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Impact of Typical Land Use Expansion Induced by Ecological Restoration and Protection Projects on Landscape Patterns

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Abstract: Land use and land cover (LULC) changes driven by ecological restoration and protection projects play a pivotal role in reshaping landscape patterns. However, the specific impacts of these projects on landscape structure remain understudied. In this research, we applied geographically weighted regression (GWR) to analyze the spatial relationships between typical land use expansion and landscape pattern characteristics in the Lesser Khingan Mountains–Sanjiang Plain region between 2017 and 2022. Our results indicate three key findings: (1) Significant spatial heterogeneity exists in the relationship between landscape patterns and land use expansion, which varies across geographic locations; (2) Ecological restoration projects generally reduce fragmentation, dominance, and heterogeneity while enhancing connectivity, particularly in forest and farmland regions. However, excessive land use expansion in certain areas may reverse these positive effects; (3) Landscape complexity increases in high-altitude mountainous regions due to land use expansion but decreases in plains, particularly in forest-to-farmland conversions. These findings provide new insights into how landscape patterns respond to ecological restoration efforts and offer actionable guidance for improving future land use planning and policy decisions. Our study highlights the need to consider local geomorphological factors when designing ecological projects, ensuring that restoration efforts align with regional landscape dynamics to maintain landscape integrity.

Keywords: land use expansion; landscape pattern; ecological restoration and protection projects; geographically weighted regression; spatial heterogeneity

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1. Introduction

The ecological phenomena of land use and land cover (LULC) changes have become increasingly frequent due to global climate change and urban expansion [1,2]. These changes are often driven by the interplay of complex factors, including climate change, human activities, habitat protection, and regional policies [3,4], with policy initiatives related to ecological restoration and protection projects exerting a significant influence on land use expansion in certain regions. As an essential aspect of studying the impacts of human activities on the earth's surface systems and global changes [5], land use change has garnered significant attention against the backdrop of global environmental changes and ecosystem degradation [6]. It is often used as a link for studying the interactions between socioeconomic activities and natural ecological processes [7]. Currently, the research frontier in this field focuses on the integrated simulation and comprehensive study of human–environment coupled systems. Globally, projects like the Global Land Project (GLP) have been initiated [8]. Countries have started to emphasize land use changes and their driving factors in decision making for protected-area construction and ecological projects [9,10]. This emphasis is primarily reflected in changes to regional landscape structures, such as fragmentation, connectivity, and diversity [1,11]. The landscape transformations caused by LULC changes also alter the ecological functions within ecosystems [12,13], leading to changes in habitat quality and ecosystem services [14], which further directly or indirectly

impact human society [15,16]. Landscape patterns are often represented by calculating characteristics like fragmentation, connectivity, and heterogeneity. The changes in land types driven by various ecological projects cause temporal and spatial dynamics in landscape configurations [17]. The influence of factors such as policies leads to directional trends in these changes, resulting in differences in landscape pattern characteristics [18]. At present, although studies in the environmental field have already conducted spatiotemporal analyses of landscape pattern heterogeneity, most of these studies focus on regional environmental quality differentiation and driver analysis [19]. However, there remains a significant research gap in the study of landscape heterogeneity within the ecological field, especially concerning land use conversions. Similarly, regarding the effectiveness of ecological projects, most landscape studies have centered on quantifying ecosystem services (ESs) at the landscape scale following the restoration of single ecosystems; for example, evaluations of ecosystem services at different scales under forest restoration projects [20–22]. However, there research is still lacking on the effects of comprehensive ecological restoration projects on landscape patterns. Particularly, the analysis of landscape pattern evolution influenced by typical land type expansions is insufficient and requires further study. This paper seeks to address this research gap by studying landscape heterogeneity under ecological restoration projects and by exploring the driving factors and general trends of landscape pattern changes.

At the regional scale, LULC change analysis mainly focuses on the expansion and conversion of typical land use types within an area. From a technical perspective, calculating and analyzing the expansion and conversion of typical land types within a region are crucial for assessing temporal and spatial changes and habitat quality. For example, Bhatta quantified the area expansion of urban land types using remote sensing images and land use data to describe the dynamics and trends of urban sprawl in assessing urban development health and sustainability [23–25]. Assefa and Zhu used the expansion of wetland land types to evaluate habitat quality improvement projects [26,27]. Liu combined cellular automata models with landscape expansion indices to simulate the expansion of typical land types under various scenarios, aiming to better understand their evolutionary processes [28,29]. These studies analyzed the expansion of specific land use types to obtain information on regional temporal and spatial dynamics and conducted correlation analyses between land type conversion and landscape pattern evolution. This is essential for evaluating ecological restoration and protection projects such as ecological restoration and habitat protection [30,31]. The analysis of typical land use expansion forms the foundation for numerous ecological engineering projects and policy planning decisions, necessitating the proposal of corresponding quantitative indicators. Currently, landscape indicators, such as the Landscape Expansion Index (LEI), have been developed to define urban expansion [32]. However, the LEI indicator is primarily designed based on the characteristics of urban planning and is aimed at analyzing the direct impacts of urbanization on ecosystems and the associated changes in landscape patterns. Most of the current studies on this topic focus on small-scale landscape simulations driven by urbanization, [33–35], which may not fully apply to regions dominated by farmland and forestland. Nevertheless, applying the principles of the LEI to quantify landscape changes in regions dominated by farmland and forestland is still feasible. Based on the natural resource characteristics of the study area, we modified the LEI indicator to better quantify landscape expansion trends in regions where farmland and forestland are the typical land use types, facilitating further analysis of the dynamic changes in these land types [36,37]. Building on this, our study introduces the Agricultural–Forest Landscape Expansion Index (AFEI) and the Forest–Agricultural Landscape Expansion Index (FAEI). The advantage of these two indicators is their ability to quantify the spatiotemporal dynamics of landscape patterns across multiple time scales, making them particularly suitable for measuring land use expansion changes and landscape structure dynamics in regions dominated by farmland and forestland [38,39]. The quantification of these indicators is crucial for monitoring ecological engineering projects and for assessing land use development. These two landscape indicators are designed to

analyze the expansion of farmland and forestland under ecological restoration and protection policies, allowing for the calculation of the transformation of and changes to these typical land use types at the landscape scale. The introduction of these indicators facilitates the quantification of spatial expansion results for typical land use types and supports spatial autocorrelation analysis, which is crucial for understanding the heterogeneity in the relationship between landscape patterns and typical land use.

This paper conducts a macro-scale spatial correlation analysis based on two critical evaluation elements: typical land type conversion expansion and landscape pattern changes. We focused on the spatial autocorrelation of regional changes and the spatial heterogeneity relationship between these two elements. The study area is the Lesser Khingan Mountains–Sanjiang Plain region in Heilongjiang Province in northeastern China. Over the past two decades, several ecological restoration and protection projects have been implemented in this area, which have significantly impacted the local natural landscape and ecosystems [40–42]. Concurrently, targeted local economic development policies have led to significant spatial clustering and heterogeneity in typical land type changes [43,44]. To describe this situation, we employed spatial autocorrelation analysis to identify hotspots of typical land type conversions, using Moran's I for comprehensive evaluation and spatial representation [45]. To reveal the spatial correlation between these changes and landscape pattern evolution, we employed regression-based model estimation [46]. Regression models are often used to study the relationships between dependent and independent variables, such as ordinary least squares (OLS) linear models [47] and spatial general linear models (GLMs) [48]. However, traditional multiple regression models are more suitable for global regional simulations and less effective in considering geographical spatial differences under economic development and policy guidance. They cannot adequately assess the spatial position impacts among different observation units under spatial heterogeneity [49]. Given the significant spatial differences in typical land type changes in our study area due to ecological project implementation, we adopted the geographically weighted regression (GWR) model. The GWR model, proposed by Fotheringham and Brunsdon in 1998, addresses spatial heterogeneity issues by allowing regression coefficients to vary with spatial location for more accurate spatial regression analysis [50]. GWR is well suited for fitting studies of spatial heterogeneity in ecological and economic fields, such as urban expansion [51,52], and often outperforms traditional regression models like GLMs and multiple linear regression (MLR). For instance, Zhao used logistic regression and GWR models to simulate and compare urban expansion in several adjacent border cities in Texas, revealing the complexity and interrelationships between land use changes and their driving factors [53]. Dong analyzed the static polycentricity of urban spatial structures in Tianjin, China, using the GWR model, revealing its spatial relationship with the local commuting distribution [54]. Yang used the Landscape Expansion Index and the multi-scale GWR (MGWR) model to reveal how urban economic development has influenced construction land expansion patterns in the Yellow River Basin [18]. The use of the GWR method for spatial heterogeneity analysis helps address the research gap in the study of landscape pattern responses. This method allows us to analyze the landscape modification ability resulting from typical land type expansions under project implementation. It also provides a new perspective for identifying how typical land use expansions influence landscape pattern changes under landscape heterogeneity. This highlights the significance of land use planning and geomorphological analysis in ecological restoration projects.

Our primary objective is to demonstrate the following: (1) The expansion of typical land use types, such as farmland and forest, driven by ecological restoration and protection projects significantly influences changes in local landscape pattern characteristics; (2) The observed spatial heterogeneity in the correlation between landscape pattern evolution and typical land use expansions is a direct result of this influence. Our findings highlight the critical role of these typical land types in the implementation of ecological restoration and protection projects, providing valuable scientific evidence and theoretical support for the

planning of future ecological restoration initiatives and the formulation of sustainable land development policies.

2. Materials and Methods

2.1. Geographical Setting

The Lesser Khingan Mountains–Sanjiang Plain area (127°37′22.86″ E—135°5′55.28″ E, 44°95′20.43″ N—49°26′16.22″ N) is in the eastern Heilongjiang Province, covering 21,392 km^2. It includes six municipal regions and encompasses all typical ecosystems of Heilongjiang Province, as shown in Figure 1. The region's main geomorphological features are the Lesser Khingan Mountains in the west, the Wanda Mountains in the south, and the Sanjiang Plain in the east. Dominant land uses are forests and farmland [55]. The climate is temperate humid to semi-humid continental monsoon, with annual temperatures of 1.4–3.6 °C and precipitation of 537.8–810.9 mm. In response to ecological issues, national projects like the Natural Forest Protection Project in 2000 and the 2016 ban on commercial logging of natural forests were implemented. In 2018, the third batch of pilot projects on the Multiple Ecosystem Integration Project was launched [56].

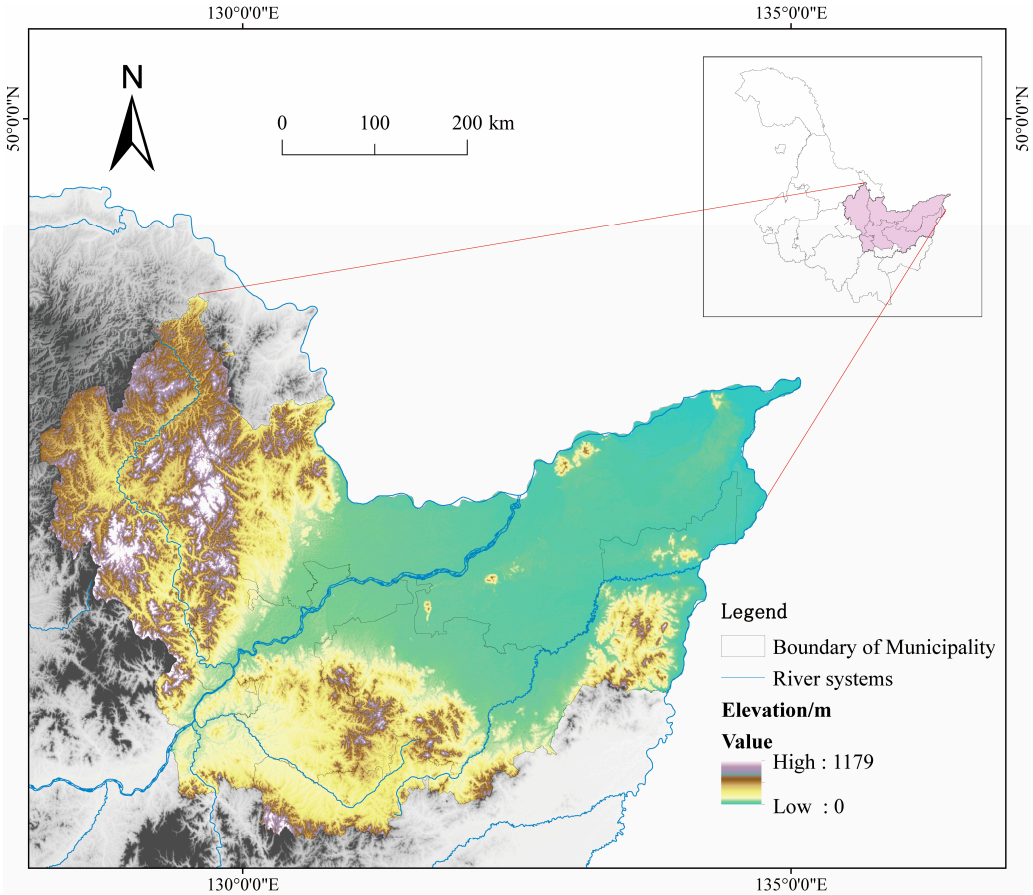


Figure 1. Scope and geographical location of the Lesser Khingan Mountains–Sanjiang Plain area, China.

2.2. Data Source

Geospatial data were obtained from various databases. Administrative boundaries were obtained from the China National Geospatial Information Center (http://www.ngcc.cn/)(accessed on 1 August 2024) and the National Earth System Science Data Center (https://www.geodata.cn) (accessed on 1 August 2024). Land use data were sourced from the Sentinel-2 10m land use/land cover time series dataset on ArcGIS 10.4 (https://livingatlas.arcgis.com/) (accessed on 1 August 2024) [57]. The division of land use types in this study

is derived from the Sentinel-2 10 m land use/land cover (LULC) time series dataset, which uses a deep learning AI classification model. This model, developed by Impact Observatory and trained on billions of human-labeled image pixels, processes over 400,000 Sentinel-2 Earth observations annually. The classification process results in the identification of eight distinct land cover classes, including agricultural areas, forests, water bodies, and urban regions, among others. These classes are generated based on spectral signatures and spatial patterns observed in the satellite imagery, ensuring accurate and consistent categorization across different regions. Digital elevation model data were obtained from the Copernicus website (https://panda.copernicus.eu/panda) (accessed on 1 August 2024) at a spatial resolution of 30 m. We used DEM data for terrain analysis, extracting elevation and slope factors. The land use and remote sensing imagery cover the period from 2017 to 2022, with DEM data using 2022 as the reference year.

2.3. Landscape Pattern Analysis

Landscape pattern analysis involves studying relationships between structural composition and configuration elements [58]. By analyzing features like patch number, density, diversity, and relative frequency [59–62], we examined changes over time using landscape metrics. We selected representative metrics to reflect specific landscape characteristics [63,64]. Five key landscape characteristics were chosen for their ability to capture critical aspects of landscape structure and function: fragmentation, connectivity, complexity, heterogeneity, and dominance. These characteristics are widely recognized for their ability to assess landscape changes and their ecological impacts. To quantify these characteristics, we selected metrics that best represented each one. For example, patch density (PD) and the Landscape Division Index (DIVISION) were used to measure fragmentation, while connectivity was captured by the Contiguity Index (CONTIG) and the Connectance Index (CONNECT). Complexity was reflected by the Landscape Shape Index (LSI) and the Fractal Dimension Index (FRAC), while heterogeneity was measured using Shannon's Diversity Index (SHDI) and Simpson's Diversity Index (SIDI) and dominance was assessed with the Largest Patch Index (LPI) [65]. These metrics are widely used in LULC and landscape pattern evaluations [66].

2.4. Identification of Typical Landscape Expansion

The Landscape Expansion Index (LEI) captures dynamic changes in landscape patterns and is used to analyze changes and expansion over time [32,67]. We modified LEI to create the Agricultural–Forest Landscape Expansion Index (AFEI) and the Forest–Agricultural Landscape Expansion Index (FAEI) for analyzing typical landscape types. These indices quantify the diffusion and aggregation characteristics of agricultural and forest landscapes. The equations are

$$AFEI = \frac{A_{af}}{A_{af} + A_{fa} + A_o} \quad (1)$$

$$FAEI = \frac{A_{fa}}{A_{af} + A_{fa} + A_o} \quad (2)$$

where A_{af} is the area converted from an agricultural to a forest landscape, A_{fa} is the area converted from a forest to an agricultural landscape, and A_o is the area of other landscapes. These indices are calculated for each grid cell in the study area.

2.5. Spatial Autocorrelation Analysis Method

To determine the spatial heterogeneity of land type expansions, we conducted a spatial autocorrelation analysis using Moran's I index. Global Moran's I assesses the overall spatial

distribution to identify clustering [45,68], while Local Moran's I pinpoints specific clusters and outliers [69]. The formulas for Global Moran's I and Local Moran's I are

$$I = \frac{n}{S_0} \frac{\Sigma_i \Sigma_j w_{ij} Z_i Z_j}{\Sigma_i Z_i^2} \tag{3}$$

$$s_0 = \Sigma_i \Sigma_j w_{ij} \tag{4}$$

where Z_i and Z_j are deviations of the attributes from their mean for features i and j, w_{ij} is the spatial weight between features i and j, n is the total number of features, and s_0 is the sum of all spatial weights.

$$I_p = \frac{x_i - x}{S^2} \sum_{q=1}^{m} w_{pq}(x_q - x) \tag{5}$$

$$S^2 = \frac{1}{m} \sum_{q=1}^{m} (x_q - x)^2 \tag{6}$$

where S^2 is the variance of observation unit x_q; m is the total number of observation units; w_{pq} is the spatial weight between units q and p.

2.6. Global Linear Regression Model

The OLS model is a linear regression method that assumes equal weights across observations, and it is used to analyze relationships between multiple independent and dependent variables [70,71]. OLS assumes global spatial stationarity, minimizing the sum of squared residuals to find optimal parameters [72,73]. The formula is

$$y = \beta_0 + \Sigma_{i=1}^{k} \beta_i \chi_i + \varepsilon \tag{7}$$

where y is the dependent variable (landscape metrics), χ_i are independent variables (land use types), β_0 and β_i are the intercept and coefficients, and ε is the error term.

2.7. Geographically Weighted Regression Model

Geographically weighted regression (GWR) models spatial relationships by incorporating geographic location information and local parameter spatial weights [74] and calculates regression coefficients for each observation point [50]. GWR performs localized regression, giving more weight to nearby observations, making it suitable for analyzing spatial heterogeneity [75]. The formula is

$$y_i = \beta_0(u_i, v_i) + \Sigma_{k=1}^{m} \beta_{bwk}(u_i, v_i) x_{ik} + \varepsilon_i \tag{8}$$

where y_i and x_{ik} are the dependent and independent variables at observation i, (u_i, v_i) are the spatial coordinates of observation i, $\beta_{bwk}(u_i, v_i)$ are the regression coefficients for variable k, bwk is the bandwidth for variable k, $\beta_0(u_i, v_i)$ is the intercept, and ε_i is the error term.

2.8. Software and Code

The study utilized R 4.3.2, ArcGIS 10.8, GeoDa 1.16, MGWR 2.2, and FRAGSTATS 4.2 for data processing and analysis. The OLS model was created using R 4.3.2, incorporating multivariate linear regression, heteroscedasticity tests, collinearity diagnostics, coefficient significance tests, and model diagnostics, outputting variable coefficients, residuals, and R-squared values.

3. Results and Analysis

3.1. Temporal and Spatial Changes of Land Use/Cover

From 2017 to 2022, significant land use conversions occurred in the Lesser Khingan Mountains–Sanjiang Plain area, primarily involving Cropland, Rangeland, and Trees.

Figures 2 and 3 illustrate these changes, showing a spatial variation in conversion areas. The combined area of Cropland and Trees increased from 89.74% to 89.80%, with Cropland decreasing by 0.72% and Trees increasing by 0.79%. Major projects influenced these conversions, with Trees expanding primarily into former Cropland and Rangeland areas, especially in the eastern part of the Lesser Khingan Mountains and Shuangyashan city in the southern part of the study area. Conversely, Cropland mainly converted into Trees, Rangeland, and occasionally Flooded Vegetation, particularly in the southern part of Jiamusi city and the eastern part of the Sanjiang Plain.

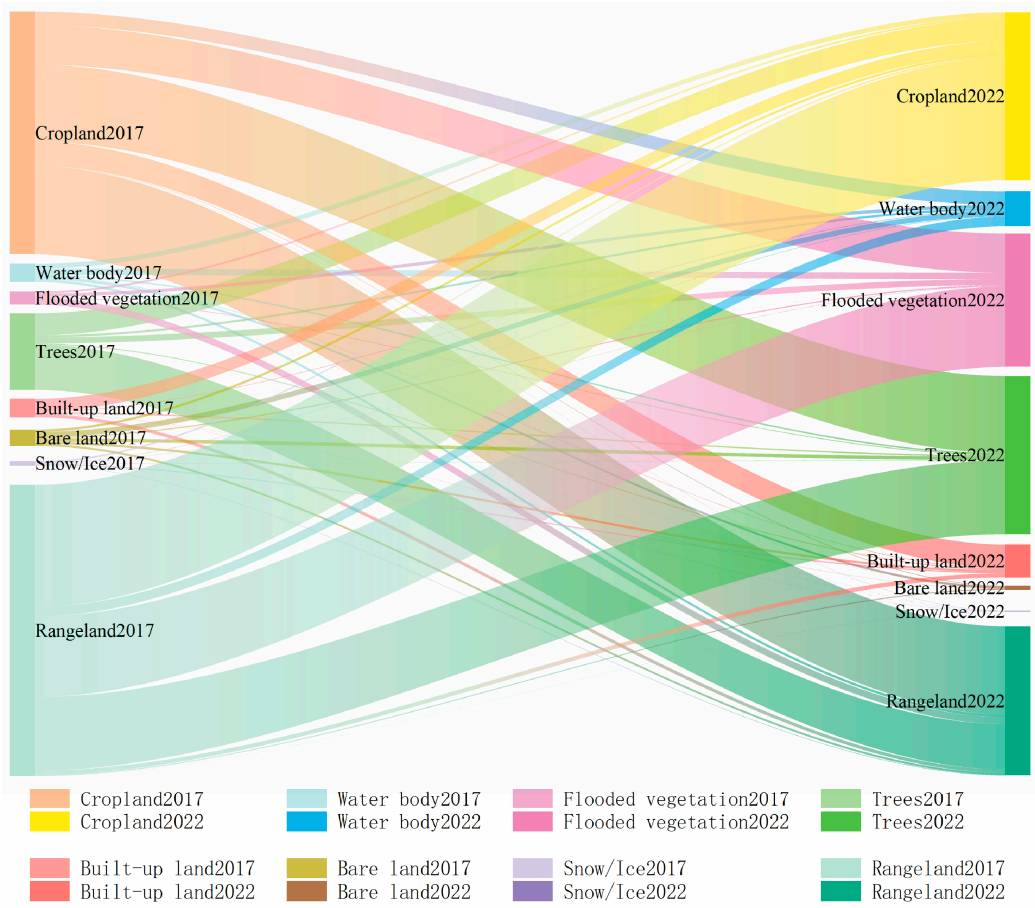


Figure 2. Sankey map of land use transfer in the study area during 2017–2022.

3.2. Expansion Analysis of Typical Land Use Types

Using the modified Agricultural–Forest Landscape Expansion Index (AFEI) and the Forest–Agricultural Landscape Expansion Index (FAEI), we further analyzed the land use conversions depicted in Figure 2. As shown in Figure 4, Trees expansion into Cropland is more concentrated, whereas Cropland expansion into Trees is more dispersed but with a higher expansion index. These indices reveal geographical disparities, with high expansion levels in the southern study area, covering the forest–farmland transition zones in the northern Wanda Mountains and the Zhangguangcai Mountains. High AFEI levels are noted in the northern Songhua River basin, while the FAEI is less prevalent there. In the eastern Sanjiang Plain, both indices are high near rivers, particularly the Naoli River basin. Lesser Khingan's expansion occurs mainly in the western Tangwang River basin and eastern foothills, with high a AFEI in the eastern mountain–farmland transition zone. In Yichun's forest area and Jiamusi's intensive farmland, no significant expansion is observed. Generally, expansions occur near ecosystem transition zones and river basins, which often overlap, but not in well-preserved, continuous land types.

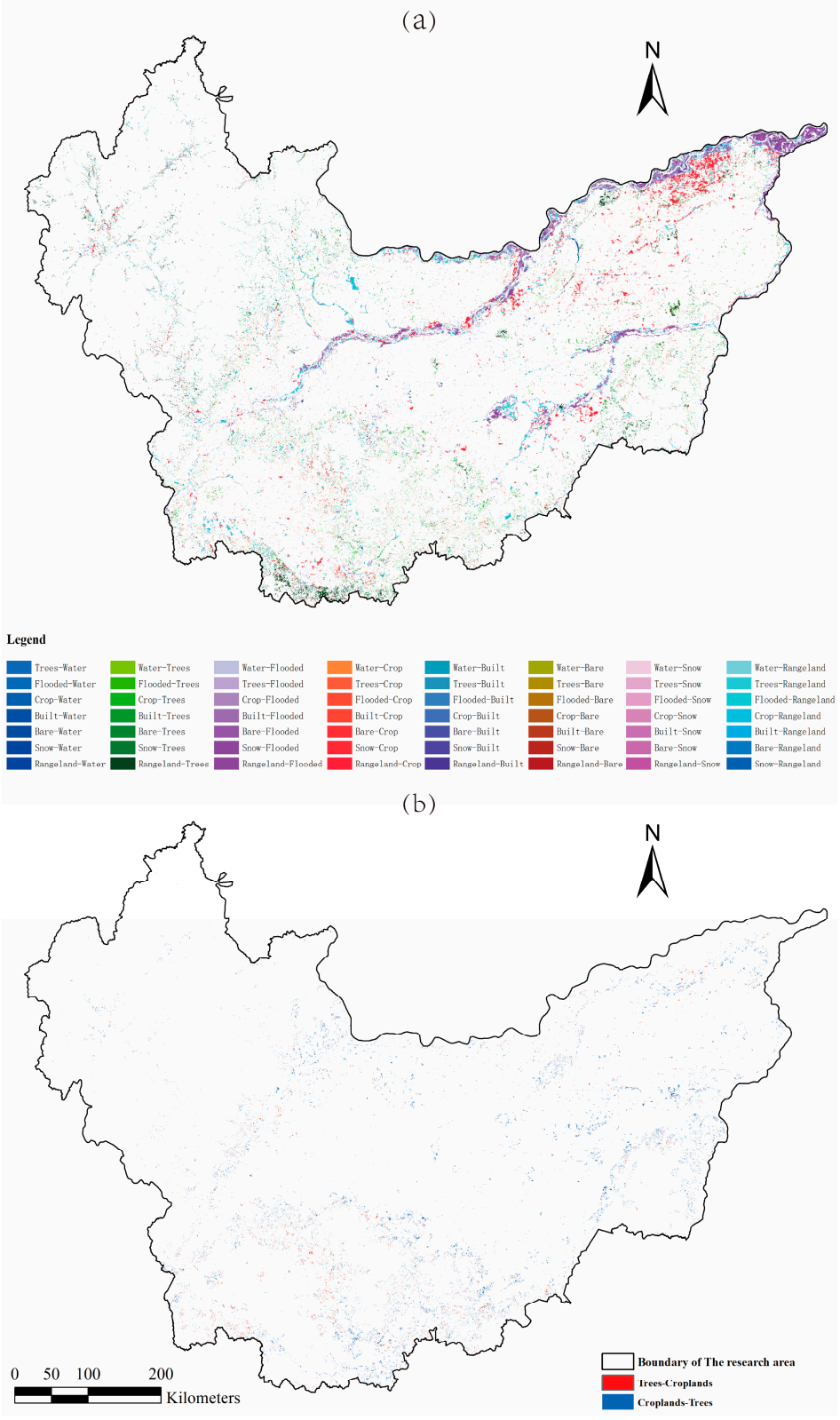


Figure 3. Dynamic transfer map of land use types and the mutual expansion map of Cropland and Trees land use in the research area from 2017 to 2022: (**a**) Distribution map of the mutual expansion of land use types. (**b**) Distribution map of typical land use types.

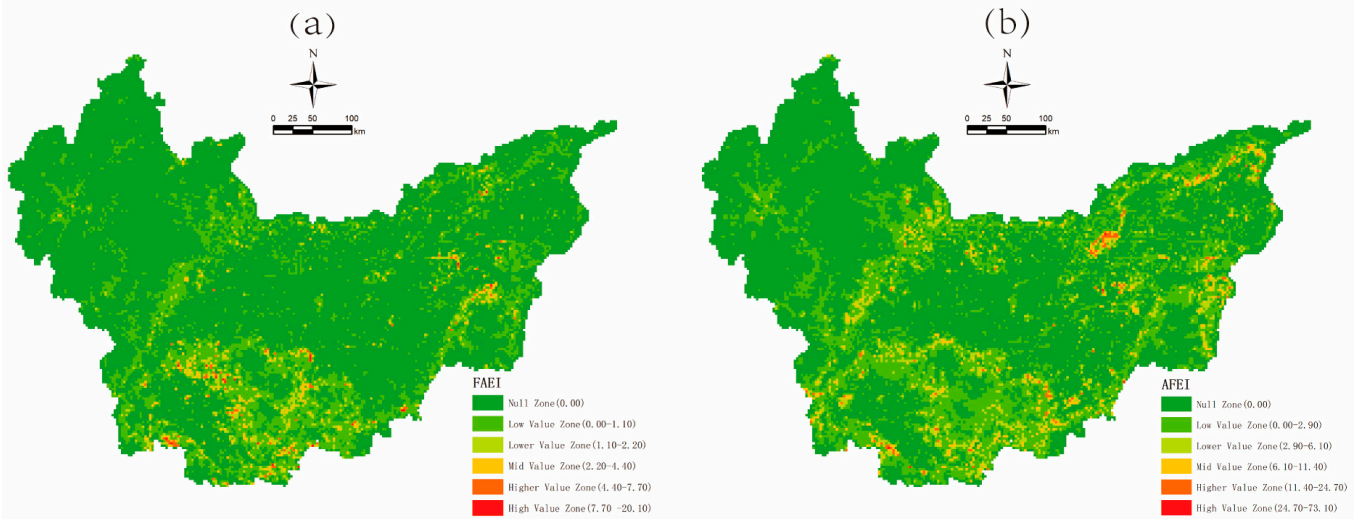


Figure 4. Spatial distribution of the Agricultural–Forest Land Expansion Index from 2017 to 2022. (**a**) Spatial distribution of the FAEI at different levels in the study area; (**b**) Spatial distribution of the AFEI at different levels in the study area.

3.3. Evolution of Landscape Patterns

We used landscape metrics calculated with Fragstats 4.2 to analyze temporal changes in landscape patterns over the period from 2017 to 2022. We selected 12 landscape metrics to dynamically analyze five important types of landscape pattern characteristics at the landscape level. Considering that some metrics showed similar trends in the actual results, only nine representative landscape metrics are displayed in the figure, as shown in Figure 5.

- For landscape fragmentation, we analyzed three indicators: PD, DIVISION, and MPS. The trends of PD and DIVISION were similar, while PD and MPS showed opposite trends. Figure 5 illustrates the changes in PD and MPS. The patch density initially decreased, then increased, and decreased again, with patch size showing the opposite pattern. In 2018, fragmentation intensified, but by 2021, it had reduced and was lower than the initial level.
- For landscape connectivity, we used four indicators: CONTAG, CONTIG_AM, CONNECT, and AI. Their overall trends were similar, and Figure 5 displays the trends of CONTAG and AI. From 2018 to 2020, these indicators significantly declined, but they increased in 2021. This suggests a reduction in landscape fragmentation, decreased spatial dispersion of land types, improved connectivity, and the phenomenon of landscape reconnection, indicating ecosystem restoration and reconstruction.
- For landscape complexity, we analyzed the FRAC_AM and the LSI. Both indicators showed consistent trends, which were opposite to those of connectivity at various stages. The initial decrease likely indicated irregular and fragmented landscape structures. The mid-period increase reflected the landscape reshaping under ecological projects, aiding in ecosystem functionality reconstruction. The subsequent decrease indicated some form of disturbance, followed by ecosystem recovery as it adapted to the disturbance.
- For landscape heterogeneity, the SHDI and the SIDI showed similar trends, which were also similar to those of complexity. This indicates that the implementation of ecological restoration and protection projects had a similar impact on heterogeneity.
- For landscape dominance, the LPI index declined after 2018, indicating significant changes in landscape dominance. This change, combined with land use variations, suggests a reduction in dominant patches such as farmland and forest land, leading to landscape structure changes. The subsequent rise indicates a gradual recovery, but not to the 2017 level.

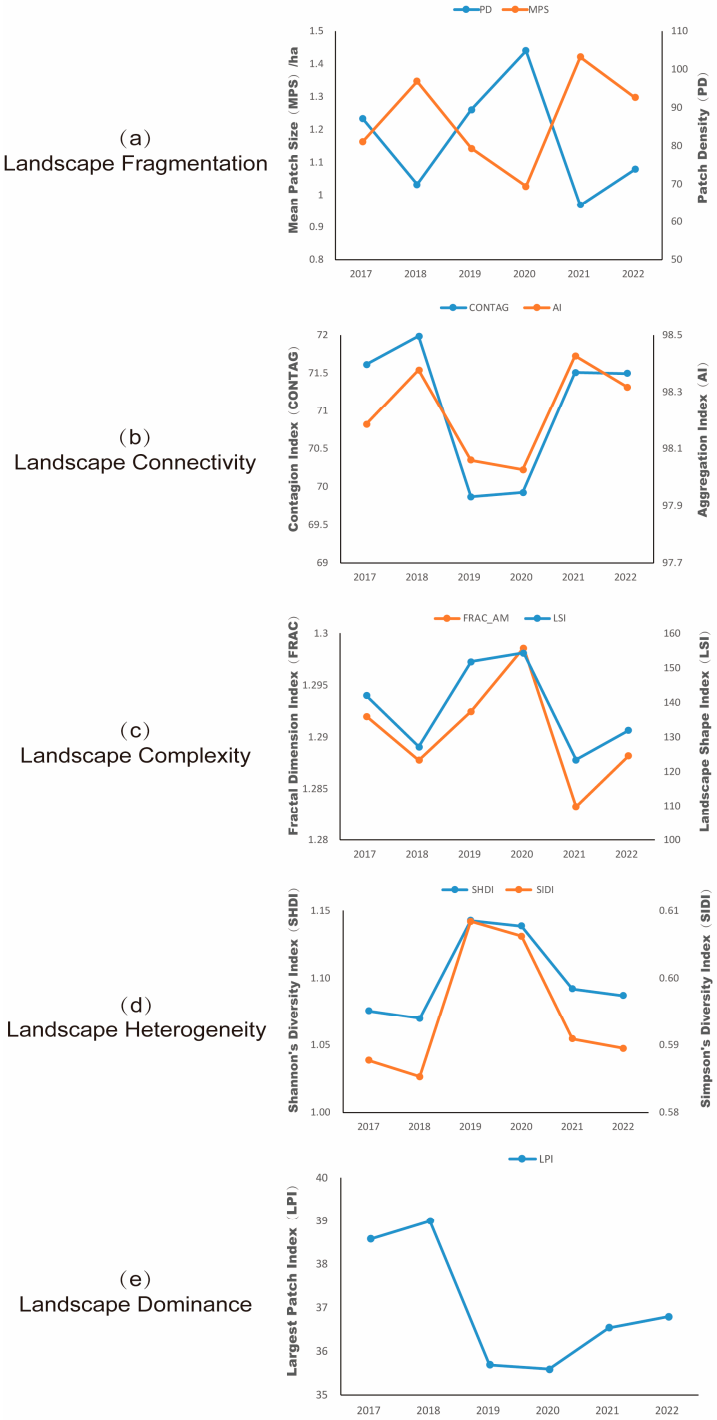


Figure 5. Results of landscape metrics at the landscape level in the study area from 2017 to 2022. (**a**) Trends in fragmentation; (**b**) Trends in connectivity; (**c**) Trends in complexity; (**d**) Trends in heterogeneity; (**e**) Trends in dominance.

3.4. Spatial Autocorrelation Analysis

Before applying GWR, we assessed spatial heterogeneity using Moran's I to test the spatial autocorrelation of typical land type expansions. The study area was divided into 3000 × 3000 m grids for expansion index calculations. As is shown in Table 1, both the FAEI and the AFEI had positive Global Moran's I values, indicating spatial autocorrelation, with the FAEI at 0.34356 and the AFEI at 0.39680, showing that the Cropland to Trees expansion had slightly higher autocorrelation than the Trees to Cropland expansion.

Table 1. Moran's Index scatter plot of the FAEI and the AFEI.

	Moran's I	Z Value	*p*-Value
FAEI	0.34356	126.3333	<0.001
AFEI	0.39680	105.1409	<0.001

Local Moran's I analysis further revealed spatial clustering and anomalies, displayed in local indicators of spatial association (LISA) maps in Figure 6. Both the Forest–Agricultural Landscape Expansion Index (FAEI) and the Agricultural–Forest Landscape Expansion Index (AFEI) showed small-scale clustering of High–High values, with Low–High values surrounding them. In the FAEI analysis, High–High clusters were mainly in the southern part of the study area, specifically within the forest–farmland transition zones of Jiamusi City and Shuangyashan City, as well as in parts of the Naoli River Basin. These regions feature relatively flat terrain and fewer steep slopes, which facilitate agricultural expansion activities due to there being fewer ecological project restrictions. In the AFEI analysis, High–High clusters were concentrated in the eastern part of the Lesser Khingan Mountains and the junction area of the Sanjiang Plain, particularly near the Dulu River and Yadan River tributaries. Additional clusters were found in the Woken River Basin of Qitaihe City, the Songhua River Basin of Jiamusi City, and the mountain–plain junction area of Shuangyashan City. The high-value areas of AFEI were closely associated with river basin distributions. Steep-slope farmlands and erosion-prone areas along riverbanks were often greened and restored under reforestation and grassland restoration projects. Consequently, more farmlands tended to be intensively managed and shifted toward urban agglomerations, leading to the observed High–High clustering.

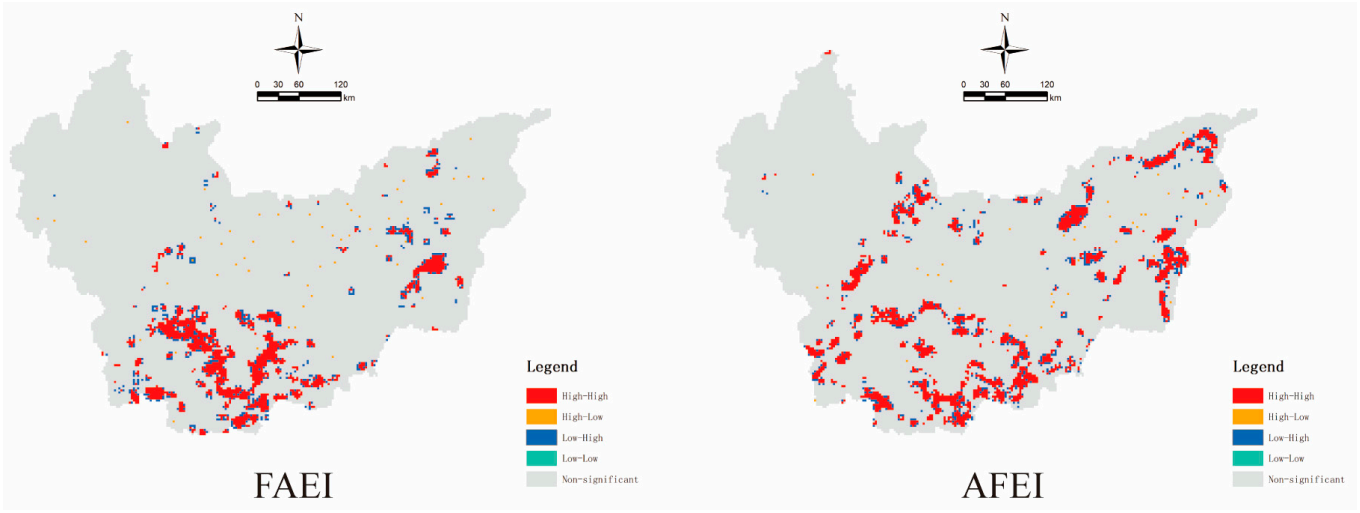


Figure 6. LISA aggregation of the land use expansion indices in the study area.

3.5. Model Construction and Analysis

Before conducting the geographically weighted regression (GWR) analysis, we first constructed a global regression model using the ordinary least squares (OLS) method. This model was used to simulate landscape metrics for the 24,469 grid cells in the study area, with the original data used to construct the model spanning the period from 2017 to 2022. Landscape indices were set as dependent variables and land use types as independent variables, which were influenced by changes in land use patterns. Based on the Pearson correlation analysis (Figure 7), we selected five strongly correlated indices—DIVISION, AI, LSI, SHDI, and LPI—as dependent variables.

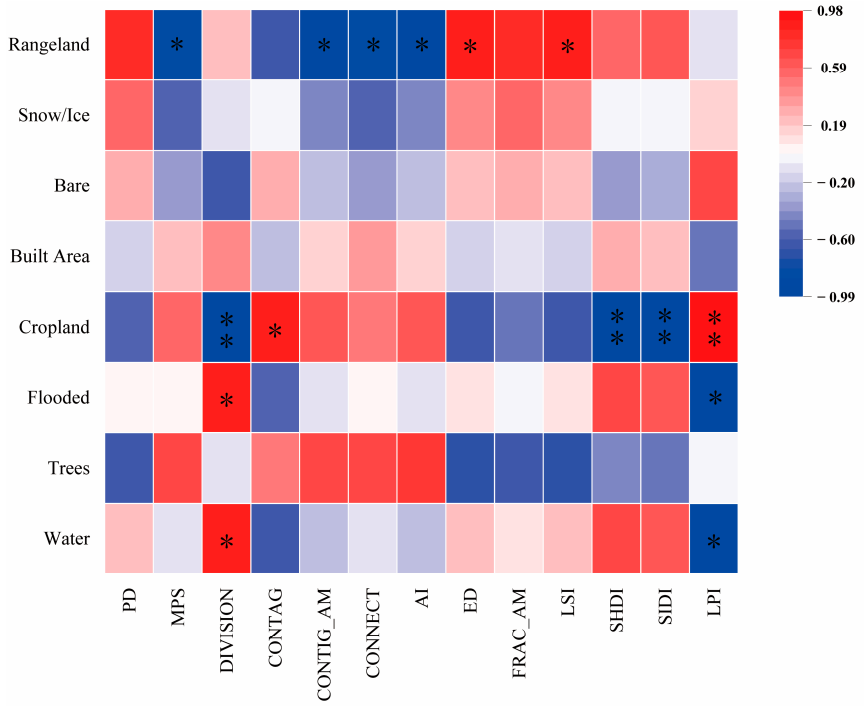


Figure 7. Correlation analysis between land use and landscape metrics ("*" indicates significance at $p < 0.05$; "**" indicates high significance at $p < 0.01$).

In constructing the OLS model, we utilized R 4.3.2 software for testing and diagnostics through appropriate function calls and coding methods. To ensure the model's robustness and validity, several key diagnostic checks were performed, including addressing collinearity issues and verifying the normality of residuals. Collinearity among independent variables is one of the primary challenges in multiple regression, as it can lead to unstable coefficient estimates. To mitigate this issue, we applied variance inflation factor (VIF) analysis, which quantifies the degree to which the variance of a regression coefficient is inflated due to collinearity. Typically, a VIF value exceeding 10 indicates problematic multicollinearity. Based on the results of the VIF analysis, variables with high VIF values were systematically removed to reduce collinearity. After removing the collinear variables, the remaining variables were reassessed, and the adjusted models were confirmed to have stable coefficients and high adjusted R^2 values. As shown in Table 2, the residual standard error for each model was small, indicating a good fit to the observed data. Both R^2 and adjusted R^2 values exceeded 0.95, highlighting the model's strong explanatory power. Additionally, the *p*-values for each model were below the 0.05 significance threshold, confirming the overall significance of the models. This process ensured that the remaining independent variables were reliable predictors of landscape changes without introducing bias or instability.

Table 2. Statistical parameters of the ordinary least square (OLS) linear regression model of the landscape pattern indices.

	Residual Standard Error	**R^2**	**Adjusted R^2**	***p*-Value**
DIVISION	0.003057	0.9712	0.9548	1.778×10^{-5}
AI	0.000326	0.9746	0.9600	1.159×10^{-5}
LSI	0.016820	0.9773	0.9643	7.837×10^{-6}
SHDI	0.000243	0.9999	0.9999	3.979×10^{-15}
LPI	0.006479	0.9805	0.9693	4.612×10^{-6}

To verify the normality of residuals, a key assumption in OLS regression, we employed both visual and statistical tests. Figure 8 presents the quantile–quantile (Q-Q) plots of the residuals for each regression model. In these plots, the residuals closely followed the 45-degree reference line, indicating that they were normally distributed. The linearity of the points in these plots confirmed that the residuals were symmetrically distributed, without significant deviations from normality. Additionally, we utilized the Global Validation of Linear Model Assumptions (gvlma) function to comprehensively assess the global regression model's assumptions. Through this function, we performed tests for skewness, kurtosis, and heteroscedasticity. The skewness test yielded a value of 0.17117, with a *p*-value of 0.679074, while the kurtosis test resulted in a value of 0.44749, with a *p*-value of 0.503527. Both *p*-values exceeded the 0.05 significance level, confirming that the residuals were symmetrically distributed and normally distributed. The heteroscedasticity test produced a result of 0.06831 with a *p*-value of 0.793811, indicating no significant heteroscedasticity issues in the models. Together, these tests confirmed that the residuals adhered to the normality assumption, ensuring the robustness of our OLS regression models and further validating the overall model fit.

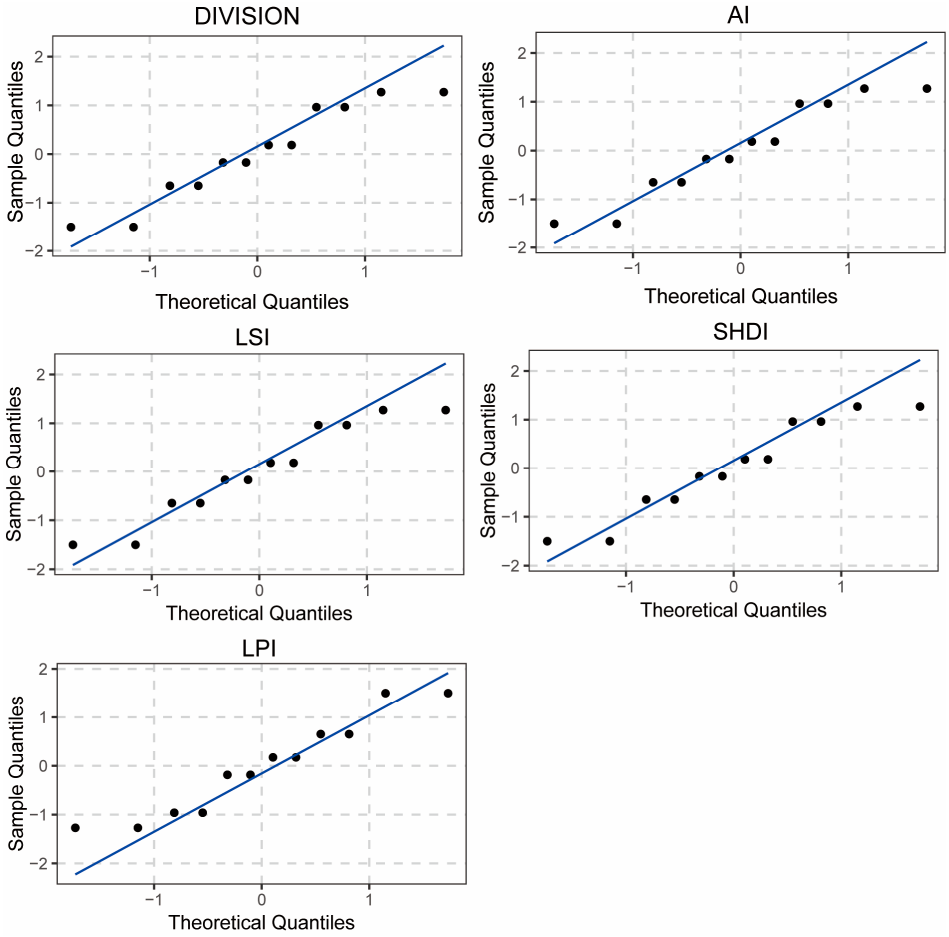


Figure 8. Regression error probability distribution.

The OLS regression results (Table 3) demonstrate the varying impacts of land use types on different landscape pattern indices, with Cropland emerging as the most influential factor. Cropland exhibited significant relationships across all five models, with a strong negative coefficient in the DIVISION model (−0.77126), indicating its role in reducing fragmentation by promoting clustering and connectivity. This clustering effect was further supported by the positive coefficient in the LPI model (2.47), emphasizing the dominance of Cropland in maintaining large, connected landscape patches. Trees, as the second major

land cover, showed a contrasting effect: while reducing dominance and fragmentation (negative coefficient in the SHDI; −0.61012), tree expansion increased landscape complexity (positive coefficient in the LSI; 0.9147). Water bodies played a dual role, enhancing landscape connectivity (positive coefficient in the LPI; 0.09) by providing corridors, yet also increasing fragmentation (negative coefficient in the LSI; −1.3775) due to their dividing nature. Built-up areas, influenced by human activity, exhibited mixed effects. While they contributed to connectivity (positive coefficient in the AI; 0.034130), they slightly reduced the dominance of other land uses (negative coefficient in the LPI; −0.03). These results underscore that Cropland, with its significant positive impact on both connectivity and dominance, is a critical driver of landscape cohesion, while Trees and Water bodies provide more nuanced, localized influences on fragmentation and complexity. The regression coefficients thus highlight the distinct and complementary roles that various land uses play in shaping landscape patterns in the study region.

Table 3. Intensity and direction of land use change in regression analysis of landscape pattern indices.

	Equation	***p*-Value**
DIVISION	DIVISION = exp(8.68580 + 0.01037 × log(Water) + 0.03421 × log(Trees) − 0.77126 × log(Cropland) −0.05492 × log(Built))	0.000 **
AI	AI = exp(2.075898+0.023982 × log(Water)−0.013259 × log(Trees) + 0.187436 × log(Cropland) + 0.034130 × log(Built)	0.000 **
LSI	LSI = exp(144.3428 − 1.3775 × log(Water) + 0.9147 × log(Trees) − 10.5208 × log(Cropland) − 1.9298 × log(Built))	0.000 **
SHDI	SHDI = exp(22.83 − 0.00618 × log(Water) − 0.61012 × log(Trees) − 1.39922 × log(Cropland) + 0.04955 × log(Built))	0.000 **
LPI	LPI = exp(−18.76 + 0.09 × log(Water) − 0.59 × log(Trees) + 2.47 × log(Cropland) − 0.03 × log(Built))	0.000 **

** The *p*-values for the coefficients indicate the statistical significance of these relationships.

In summary, the constructed OLS model, validated through rigorous testing and diagnostic procedures, provided significant insights into the varying impacts of different land use types on landscape pattern characteristics. This model's results underscores the pivotal role of the types of Cropland and Trees in influencing landscape changes, with distinct effects observed for other land use types.

The expansion of typical land use types in the region has been shown to exhibit significant spatial heterogeneity, making it suitable for spatial regression modeling using the geographically weighted regression (GWR) method. In the GWR analysis, we utilized the research area's grid system and the OLS global regression model previously constructed to simulate landscape metrics for 24,469 grid units. Using the FAEI and the AFEI as independent variables, we then calculated and constructed spatial regression models for landscape pattern characteristics through the GWR method. During the GWR execution, a fixed-kernel-type method was used to determine the spatial environment distance for local regression analysis, and the AICc bandwidth method was employed to define the kernel range. This approach identified the optimal distance and the number of neighboring elements for each local observation unit. Finally, we calculated the correlation results and regression model parameters for each local grid unit. The result parameters for each grid unit include the local R^2, coefficients, and residuals, which can express the connectivity impact at different spatial locations, thereby illustrating the influence of typical land use type expansions on landscape pattern characteristics. On the other hand, the regression model parameters evaluate the model's feasibility and accuracy, as shown in Table 4.

Table 4. Parameters of the GWR method result.

Parameters	DIVISION	AI	LSI	SHDI	LPI
Bandwidth	17,122.0358	17,122.0358	17,122.0358	17,122.0358	17,122.0358
AICc	891,516.9556	79,026.4133	405,217.2804	2,249,135.4451	−484,923.7670
Residual sum of squares	9.1104×10^{18}	34,580.8717	21,297,093,238.9908	1.13654×10^{43}	45,025.9119
R^2	0.4879	0.4986	0.2467	0.2851	0.2299
Adjusted R^2	0.4711	0.4822	0.2221	0.2617	0.2046

We spatially visualized the correlation coefficients between five landscape metrics and the typical land use expansion indices to further analyze the spatial variation trends under the influence of ecological restoration and protection projects. As shown in Figure 9, the spatial correlation between the conversion expansion of typical land types, namely Cropland and Trees, and landscape pattern characteristics exhibits different geographical variations that change with the spatial locations. The expansion of DIVISION, the SHDI, and the LPI consistently shows an overall negative correlation with the typical land type expansion, with a noticeable north–south differentiation. The negative correlation is most prominent in the Lesser Khingan Mountains area. For the LPI, the two types of expansion exhibit a weak positive correlation in a few high-value expansion areas in the Sanjiang Plain, while a strong positive correlation is observed in the high-value AFEI expansion areas in parts of the Sanjiang Plain for DIVISION. These GWR results demonstrate that landscape fragmentation, heterogeneity, and dominance are consistently influenced by the expansion of typical land types. The forest area of the Lesser Khingan Mountains shows the most significant landscape pattern changes, where ecological projects cause land type changes that reduce landscape fragmentation and heterogeneity, thus promoting landscape integrity. The northern intensive agricultural area of the Sanjiang Plain is more affected by the expansion of Trees to Cropland, while the southern area is less impacted, showing a declining negative influence from the north to the south. In some high-value FAEI and AFEI areas, fragmentation and dominance are even positively influenced by the expansion. Considering the actual land use, regions with concentrated forests and farmland are more negatively impacted by land type expansion, while areas with frequent land type changes are less affected.

The influence on the AI varies with the type of land expansion. According to the FAEI and AFEI correlations, the expansion of Trees to Cropland generally shows a positive correlation, most significantly in the Lesser Khingan Mountains and the northern Sanjiang Plain, while the correlation is low in the high-value expansion areas in the southern part of the study area. The expansion of Cropland to Trees shows a negative correlation in some high-value expansion areas in the Sanjiang Plain, with positive correlations in Lesser Khingan Mountains and other areas. Overall, this demonstrates that land type expansion under ecological projects enhances connectivity in parts of the Lesser Khingan Mountains and the Sanjiang Plain, where the land use types are relatively homogeneous. This expansion can improve connectivity between different patches and reduce fragmentation. However, this influence is limited or even reversed in high-value expansion areas, indicating that further ecological projects may not be suitable.

The impact on the LSI shows an east–west directional difference, with negative correlations in the northeastern and central parts of the study area and positive correlations in the northwestern and southern parts. Considering the actual land use, the central and northeastern plain areas of the Sanjiang Plain have reduced complexity due to land type expansion, while the Lesser Khingan Mountains and the Shuangya Mountain areas in the southern part of the study area show an increase in complexity. The differences in landscape complexity correlation may be related to the altitude of the ecological project modifications. Land type expansion in high-altitude mountainous areas tends to cause

landscapes to become more irregular and fragmented, while expansion in low-altitude plains reduces these changes.

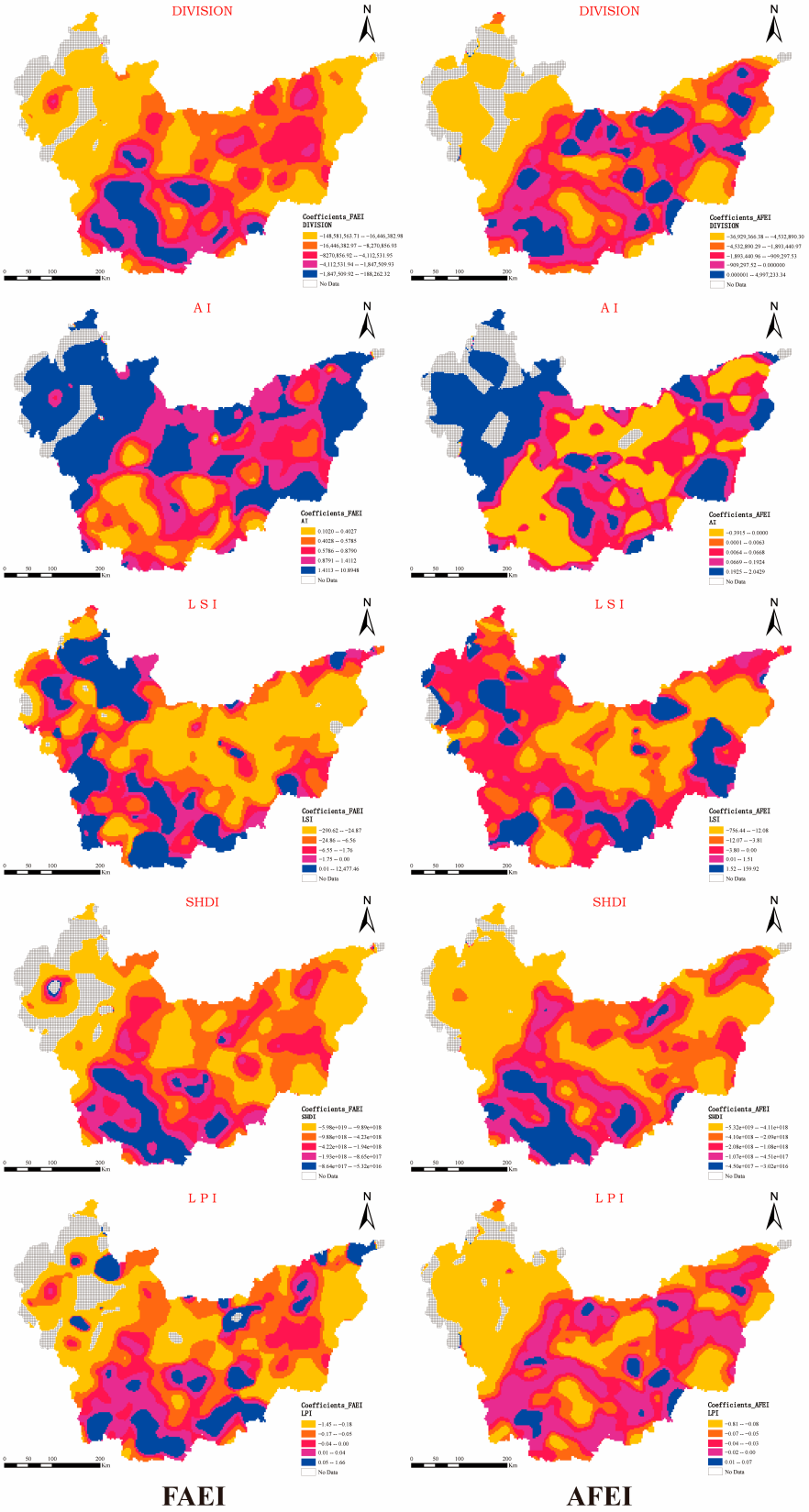


Figure 9. Spatial pattern of the correlation coefficient between the FAEI and the AFEI and the landscape indices in the study area.

4. Discussion

4.1. The Significant Impact of Ecological Restoration and Protection Projects on the Lesser Khingan Mountains–Sanjiang Plain Area

Ecological restoration and protection projects, as extensive ecological restoration initiatives, are implemented with region-specific considerations based on local conditions. These projects significantly influence the internal structure of the regional meta-ecosystem, particularly through changes in typical land use types. Among these projects, such as the Natural Forest Protection Program, the Grain-for-Green Program, and the Mountain–River Project, the most frequently modified land types are Cropland and Trees [76]. Research by Xu et al. [77] has confirmed that these projects yield substantial ecological benefits, as demonstrated by the notable recovery of local forest resources. This finding is consistent with the land type expansion results in this study. The region's landscape connectivity, among other metrics, experienced significant fluctuations during the project's implementation but gradually improved as the ecosystem stabilized over time. This evolutionary pattern aligns with the findings of Mao et al. [78]. The evolution of these landscape pattern characteristics is closely linked to changes in dominant patches, such as typical land types, under human influence [79]. Therefore, models that establish correlations based on these two elements are essential for accurately analyzing regional landscape changes. In studies on the impact of urbanization on landscape patterns, different urbanization models exhibit varying effects on the landscape. For instance, the spatial changes in edge expansion urbanization resemble the farmland and forest expansion processes in this study. However, urban expansion generally intensifies landscape fragmentation and complexity [80–82], which differs from the landscape responses observed in the typical land use expansions of farmland and forests in this study. This difference primarily stems from the driving factors of land use expansion. Urban expansion is influenced by development policies, urban planning, population growth, and resource flows, with significant marginal effects [83]. Many studies show that the areas most strongly affected by urbanization are often ecologically fragile zones, leading to increased fragmentation and complexity [84,85]. However, in this study, land use expansion was guided by ecological restoration projects, which is heavily influenced by policy planning, and avoided negative impacts on degraded and ecologically sensitive areas during implementation [86]. Consequently, the results show reduced fragmentation and heterogeneity and improved connectivity. Through landscape pattern analysis under ecological restoration projects, this study clarifies how ecologically beneficial policy planning can affect landscape spatial patterns, contributing new insights to the field.

4.2. Spatial Correlation Differences between the Expansion of Typical Land Types and the Evolution of Landscape Patterns

This study used the GWR method to analyze the spatial correlation between land type expansion and landscape patterns, revealing significant spatial differences across different locations in the Lesser Khingan Mountains–Sanjiang Plain area. These findings underscore the substantial impact of spatial heterogeneity in land type expansion resulting from ecological restoration and protection projects on the correlation between the two [87]. In areas with high FAEI indices, the negative correlation between landscape characteristics such as fragmentation, heterogeneity, and dominance, and land type expansion tends to decrease, while the positive correlation with connectivity also diminishes. Conversely, in regions with lower FAEI indices, meaning areas with less land type expansion, the negative correlation is more pronounced, particularly in forest- or farmland-concentrated areas. In areas with high AFEI indices, the reduction in the negative correlation for fragmentation, heterogeneity, and dominance is similarly observed, alongside a decrease in the positive correlation for connectivity, sometimes even shifting to a negative correlation. Additionally, in areas where Cropland expands into Trees within the Sanjiang Plain, the AFEI index also shows an increase in the correlation with fragmentation. Overall, implementing ecological projects in areas with infrequent land type expansion can enhance connectivity

and reduce fragmentation and heterogeneity. However, in ecotones or areas with high land expansion indices, the effectiveness of these projects diminishes, potentially compromising landscape integrity and the stability of local coupled ecosystems. Therefore, it is advisable to limit ecological projects in areas with frequent land conversion and control changes in land type expansion in these regions. This study's findings are consistent with those of Liu and Liao et al. [42,88]. Additionally, the spatial variation in the LSI does not show a significant correlation with the magnitude of geographic expansion. Analyzing this alongside geomorphological features suggests that this may be related to the expansion of typical land types in mountainous versus plain areas. In the Lesser Khingan Mountains, Shuangya Mountains, and Wanda Mountains regions, complexity positively correlates with land type expansion, while other plain areas show a negative correlation. The impact of elevation likely plays a more significant role, and future studies should consider remodeling to include altitude factors. This conclusion is supported by studies from Chen et al. [89] and Gao et al. [43,90].

In studies on agricultural intensification and urban expansion in China, scholars have found that the expansion of farmland significantly affects landscape patterns, especially the relationship between farmland intensification and connectivity. Additionally, as labor migration driven by urbanization progresses, the landscape patterns of farmland areas also change accordingly [91]. These results differ from the spatial heterogeneity findings in this study, particularly regarding the impact of farmland intensification expansion [92]. However, in this study, farmland expansion primarily involved the conversion of forestland, which is a characteristic of the Lesser Khingan Mountains–Sanjiang Plain region. Moreover, the spatial structure of frequently expanded areas had already undergone ecological modifications, so excessive project interference did not weaken fragmentation, complexity, or heterogeneity, nor did it significantly enhance connectivity. These differences are rooted in the specific ecological protection policies of the Lesser Khingan Mountains–Sanjiang Plain region and the characteristics of areas dominated by farmland and forests as typical land types. Likewise, there are differences in research on the trade-offs between farmland and ecological land expansion. Studies have shown that as farmland and ecological land expansion intensifies, the impact on landscape patterns increases [93,94]. These differences are primarily due to variations in population density trends and land use efficiency. The Lesser Khingan Mountains–Sanjiang Plain region, located in northeastern China, has experienced ongoing population outflows over the past decade, with urbanization progressing much more slowly than in southern China. These social factors have had varying degrees of influence on the expansion of farmland and other land types, leading to differences in research results.

This study provides a new method for analyzing the spatial heterogeneity of landscape patterns under the influence of ecological restoration projects and has broader applicability. Although this study focuses on the Lesser Khingan Mountains–Sanjiang Plain region, the findings have broader applicability to other regions experiencing similar ecological and land use challenges. The approach and methods used, particularly the application of GWR in analyzing spatial heterogeneity, can be adapted and applied to other geographical contexts. Regions that are undergoing rapid land use changes, particularly those that are implementing large-scale ecological restoration projects, can benefit from the insights gained in this study. Moreover, the findings regarding the importance of accounting for geomorphological factors when planning restoration efforts can be generalized to other areas with complex terrain and varying land use patterns.

4.3. Limitations and Prospects of the Current Research

While this study provides a detailed discussion on the spatial correlation between typical land type expansion and changes in landscape patterns, certain limitations necessitate further investigation. Although models based on land type changes can broadly simulate landscape patterns across the study area, they cannot precisely account for all the driving factors that influence local landscape patterns. For instance, factors such as

elevation, climatic conditions affecting habitat patches [95], and the impact of human economic development on landscape patterns were not fully incorporated [96]. Additionally, this study only analyzed the impacts of ecological restoration and protection projects during 2017–2022. During this period, the Natural Forest Protection Program implemented a complete ban on commercial logging, and the second phases of the Grain-for-Green Program and the Mountain–River Project were initiated, making this period representative. However, the long-term effects of subsequent ecological projects still require a new round of impact analysis. Future research should aim to integrate methods such as future scenario simulations to optimize the research framework and to conduct a more comprehensive and accurate assessment [97–99].

This study further analyzes the impact of already implemented ecological restoration and protection projects, revealing trends in the spatial correlation of landscape patterns. These findings are of great significance for the implementation of subsequent policies and sustainable development. For the two typical land types, namely farmland and forest land, the Natural Forest Protection Program and the Grain-for-Green Program have provided years of protection, which have been mainly distributed in the mountainous areas at the edge of the Lesser Khingan Mountains and the steep slope farming areas adjacent to mountains in the Sanjiang Plain. These regions have undergone multiple land use expansions due to local economic development policies and are considered ecologically sensitive areas. Although the implementation of ecological restoration and protection projects has led to significant improvements in ecological functions and landscape integrity in these areas, due to the heavy focus of government policies, the excessive implementation of similar ecological restoration projects may hinder the natural restoration and stabilization functions of local ecosystems. Over time, it is essential to avoid frequent ecological restoration projects in the same area and, instead, shift toward the supervision of ecological reserves, allowing the natural rewilding of these areas to occur without human interference. Policymakers and planners should also consider the historical success of previous ecological engineering projects when designing future interventions, as these past efforts can provide valuable insights into what works best for maintaining landscape integrity.

5. Conclusions

This study conducted a landscape-level analysis of the Lesser Khingan Mountains–Sanjiang Plain region, focusing on the impact of ecological restoration and protection projects on typical land use expansion and landscape pattern changes. This study conducted a comprehensive landscape-level analysis of the Lesser Khingan Mountains–Sanjiang Plain region, with a particular focus on the impact of ecological restoration and protection projects on typical land use expansion and landscape pattern changes. By employing the geographically weighted regression (GWR) method, we examined the spatial heterogeneity and the correlation between land use expansion and landscape patterns within the study area, contributing to a more localized understanding of how land use interventions shape landscape dynamics. The GWR results reveal several key findings: First, typical land use expansions driven by ecological projects generally reduce fragmentation, heterogeneity, and dominance across most parts of the region. Additionally, these projects enhance landscape connectivity, particularly in areas where forests and farmland are concentrated. This highlights the positive role of these projects in improving landscape integrity and ecosystem functionality. However, in regions with frequent and large-scale land use expansion, further ecological restoration and protection projects may not be advisable. Such interventions could diminish the positive effects of previous restoration efforts, leading to excessive land conversion and, ultimately, a loss of landscape integrity. Moreover, spatial correlation analysis also highlights the heterogeneity in the relationship between landscape complexity and land use expansion. In high-altitude mountainous areas, land use expansion increases regional landscape complexity due to the challenging terrain and the resulting variability in land use patterns. Conversely, in plains and low-altitude regions, particularly where Trees are converted to Cropland, a decrease in landscape complexity is

observed. This indicates that different regions within the study area respond differently to land use changes, emphasizing the need for tailored restoration strategies based on local geomorphological and landscape characteristics.

In conclusion, this study makes several significant contributions to the understanding of landscape dynamics and the role of ecological restoration and protection projects. First, by integrating the GWR method, we offer a novel approach to analyzing spatial heterogeneity in the relationship between land use expansion and landscape pattern changes. This method allows for a localized understanding of landscape changes, which can vary significantly across different regions. Second, our findings underscore the importance of considering geomorphological and elevation factors when planning ecological interventions. By demonstrating how different regions exhibit varied responses to land use changes, this study provides crucial insights into the need for more geographically tailored ecological restoration strategies. Finally, we offer planning recommendations for ecological restoration and protection projects tailored to different regions, advocating for the consideration of historical instances of ecological engineering in policy decisions. This approach aims to implement ecological restoration measures that align with the local spatial relationships and further preserve landscape integrity.

Moving forward, future research should explore the mechanisms driving landscape pattern evolution under the influence of multiple factors, such as social dynamics, development policies, and climate change, to develop more scientifically grounded and sustainable principles for ecological project planning.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13091513/s1, Table S1: Landscape Metrics.

Author Contributions: Conceptualization, X.K.; methodology, X.K. and W.S.; software, X.K.; validation, X.K. and W.S.; formal analysis, X.K. and J.Z.; investigation, X.K.; resources, X.K. and W.S.; data curation, X.K.; writing—original draft preparation, X.K. and W.S.; writing—review and editing, X.K., J.Z. and W.S.; visualization, X.K.; supervision, X.K. and W.S.; project administration, X.K.; funding acquisition, W.S. All authors have read and agreed to the published version of the manuscript.

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