUCs Are Related to the State of Social Development in Shenyang

From 1986 to 1997, Shenyang entered the stage of rapid urbanization and industrialization, actively expanding its boundaries and converting cultivated land into other land types. Consequently, LUCs became more intense. From 1997 to 2008, the Shenyang municipal administration developed comprehensive land use planning and urban and rural planning papers, concentrating on the urban growth and development of Hunnan, Shenbei, Sujiatun, and other suburban areas. Maximize location and environmental optimization's potential benefits, attracting capital investments. During this period, Kangping, Faku, Xinmin, and Liaozhong, along with other exurban areas, experienced a notable acceleration in their economic development. The original rural populace has begun migrating towards urban areas. Suburban areas have emerged as significant points of LUCs in areas of high value. From 2008 to 2017, China vigorously carried out land use control and the economic and intensive utilization of land, strictly controlled the structural conversion and disorderly expansion of land use, and effectively mitigated regional LUCs. From 2017 to 2020, China began to implement a strategy for revitalizing the northeastern region, focusing on optimizing the industrial structure and layout of the northeastern region. Consequently, the land use structure in Shenyang district has undergone noticeable transformations, resulting in increased LUCs.

In general, the spatial and temporal evolution characteristics of LUCs in Shenyang were closely related to the state of urban socio-economic development. Throughout the research period, Shenyang has always advocated the development mode of saving and intensive land use. The factor agglomeration capacity of the core urban area was enhanced, the land use structure was mainly transformed from other land types to construction land, the landscape stability was enhanced, and the intensity of LUCs was weakened. The suburban areas gradually became the gathering place of industry and high-tech industry, and a large amount of agricultural land was converted to construction land for industrial development in the early period, and there was a significant downward trend in LUCs. After 2017, the phenomenon of illegally occupying agricultural land for non-agricultural activities was rectified, the strategy of building an ecological civilization was put forward, and the protection of agricultural and ecological land increased. Some of the more stable construction land was converted to agricultural and ecological land, and the intensity of LUCs increased. Distant suburban districts were mainly engaged in agricultural production. Still, their county centers continued to promote socio-economic development, expanding the size of their towns and cities, and LUCs were apparent.

What are the Reasons for Differences in the Effects of Driving Factors?

Climatic factors had a greater intensity of action in exurban areas. The exurban areas were dominated by agricultural production. Climate change can alter regional water circulation and the overall environment, thereby affecting the crop farming system, food production potential, and land use types and patterns, eventually leading to LUCs. Socio-economic factors have a more pronounced effect on the core and suburban areas. Shenyang is a famous old industrial base in China. The core areas, particularly the southern suburbs, were primarily focused on industrial activities, resulting in high building density and intensive land use. Under the background of promoting economic and intensive land use in Shenyang city, the industrial land areas were continuously compressed, the intensity of land use was increased, the land use types were transformed, and the LUCs were fierce.

From 1986 to 1997, urban building was in its early phases. The population shift brought about by the movement of excess labor from rural areas would inevitably propel the growth of housing, business, and transportation. As a result, population density influenced the direction of regional development and industrial layout, promoted the change of the land use structure, and resulted in conflict between different land use types. From 1997 to 2020, urbanization entered a stage of coordinated development, with the urbanization rate becoming an essential figure for judging the urban development process. The higher the urbanization rate, the better the level and quality of urban development, the more substantial cities' traction and aggregation ability, the relatively faster the land use structure and rate of change, and the greater the apparent impact on LUCs. However, too high an urbanization rate may lead to too rapid an expansion of cities and problems such as traffic congestion, environmental pollution, and resource shortages [26], affecting the development of cities and the quality of life of the people. Therefore, the driving factors affecting LUCs in the later stage were gradually diversified and tended to be balanced.

Exploration of Ways to Mitigate LUCs

Shenyang is the only megacity in Northeast China with a high degree of urbanization and a well-developed economy. In addition, it is an essential nodal city for food production and ecological protection. The contradiction between urban construction, agricultural production, and ecological protection significantly affects the evolution of the regional LUC pattern. The research results showed that the urbanization level, the growth rate of tertiary industry, the growth rate of secondary industry, and population density were the core factors driving the evolution of LUCs in Shenyang. Therefore, strengthening land use control and promoting industrial transformation and population mobility may effectively mitigate LUCs.

At first, the government must compile the territorial spatial plans scientifically and enhance the efficacy of planning constraints. The division of urban, agricultural, and ecological space should be conducted rationally based on evaluating resource and environmental carrying capacity and the suitability of territorial space development. It should prevent significant spatial changes in the positioning of cultivated land, enhance the spatial appropriateness of cultivated land use, implement stringent regulations on the construction land index, curb the uncontrolled expansion of urban areas, and enhance the effectiveness of urban agglomeration.

In addition, the government must optimize the layout of the industrial structure. The growth rate of the secondary industry, the growth rate of the tertiary industry, and economic density are closely related to the distribution of the industrial structure. Shenyang city has an excellent industrial foundation, and in the future, it should do an excellent job of upgrading and transforming traditional industries, increasing the remediation of low utility land, strengthening the scale of saving and intensifying land use, building industrial parks and clusters, and striving to improve the output value and efficiency of industries.

Finally, in the northwestern region of Shenyang, there is a significant issue of land desertification. In contrast, in the southeastern part, there is a notable problem of soil erosion in the low mountain hills. As a result, a proactive effort is to promote comprehensive land improvement and ecological restoration projects, restore farmland on steep slopes to their natural states of woods and grasslands, construct shelterbelts, and establish measures for preserving and managing small-scale water resources in these areas. The objective is to address the inherent conflict between protecting the environment and developing the economy, facilitate the alignment of crucial ecological resources with their corresponding geographical areas, give full play to the regional ecological conservation function, and build a solid regional ecological security barrier.

Limitations of the Research

Our study mainly explored the evolution of LUCs from the perspective of the interaction between ecology and geography. However, it does not consider its social attributes or explore the influence of human social behavior on LUCs. In the future, we will further reveal the characteristics and driving mechanisms of LUCs from a sociological perspective.

Conclusions

This paper utilized a combination of remote sensing, meteorology, land use, and social economy data to analyze the intensity of LUCs in Shenyang City from 1986 to 2020. The study used the complexity index, vulnerability index, and stability index to measure the intensity of LUCs and showed how the rules for LUCs have changed over time. The research used the GTWR model to explore the leading causes of LUCs at different times.

The main conclusions of this study can be drawn as follows:

(1) The measurement model constructed through the landscape pattern index can effectively reflect the spatial and temporal evolution of LUCs.

(2) The LUC value of Shenyang showed a decreasing trend in general, with its value decreasing from 0.9814 at the beginning of the study to 0.9348 at the end. Regions with higher conflict values were mainly distributed in densely populated and economically developed areas around the city. Regions with lower conflict values were concentrated in the core urban area, primarily built-up land.

(3) Socio-economic factors were crucial influences on LUCs in Shenyang. The overall performance in order from high to low was as follows: urbanization level > population density > secondary industry growth rate > tertiary industry growth rate > NPP > terrain > annual precipitation > annual sunshine hours > economic density. Natural factors mainly drove LUCs in exurban areas. The importance of driving factors for LUCs in Shenyang varied in different periods. From 1986 to 1997, population density was the core element driving LUCs. From 1997 to 2020, urbanization level was the core element driving LUCs.

(4) The above findings showed that changes in land use structure due to population density, urbanization level, and industrial restructuring were the key factors leading to changes in LUCs in Shenyang. Therefore, full consideration should be given to balancing the triple spaces of agricultural production, urban development, and ecological protection. In the future, the government can use planning tools to effectively control urban expansion, guide the orderly movement of the population, enhance the degree of industrial agglomeration, and aim to maximize the overall benefits of the land use system, rationally distribute land resources, and mitigate LUCs.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 41971247), and the Key Construction Discipline Project of the Social Science Foundation of Liaoning Province in 2023 (Grant no. L23ZD027).

Conflict of Interest

The authors declare no conflict of interest.

References

1. ZHENG W., GUO B., SU H., LIU Z.J. Study on multi-scenarios regulating strategy of land use conflict in urban agglomerations under the perspective of “three-zone space”: a case study of Harbin-Changchun urban agglomerations, China. Frontiers in Environmental Science, **11**, 1288933, **2024**.

2. WANG C., WANG H.W., WU J.H., HE X., LUO K., YI S.Y. Identifying and warning against spatial conflicts of land use from an ecological environment perspective: A case study of the Ili River Valley, China. Journal of Environmental Management, **351**, 119757, **2024**.
3. YANG Z., ZHU H.X., ZHANG X.L., OU X.J. Examining the Spatiotemporal Dynamics and Determinants of Land Urbanization in Prefecture-level Cities, China. Chinese Geographical Science, **34**, 19, **2024**.
4. ZOU L.L., LIU Y.S., WANG J.Y., YANG Y.Y., WANG Y.S. Land use conflict identification and sustainable development scenario simulation on China's southeast coast. Journal of Cleaner Production, **238**, 117899, **2019**.
5. ZHOU Y., DONG J.W., XIAO X.M., LIU R.G., ZOU Z.H., ZHAO G.S., GE Q.S. Continuous monitoring of lake dynamics on the Mongolian Plateau using all available Landsat imagery and Google Earth Engine. Science of the Total Environment, **689**, 366, **2019**.
6. QIN Y.W., XIAO X.M., DONG J.W., ZHANG Y., WU X.C., SHIMABUKURO Y., ARAI E., BIRADAR C., WANG J., ZOU Z.H., LIU F., SHI Z., DOUGHTY R., MOORE B. Improved estimates of forest cover and loss in the Brazilian Amazon in 2000-2017. Nature Sustainability, **2**, 764, **2019**.
7. CHEN X.H., WU S.Q., WU J. Characteristics and formation mechanism of Land use conflicts in northern Anhui: A Case study of Funan county. Heliyon, **10** (1), e22923, **2024**.
8. CAI D.R., HU J., JIANG H.T., AI F.Y., BAI T.T. Research on the relationship between defense technology innovation and high-quality economic development: Gray correlation analysis based on panel data. Managerial and Decision Economics, **44** (7), 3867, **2023**.
9. LI S.N., ZHAO X.Q., PU J.W., MIAO P.P., WANG Q., TAN K. Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. Land Use Policy, **100**, 104940, **2020**.
10. QU Y.B., WANG S.L., TIAN Y.Y., JIANG G.H., ZHOU T., MENG L. Territorial spatial planning for regional high-quality development-An analytical framework for the identification, mediation and transmission of potential land utilization conflicts in the Yellow River Delta. Land Use Policy, **125**, 106462, **2023**.
11. MO J.X., SUN P.L., SHEN D.D., LI N., ZHANG J.Y., WANG K. The dynamic patterns and driving factors of land use conflict in the Yellow River basin of China. Environmental Science and Pollution Research, **30**, 108649, **2023**.
12. XIE Q., LU M. Measures of spatial and demographic disparities in access to urban green space in Harbin, China. Complexity, **6**, 8832343, **2020**.
13. JIANG S., MENG J.J., ZHU L.K., CHENG H.R. Spatial-temporal pattern of land use conflict in China and its multilevel driving mechanisms. Science of the Total Environment, **801**, 149697, **2021**.
14. MO J.X., SUN P.L., SHEN D.D., LI N., ZHANG J.Y., WANG K. Simulation analysis of land-use spatial conflict in a geopark based on the GMOP-Markov-PLUS model: A case study of Yimengshan Geopark, China. **Land**, 12, 1291, **2023**.
15. BAO W.K., YANG Y.Y., ZOU L.L. How to reconcile land use conflicts in mega urban agglomeration? A scenario-based study in the Beijing-Tianjin-Hebei region, China. Journal of Environmental Management, **296**, 113168, **2021**.
16. JIANG S., MENG J.J., ZHU L.K. Spatial and temporal analyses of potential land use conflict under the constraints of water resources in the middle reaches of the Heihe River. Land Use Policy, **97**, 104773, **2021**.
17. WANG Y., JIANG Y.T., LI W.Y., DONG S.Z., GAO C. Determinants of land use conflicts with the method of cross-wavelet analysis: Role of natural resources and human activities in spatial-temporal evolution. Journal of Cleaner Production, **429**, 139498, **2023**.
18. CIESLAK I. Identification of areas exposed to land use conflict with the use of multiple-criteria decision-making methods. Land Use Policy, **89**, 104225, **2019**.
19. LIU X.P., ZHANG Z., LI M.X., FU Y.H., HUI Y. Spatial conflict simulation of land-use based on human-land-landscape elements intercoordination: a case study in Tianjin, China. Environmental Monitoring and Assessment, **194**, 317, **2022**.
20. SUI H.J., SONG G., LIU W.Y., ZHANG Y.X., SU R.Q., WANG Q.X., REN G.F., MI Y.Q. Spatiotemporal variation of cultivated land ecosystem stability in typical regions of Lower Liaohe Plain China based on stress- buffer-response. Science of the Total Environment, **858**, 160213, **2023**.
21. YANG G., FU Y.P., YAN M.H., ZHANG J. Exploring the distribution of energy consumption in a northeast Chinese city based on local climate zone scheme: Shenyang city as a case study. Energy Exploration & Exploration, **38** (5), 2079, **2020**.
22. XIAO P.N., XU J., ZHAO C. Conflict identification and zoning optimization of "production-living-ecological" space. International Journal of Environmental Research and Public Health, **19**, 7990, **2022**.
23. ZUO Q., ZHOU Y., WANG L., LI Q., LI J.Y. Impacts of future land use changes on land use conflicts based on multiple scenarios in the central mountain region, China. Ecological Indicators, **137**, 108743, **2022**.
24. REN Y.F., FANG C.L., LI G.D. Spatiotemporal characteristics and influential factors of eco-efficiency in Chinese prefecture-level cities: A spatial panel econometric analysis. Journal of Cleaner Production, **260**, 120787, **2020**.
25. JING W.L., YU K.H.,WU L., LUO P.P. Potential land use conflict identification based on improved multi-objective suitability evaluation. Remote Sensing, **13**, 2416, **2021**.
26. XIAO Y., ZHONG J.L., WANG J., ZHANG L.Y., QIAN X.M., LIU W., HUANG H. Exploring the Coupling Coordination Relationship of Urban Resilience System in Ecologically Fragile Areas: Case Study of the Loess Plateau in China. Land, **12** (11), 1997, **2023**.