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Spatially heterogeneous effects of landscape pattern evolution on water yield in the Liaodong Green Economic Zone (China): an integrated InVEST–MGWR analysis

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Abstract

Understanding the spatially heterogeneous drivers of water yield is essential for effective environmental monitoring and landscape-oriented water-resource management. Taking the Liaodong Green Economic Zone as the study area, this study integrated the InVEST model, landscape pattern indices, and multiscale geographically weighted regression (MGWR) to investigate the spatiotemporal dynamics of water yield and its landscape-pattern drivers from 2003 to 2023. The results show that water yield exhibited a fluctuating but overall increasing trend during the study period, with pronounced interannual variability. Spatially, water yield displayed a clear gradient decreasing from southeast to northwest, reflecting strong spatial heterogeneity. Landscape pattern analysis indicated a general tendency toward reduced fragmentation, enhanced connectivity, and increased compositional diversity at the landscape level. MGWR results revealed significant spatial heterogeneity in the relationships between landscape pattern indices and water yield. Mean patch area and contagion index were predominantly positively associated with water yield, whereas patch density, aggregation index, and Shannon's diversity index mainly exhibited negative effects. At the class level, farmland-related landscape indices were predominantly negatively associated with water yield across most areas, while forest proportion showed predominantly positive effects. Overall, the integrated InVEST–MGWR framework effectively captured the spatially heterogeneous influences of landscape pattern on water yield, providing a practical methodological reference for environmental monitoring and landscape-oriented water-resource management in ecologically heterogeneous regions.

1 Introduction

Ecosystem services refer to the direct and indirect benefits that ecosystems provide for human survival and development, encompassing provisioning, regulating, supporting, and cultural services (Xie et al., 2015). Among these services, water yield represents a key regulating function that underpins ecosystem stability and plays a vital role in supporting regional socioeconomic development and ensuring water-resource security (Sánchez-Canales et al., 2012). Under the combined influences of climate change and intensified human activities, regional water-yield processes and their driving mechanisms have become an important focus of ecosystem service research (Ouyang et al., 2016; Wu, 2013). Landscape pattern describes the spatial composition and configuration of land-use and land-cover types and reflects the heterogeneity of landscapes (Liang et al., 2015). Landscape patterns are jointly shaped by natural environmental conditions and human activities and, in turn, regulate hydrological processes and ecosystem services by modifying surface characteristics, evapotranspiration intensity, and water-flow pathways (Wu, 2013). Numerous studies have demonstrated that variations in landscape composition and configuration can significantly influence water yield and water conservation functions; however, the magnitude and direction of these effects often vary spatially, resulting in pronounced spatial heterogeneity (Zhang et al., 2025; Wang et al., 2023).

Water yield is widely used as an indicator for evaluating the hydrological regulation function of ecosystems. Based on the water balance principle, the InVEST model enables continuous estimation of

water yield at regional scales and has been extensively applied in ecosystem service assessments due to its transparent structure and relatively low data requirements (Sun et al., 2015; Zhang et al., 2025; Jia et al., 2025; Liu et al., 2025). However, water-yield simulations alone are insufficient to capture the spatially heterogeneous influences of landscape pattern on hydrological processes, highlighting the need to integrate ecosystem service modeling with spatial statistical approaches to explore underlying driving mechanisms (Liu et al., 2023; Sheng et al., 2023; Dong et al., 2024; Wang et al., 2024). Multiscale geographically weighted regression (MGWR) provides an effective framework for addressing spatial non-stationarity by allowing different explanatory variables to operate at distinct spatial scales (Zhu et al., 2021). In recent years, MGWR has been increasingly applied in studies of ecosystem services and their driving factors, offering new insights into the spatial heterogeneity of complex environmental processes and improving the interpretation of spatially varying relationships (Liu et al., 2023; Sheng et al., 2023). Although previous studies have combined ecosystem service models with spatial regression approaches to explore water-yield drivers, most analyses have relied on single-scale GWR or focused primarily on climatic controls. The scale-dependent effects of landscape configuration on water yield remain insufficiently quantified, particularly in ecologically heterogeneous mountainous regions. This study explicitly addresses this gap by employing MGWR to disentangle multi-scale landscape–hydrology relationships.

The Liaodong Green Economic Zone is an important ecological function and water-conservation region in Liaoning Province, China. The region is characterized by high forest coverage, pronounced topographic variability, and the combined influences of ecological restoration initiatives and human activities (Xu, 2023; Chang, 2025). In this context, systematically examining the spatially heterogeneous effects of landscape pattern evolution on water yield is essential for improving the understanding of regional hydrological dynamics and supporting effective water-resource management. Accordingly, this study takes the Liaodong Green Economic Zone as the study area and integrates the InVEST model, landscape pattern indices, and multiscale geographically weighted regression to (1) analyze the spatiotemporal variations in water yield from 2003 to 2023 and (2) quantify the spatially heterogeneous impacts of landscape pattern evolution on water yield. The results are expected to provide scientific evidence for landscape-oriented water-resource protection and ecological management at regional scales.

2 Methods (EMA-polished)

2.1 Study area

The study area is shown in Fig. 1.The Liaodong Green Economic Zone is located in eastern Liaoning Province, China (122°30'–125°30'E, 40°00'–43°30'N)(Fig. 2). The region is characterized by an overall topographic gradient descending from southeast to northwest and is dominated by mountainous and hilly terrain. The study area includes nine counties (Xiuyan, Fengcheng, Kuandian, Benxi, Huanren, Fushun, Xinbin, Qingyuan, and Xifeng).

The climate of the region is classified as temperate monsoon, with distinct seasonal variation and relatively abundant precipitation. Mean annual precipitation ranges from approximately 800 to 1200 mm, making the Liaodong Green Economic Zone one of the most humid regions in Liaoning Province. Forest ecosystems dominate the landscape, with forest coverage exceeding 70%, and vegetation is mainly composed of temperate mixed coniferous–broadleaf forests. Owing to its ecological importance, the region serves as a key ecological barrier and water-conservation area while simultaneously experiencing increasing pressure from land-use change and human activities.

2.2 Data sources and preprocessing

Multiple datasets were used to quantify water yield and landscape pattern dynamics from 2003 to 2023. Land-use/land-cover data with a spatial resolution of 30m were obtained from the National Earth System Science Data Center of China. Monthly precipitation and potential evapotranspiration datasets at a spatial resolution of 1km were acquired from the National Tibetan Plateau Data Center. Soil property data were derived from the FAO–IIASA World Soil Database.

To ensure spatial consistency, all datasets were projected to the WGS_1984_UTM_Zone_51N coordinate system and resampled to a uniform spatial resolution of 30m × 30m. Temporal consistency among datasets was maintained by aggregating climate variables to annual values for subsequent analysis. These preprocessing steps ensured the comparability of spatial and temporal patterns across datasets.

2.3 Water yield estimation using the InVEST model

Water yield was estimated using the water yield module of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, which is based on the annual water balance principle. For each raster cell *x*, annual water yield (*Yx*) was calculated as:

$$Y_{xj} = \left(1 - \frac{AET_{xj}}{P_x}\right) P_x \#(1)$$

where $P_x$is the annual precipitation (mm) and $AET_x$is the actual evapotranspiration (mm) for pixel *x*. Actual evapotranspiration was estimated using a Budyko-based framework implemented in the InVEST model:

$$AET_x = P_x \cdot \frac{1}{1+\left(\frac{P_x}{PET_x}\right)^{\omega_x}} \#(2)$$

where $PET_x$is the annual potential evapotranspiration (mm), and $\omega_x$is a non-physical parameter that reflects soil–vegetation–climate interactions.The parameter $\omega_x$was calculated as:

$$\omega_x = Z \cdot \frac{AWC_x}{P_x} \#(3)$$

where Z is a seasonality factor reflecting precipitation distribution and regional hydroclimatic characteristics, and AWC_xrepresents the plant-available water content of the soil, determined by soil

depth and texture.Potential evapotranspiration was calculated using the Penman–Monteith equation:

$$PET = \frac{0.408\Delta\ (R_n - G) + \gamma\ \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta\ + \gamma\ (1 + 0.34 u_2)} \#\ (4)$$

where $\mathrm{R_n}$is net radiation at the surface (MJ $\mathrm{m^{-2}\ d^{-1}}$), $\mathrm{G}$is soil heat flux density (MJ $\mathrm{m^{-2}\ d^{-1}}$), $\mathrm{T}$is mean daily air temperature (°C), $\mathrm{u_2}$is wind speed at 2 m height (m $\mathrm{s^{-1}}$), $\mathrm{e_s}$is saturation vapor pressure (kPa), $\mathrm{e_a}$is actual vapor pressure (kPa), Δ is the slope of the saturation vapor pressure curve (kPa ° $\mathrm{C^{-1}}$), and γ is the psychrometric constant (kPa ° $\mathrm{C^{-1}}$).

All parameters were kept consistent across the study period to ensure comparability of water-yield estimates from 2003 to 2023.

2.4 Landscape pattern indices

Landscape pattern indices were calculated to characterize landscape structure and configuration. Based on previous studies and data availability, eight commonly used indices were selected and calculated using FRAGSTATS software.The definitions of the eight indices are shown in Table 1.

At the landscape level, patch density (PD), largest patch index (LPI), mean patch area (AREA_MN), contagion index (CONTAG), aggregation index (AI), and Shannon’s diversity index (SHDI) were used to describe fragmentation, dominance, connectivity, aggregation, and compositional diversity. At the class level, patch density (PD), edge density (ED), aggregation index (AI), mean patch area (AREA_MN), largest patch index (LPI), and percentage of landscape (PLAND) were calculated for major land-use types, with particular attention given to forest and farmland classes due to their large spatial extent in the study area.

Table 1
Landscape pattern indices and their ecological meanings used in this study

Landscape pattern index	Ecological meaning	Analysis level
Patch density (PD)	Indicates the degree of landscape fragmentation by quantifying the number of patches per unit area.	Landscape / Class
Largest patch index (LPI)	Reflects landscape dominance by measuring the proportion of the largest patch within the landscape.	Landscape / Class
Mean patch area (AREA_MN)	Represents the average size of landscape patches, indicating patch-scale spatial structure.	Landscape / Class
Contagion index (CONTAG)	Describes the degree of aggregation and spatial connectivity among landscape patches.	Landscape
Aggregation index (AI)	Measures the tendency of similar patches to be spatially aggregated.	Landscape / Class
Shannon's diversity index (SHDI)	Characterizes landscape compositional diversity by integrating richness and evenness of patch types.	Landscape
Edge density (ED)	Quantifies the length of edges between different patch types per unit area, reflecting landscape boundary complexity.	Class
Percentage of landscape (PLAND)	Indicates the proportional area occupied by a specific land-use type.	Class

Note: Landscape-level indices describe the overall spatial structure of the landscape, whereas class-level indices characterize the spatial configuration of specific land-use types.

2.5 Multiscale geographically weighted regression (MGWR)

Multiscale geographically weighted regression (MGWR) was employed to characterize the spatially non-stationary relationships between landscape pattern indices and water yield. MGWR extends geographically weighted regression by allowing each explanatory variable to operate at its own spatial scale (i.e., variable-specific bandwidths), thereby providing a more detailed representation of spatial heterogeneity. The MGWR model can be written as:

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)\, x_{ij} + \epsilon_i \quad \#(5)$$

where y_i denotes the dependent variable (water yield) at location i, x_{ik} is the k-th explanatory variable (landscape pattern index), (u_i, v_i) represents the spatial coordinates, $\beta_k(u_i, v_i)$ is the location-specific coefficient, ϵ_i is the random error term, and p is the number of explanatory variables. In MGWR, each coefficient surface is calibrated with a variable-specific bandwidth b_k, capturing scale-dependent spatial effects.

For model implementation, the study area was organized into a 3 km × 3 km fishnet spatial unit to support the MGWR-based assessment of the spatial effects of landscape pattern evolution on water yield.

2.6 Analytical workflow

The overall analytical workflow consisted of three main steps. First, the InVEST model was applied to estimate annual water yield from 2003 to 2023 and to characterize its spatiotemporal variation. Second, landscape pattern indices were calculated to quantify changes in landscape structure and configuration over the same period. Third, MGWR was employed to explore the spatially heterogeneous relationships between landscape pattern indices and water yield. This integrated workflow enabled a systematic assessment of water-yield dynamics and their landscape-scale drivers.

3 Results

3.1 Spatiotemporal variation of water yield

3.1.1 Interannual variation

Figure 2 shows the interannual variations in mean annual precipitation, potential evapotranspiration, and water yield in the Liaodong Green Economic Zone from 2003 to 2023. Over the study period, mean annual precipitation averaged 909.34 mm and exhibited a slight increasing trend, with a rate of 7.33 mm per decade, although the trend was not statistically significant. In contrast, potential evapotranspiration showed a significant increasing trend ($p < 0.05$), with an increase rate of 29.93 mm per decade.

Mean annual water yield averaged 670.17 mm during the study period and displayed a fluctuating but overall increasing trend, with an increase rate of 0.197 mm per decade. The highest water-yield value occurred in 2010 (1008.24 mm), while the lowest value was observed in 2014 (443.45 mm). Overall, interannual variations in water yield were generally consistent with those of precipitation.

3.1.2 Spatial distribution of water yield

The spatial distributions of mean annual precipitation, potential evapotranspiration, and water yield are presented in Fig. 3. Water yield exhibited a distinct spatial pattern characterized by a gradual decrease from southeast to northwest across the study area. High water-yield values (723.68–858.95 mm) were mainly concentrated in the southeastern mountainous areas, including Huanren and Kuandian counties. Moderate water-yield values (564.74–723.68 mm) were distributed across transitional zones such as Qingyuan, Xiuyan, Xinbin, Benxi, and Fengcheng. Low water-yield values (304.35–564.74 mm) were primarily observed in the northwestern and inland areas, including Xifeng and Fushun counties.

3.2 Spatiotemporal evolution of landscape pattern

3.2.1 Land-use change characteristics

Spatial changes in land use from 2003 to 2023 are shown in Fig. 4, and land-use transfer relationships are illustrated in Fig. 5. Forest land dominated the landscape throughout the study period, while other land-use types were distributed in a scattered pattern.

During the study period, shrubland, water bodies, and impervious surfaces increased by 0.40 km², 61.62 km², and 264.89 km², respectively, corresponding to increases of 298%, 19.26%, and 35.71%. In contrast, the areas of farmland, forest, grassland, bare land, and wetland decreased by 87.36 km², 210.45 km², 23.75 km², 5.28 km², and 0.07 km², respectively, with reduction rates of 1.33%, 0.74%, 28.23%, 66.94%, and 26.15%.

3.2.2 Changes in landscape-level indices

Changes in landscape-level indices from 2003 to 2023 are summarized in Table 2. The largest patch index (LPI) remained relatively stable at approximately 52, with a slight decrease of 0.49%. Mean patch area (AREA_MN) increased from 20.037 to 24.004, representing an increase of 19.80%.

Patch density (PD) decreased by 16.53%, while the contagion index (CONTAG) exhibited a slight decrease of 0.63% but remained above 79 throughout the study period. The aggregation index (AI) showed a slight increase of 0.20% and consistently exceeded 94. Shannon's diversity index (SHDI) increased from 0.635 to 0.659, representing a growth of 3.83%.

Table 2
Changes in landscape-level pattern indices in the Liaodong Green Economic Zone from 2003 to 2023

Landscape pattern index	2003	2023	Change (%)
LPI	52.104	51.848	−0.49
AREA_MN	20.037	24.004	+ 19.80
PD	4.991	4.166	−16.53
CONTAG	79.659	79.157	−0.63
AI	94.704	94.889	+ 0.20
SHDI	0.635	0.659	+ 3.83

3.2.3 Changes in class-level indices

Figure 6 illustrates changes in class-level landscape indices from 2003 to 2023. For forest and farmland, the largest patch index (LPI) decreased by 0.49% and 2.92%, respectively, and the percentage of landscape (PLAND) decreased by 0.74% and 1.33%, respectively.

Mean patch area (AREA_MN) decreased for forest (− 2.92%) but increased substantially for farmland (39.09%). Patch density (PD) increased for forest, shrubland, and impervious surfaces, while it decreased for other land-use types, with farmland showing the largest decrease (− 29.10%). Edge density (ED) decreased for forest and farmland but increased for impervious surfaces. Aggregation index (AI) increased slightly for forest and farmland and increased markedly for shrubland.

3.3 Spatial relationships between landscape pattern and water yield

3.3.1 Spatial autocorrelation analysis

Results of local spatial autocorrelation analysis between landscape-level indices and water yield are presented in Table 3. All indices showed statistically significant spatial correlations ($p < 0.05$). Patch density (PD) and Shannon's diversity index (SHDI) were negatively correlated with water yield, whereas other landscape-level indices exhibited positive spatial correlations.

At the class level, results for farmland and forest are summarized in Table 4. For farmland, all indices showed significant negative spatial correlations with water yield. For forest, patch density (PD) and edge density (ED) were negatively correlated with water yield, while other indices exhibited positive spatial correlations.

Table 3
Spatial autocorrelation between landscape-level pattern indices and water yield

Statistic	LPI	AREA_MN	PD	CONTAG	AI	SHDI
Moran's I	0.204	0.134	−0.035	0.169	0.253	−0.251
p-value	0.001	0.001	0.004	0.001	0.001	0.001

Note: LPI = largest patch index; AREA_MN = mean patch area; PD = patch density; CONTAG = contagion index; AI = aggregation index; SHDI = Shannon's diversity index.

Table 4
Spatial autocorrelation between class-level landscape pattern indices and water yield

Landscape pattern index	Farmland (Moran's I)	Farmland (*p*)	Forest (Moran's I)	Forest (*p*)
LPI	−0.286	0.001	0.280	0.001
PLAND	−0.313	0.001	0.323	0.001
AREA_MN	−0.164	0.001	0.251	0.001
PD	−0.043	0.001	−0.009	0.001
ED	−0.286	0.001	−0.323	0.001
AI	−0.155	0.001	0.237	0.001

Note: LPI = largest patch index; PLAND = percentage of landscape; AREA_MN = mean patch area; PD = patch density; ED = edge density; AI = aggregation index.

3.3.2 MGWR results at the landscape level

Figure 7 presents the spatial distributions of MGWR coefficients for landscape-level indices. Patch density (PD) and largest patch index (LPI) showed negative effects on water yield across the entire study area. In contrast, mean patch area (AREA_MN) and contagion index (CONTAG) exhibited predominantly positive effects, accounting for 56.25% and 66.23% of the study area, respectively.

Shannon's diversity index (SHDI) and aggregation index (AI) showed predominantly negative effects on water yield, with negative-effect areas accounting for 94.35% and 93.43% of the study area, respectively.

3.3.3 MGWR results at the class level

Farmland: Figure 8 shows the spatial distributions of MGWR coefficients for farmland-related indices. The largest patch index (LPI) exhibited positive effects on water yield across the entire study area, whereas mean patch area (AREA_MN) showed negative effects throughout the study area. The percentage of landscape (PLAND), patch density (PD), edge density (ED), and aggregation index (AI) were predominantly negatively associated with water yield, with negative-effect areas accounting for 97.89%, 93.16%, 76.65%, and 53.57% of the study area, respectively.

Forest: Figure 9 presents the spatial distributions of MGWR coefficients for forest-related indices. The largest patch index (LPI), mean patch area (AREA_MN), patch density (PD), edge density (ED), and aggregation index (AI) exhibited predominantly negative effects on water yield, with negative-effect areas ranging from 62.91% to 78.33%. In contrast, the percentage of landscape (PLAND) for forest showed predominantly positive effects, accounting for 93.99% of the study area.

4 Discussion

4.1 Spatiotemporal characteristics of water yield and climatic background

The results indicate that water yield in the Liaodong Green Economic Zone exhibited a fluctuating but overall increasing trend from 2003 to 2023, with pronounced interannual variability. This pattern is generally consistent with precipitation dynamics, indicating that climatic inputs remain the primary driver of regional water-yield processes (Ouyang et al., 2016; Wu, 2013). From a theoretical perspective, long-term water yield is fundamentally constrained by the balance between water supply and atmospheric evaporative demand, as conceptualized in the Budyko framework (Budyko, 1974).

The spatial pattern of water yield, characterized by a gradual decrease from southeast to northwest, reflects the combined influence of topography, vegetation cover, and climatic gradients. Mountainous areas with higher forest coverage tend to receive greater orographic precipitation and exhibit stronger hydrological regulation capacity, resulting in higher water-yield values (Sánchez-Canales et al., 2012; Liu et al., 2025). These spatial contrasts highlight the necessity of incorporating spatial heterogeneity into regional water-yield assessments, rather than relying solely on spatially averaged indicators.

4.2 Landscape pattern evolution and its hydrological relevance

Landscape pattern analysis revealed an overall tendency toward reduced fragmentation, enhanced connectivity, and increased compositional diversity during the study period. Similar landscape evolution patterns have been observed in regions undergoing ecological restoration or land-use optimization, where landscape consolidation contributes to improved ecosystem integrity (Liang et al., 2015; Zhang et al., 2025). Reduced fragmentation and increased patch size can alter surface connectivity and vegetation continuity, thereby influencing hydrological processes such as runoff generation and evapotranspiration (Wu, 2013).

At the class level, forest and farmland, as the dominant land-cover types in the study area, exhibited distinct structural changes. These differences provide an important landscape context for understanding subsequent spatial variations in water yield, as different land-cover types regulate hydrological processes through variations in vegetation characteristics, rooting depth, and land management practices (Ouyang et al., 2016; Wang et al., 2023).

4.3 Spatially heterogeneous effects of landscape pattern on water yield

The MGWR results demonstrate pronounced spatial non-stationarity in the relationships between landscape pattern indices and water yield, indicating that landscape–hydrology interactions vary substantially across space. This finding is consistent with previous studies showing that spatially explicit approaches are essential for capturing localized environmental processes that are obscured by global regression models (Zhu et al., 2021; Liu et al., 2023).

At the landscape level, the predominantly positive associations of mean patch area and contagion index with water yield suggest that larger and more contiguous landscape patches may enhance hydrological regulation in many parts of the study area. Similar relationships between landscape connectivity and hydrological performance have been reported in other regional studies (Wu, 2013; Zhang et al., 2025). In contrast, the negative effects associated with patch density and Shannon's diversity index imply that excessive fragmentation and compositional heterogeneity may weaken water-yield capacity under certain environmental conditions (Wang et al., 2023; Sheng et al., 2023).

4.4 Class-level differences in landscape–water yield relationships

At the class level, farmland-related landscape indices exhibited predominantly negative associations with water yield across most of the study area. This pattern is consistent with previous findings that agricultural land use often increases evapotranspiration and alters soil structure, thereby reducing effective water yield at catchment and regional scales (Zhang et al., 2001; Sun et al., 2015; Dong et al., 2024). The spatial consistency of these negative effects indicates that farmland configuration plays an important role in shaping regional water-yield patterns.

In contrast, the positive association between forest proportion and water yield across most areas supports the widely recognized role of forest ecosystems in hydrological regulation. Numerous studies have demonstrated that changes in forest cover can significantly influence evapotranspiration, runoff generation, and soil-water retention, although the direction and magnitude of these effects depend on climatic conditions and spatial scale (Zhang et al., 2001; Sánchez-Canales et al., 2012; Liu et al., 2025). However, the predominantly negative effects of forest fragmentation indicators further suggest that forest configuration, in addition to forest extent, is critical for sustaining water-yield functions, consistent with landscape ecology theory (Liang et al., 2015).

4.5 Methodological and management implications for environmental monitoring

The integration of the InVEST model with multiscale geographically weighted regression (MGWR) provides an effective framework for identifying spatially heterogeneous drivers of water yield. The InVEST model enables spatially explicit estimation of water yield based on the water balance principle, while MGWR enhances interpretability by allowing the relationships between landscape pattern and water yield to vary across multiple spatial scales (Fotheringham et al., 2017). This multiscale analytical perspective is particularly valuable for environmental monitoring in ecologically heterogeneous regions, where single-scale or global models may obscure localized hydrological processes (Zhu et al., 2021; Liu et al., 2023).

The spatial heterogeneity revealed in this study indicates that uniform water-resource management strategies may be ineffective across the entire region. Instead, landscape-oriented and region-specific management approaches that account for local landscape structure and dominant land-use types are

more likely to enhance water-yield capacity and ecosystem resilience. In mountainous and forest-dominated areas, maintaining contiguous forest patches and avoiding excessive fragmentation may help strengthen hydrological regulation functions. In contrast, in agriculturally intensive areas, optimizing farmland configuration may mitigate negative impacts on water-yield processes. These findings provide a scientific basis for integrating landscape planning with water-resource protection and ecological conservation in environmentally sensitive regions.

5 Conclusion

This study investigated the spatiotemporal dynamics of water yield and its landscape-pattern drivers in the Liaodong Green Economic Zone from 2003 to 2023 by integrating the InVEST model with multiscale geographically weighted regression (MGWR). The main conclusions are as follows:

1. 1.Water yield exhibited a fluctuating but overall increasing trend, with pronounced interannual variability. Spatially, water yield showed a clear gradient decreasing from southeast to northwest, highlighting strong spatial heterogeneity in regional hydrological conditions.
2. 2.Landscape pattern evolution was characterized by reduced fragmentation, enhanced connectivity, and increased compositional diversity over the study period. At the landscape level, patch density decreased while mean patch area and Shannon's diversity index increased, indicating a gradual consolidation and reorganization of landscape structure.
3. 3.The effects of landscape pattern on water yield were strongly spatially heterogeneous, as revealed by MGWR analysis. Landscape-level indices such as mean patch area and contagion index exhibited predominantly positive associations with water yield, whereas patch density, aggregation index, and Shannon's diversity index mainly showed negative effects.
4. 4.Distinct class-level differences were observed in landscape–water yield relationships. Farmland-related landscape indices were predominantly negatively associated with water yield across most of the study area, while forest proportion showed predominantly positive effects, emphasizing the contrasting hydrological roles of different land-use types and their spatial configurations.
5. 5.The integrated InVEST–MGWR framework proved effective for identifying spatially heterogeneous drivers of water yield, providing a practical methodological reference for environmental monitoring and landscape-oriented water-resource management in ecologically heterogeneous regions.

Declarations

Conflict of interest

The authors declare no competing interests.

Author Contribution

LYU Leting and JIANG Junchao:Conceptualization and MethodologyLYU Leting and YANG Runcai:Writing - original draftYANG Runcai and HOU Mengjiao:Software and model implementationLYU Leting:ValidationAll authors reviewed and approved the final version of the manuscript.

Data Availability

Data used in this study are available from the National Earth System Science Data Center (https://www.geodata.cn/) and the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/).

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Figures



Figure 1

Location of the Liaodong Green Economic Zone and its administrative divisions in Liaoning Province, China

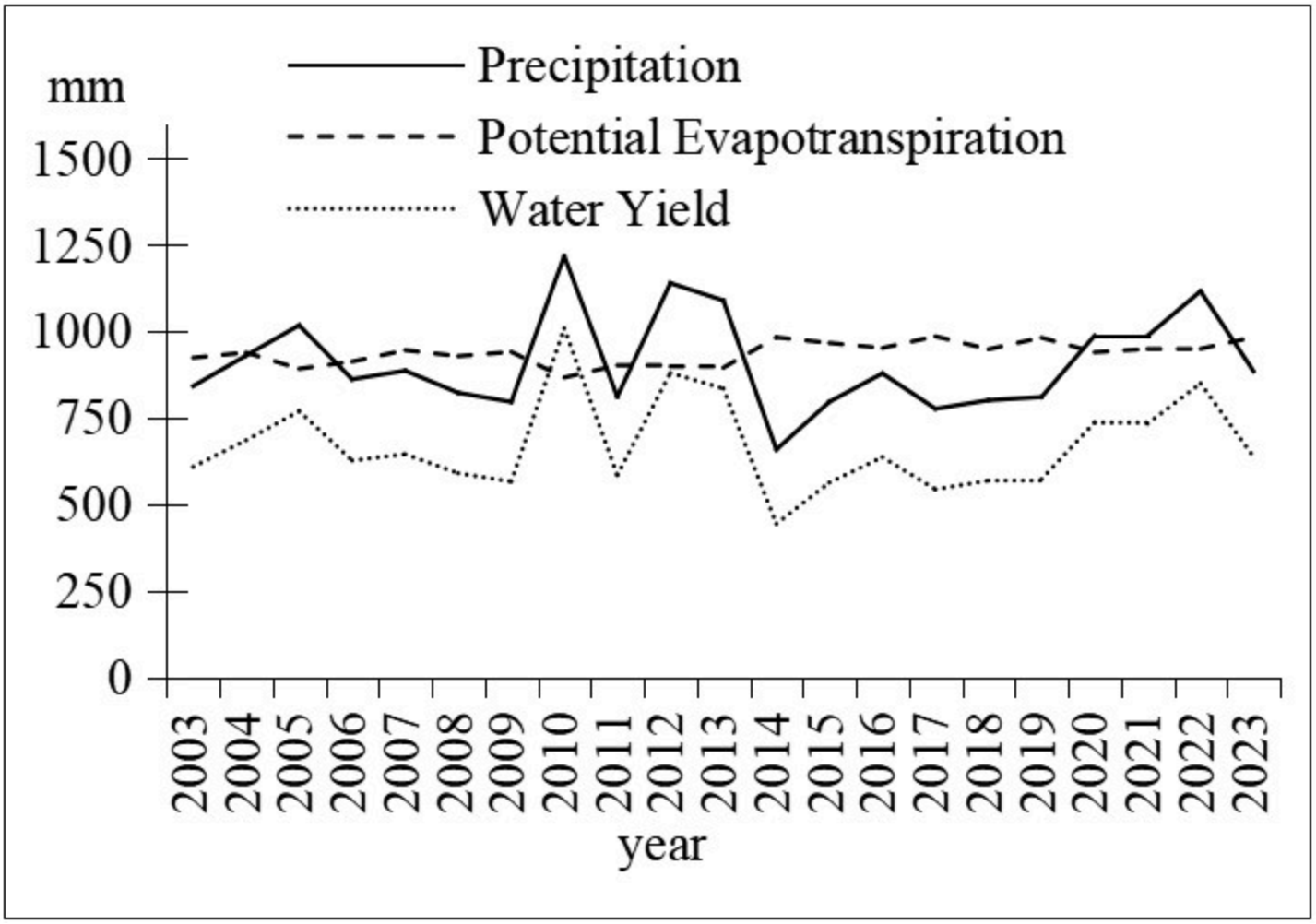


Figure 2

Interannual variations in precipitation, potential evapotranspiration, and water yield in the Liaodong Green Economic Zone from 2003 to 2023

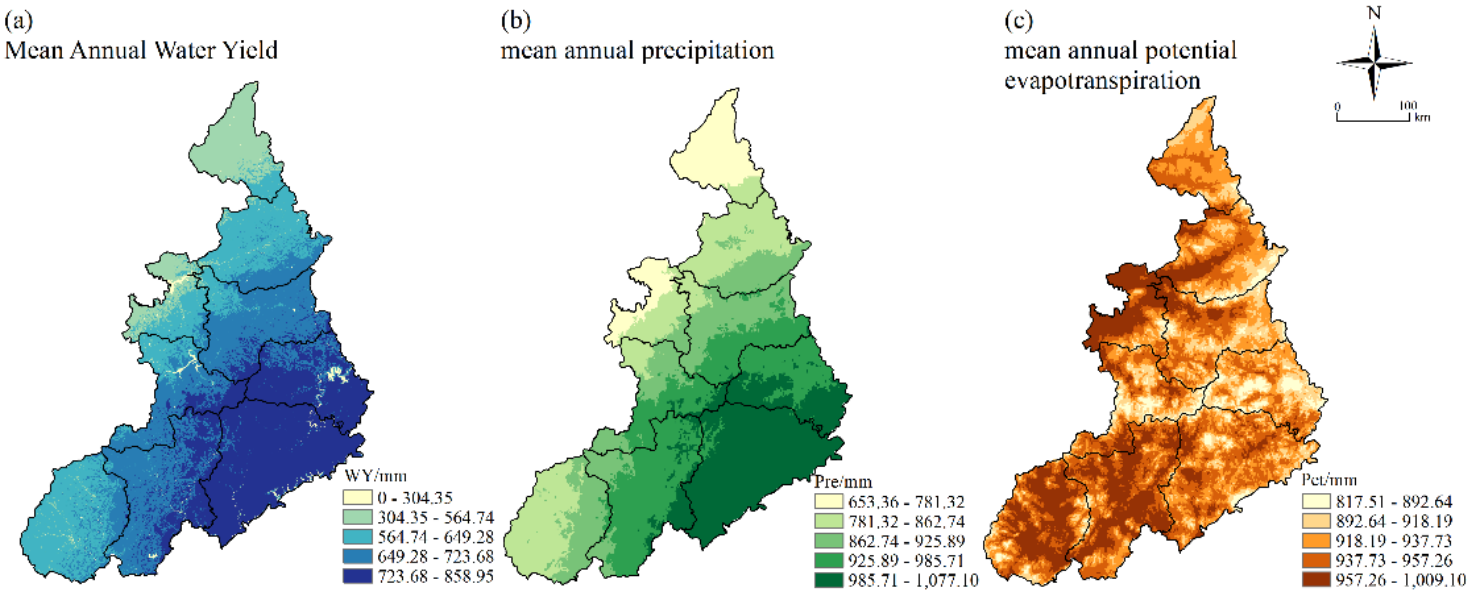


Figure 3

Spatial distribution of mean annual water yield in the Liaodong Green Economic Zone during 2003–2023

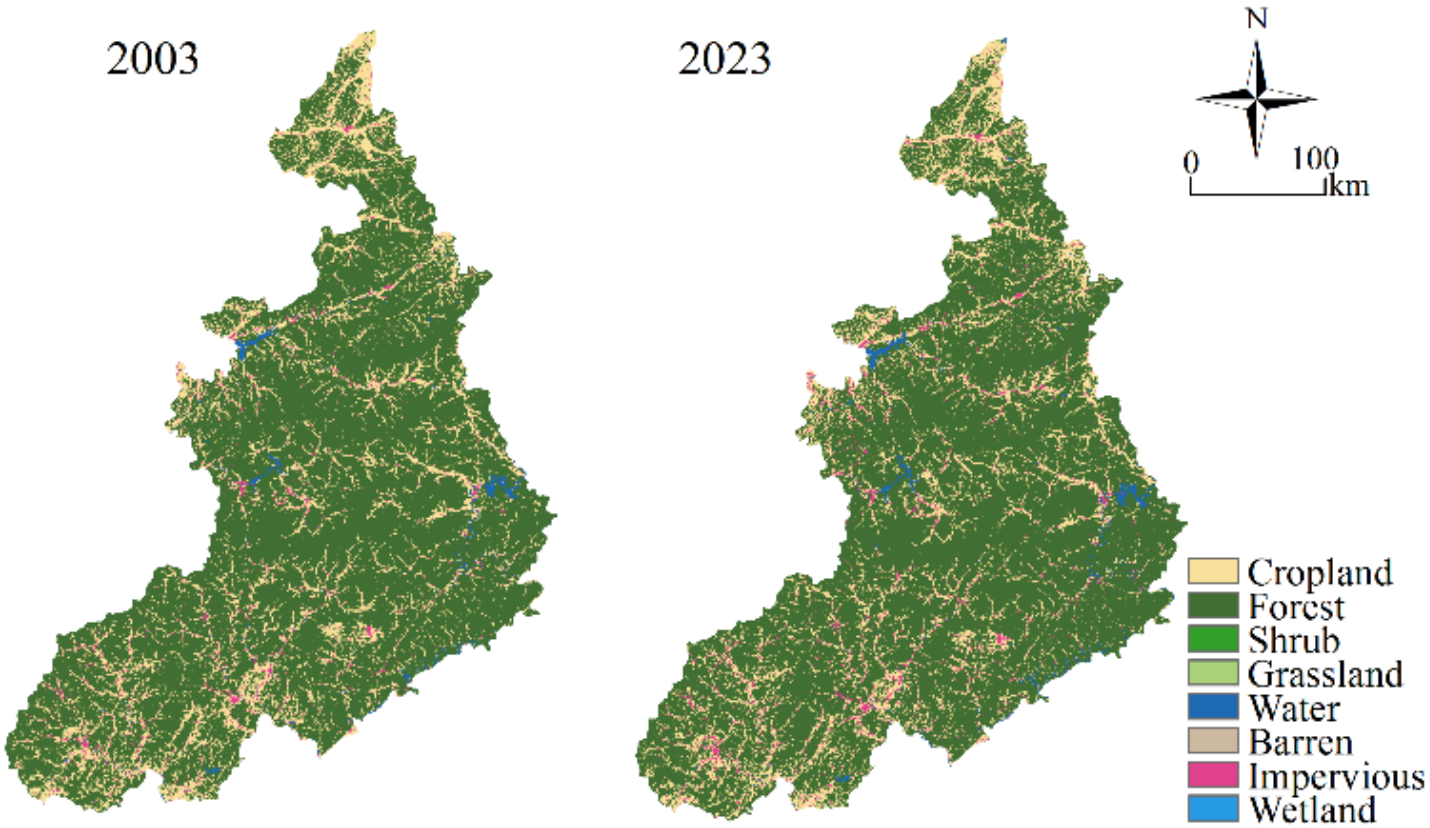


Figure 4

Spatial distribution of land-use types in the Liaodong Green Economic Zone in 2003 and 2023

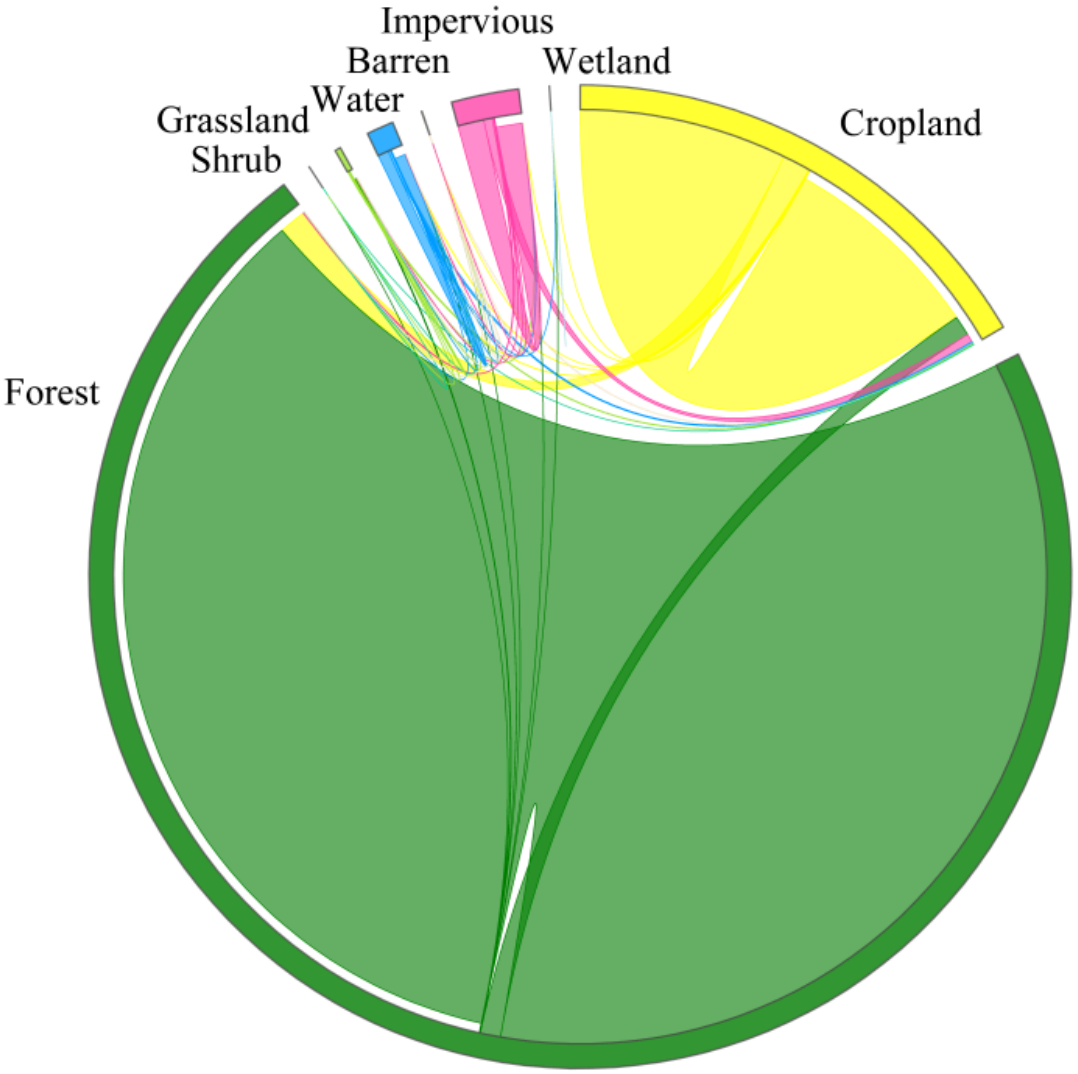


Figure 5

Land-use transition matrix illustrating area conversions between different land-use types from 2003 to 2023

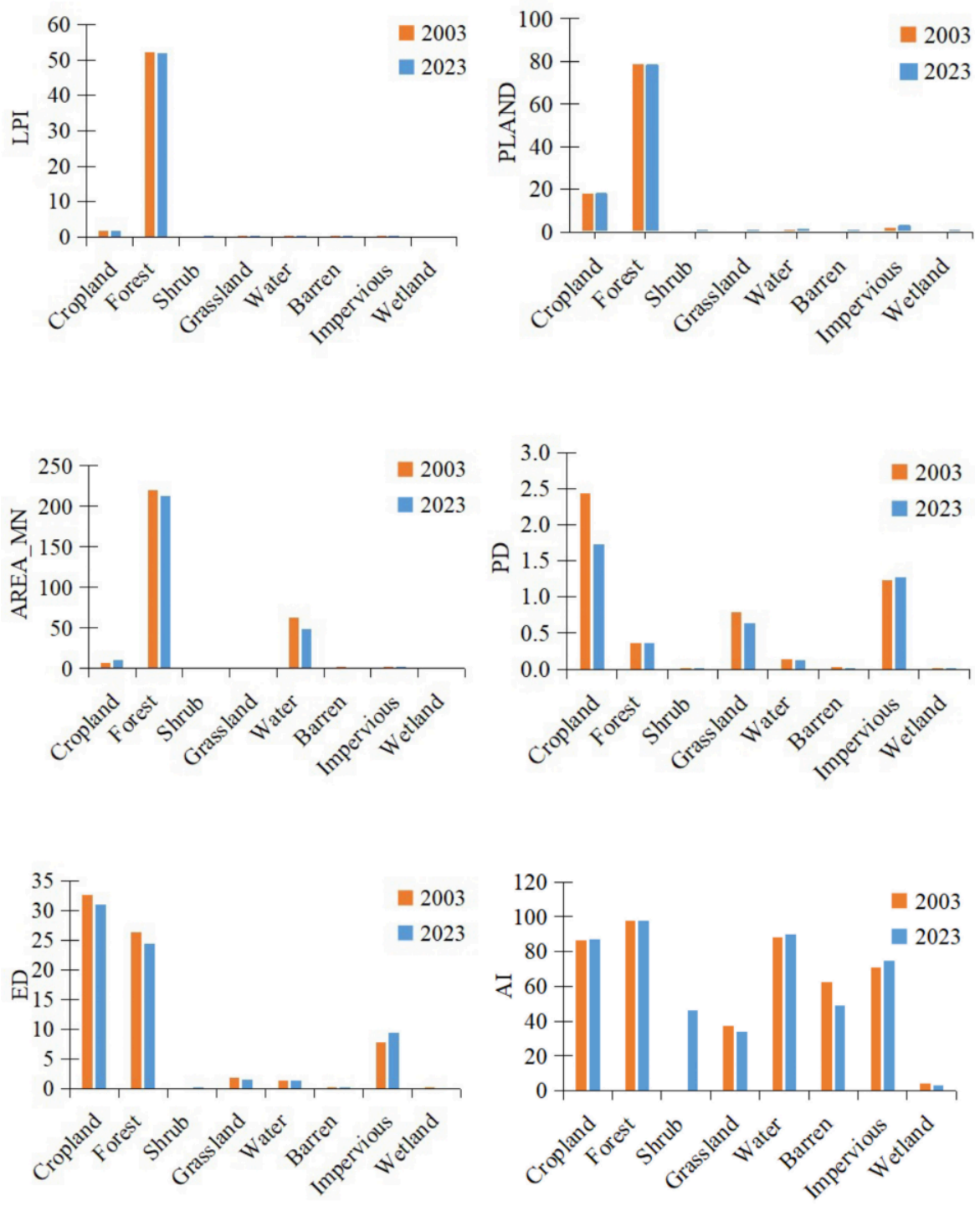


Figure 6

Temporal changes in selected landscape-level indices from 2003 to 2023

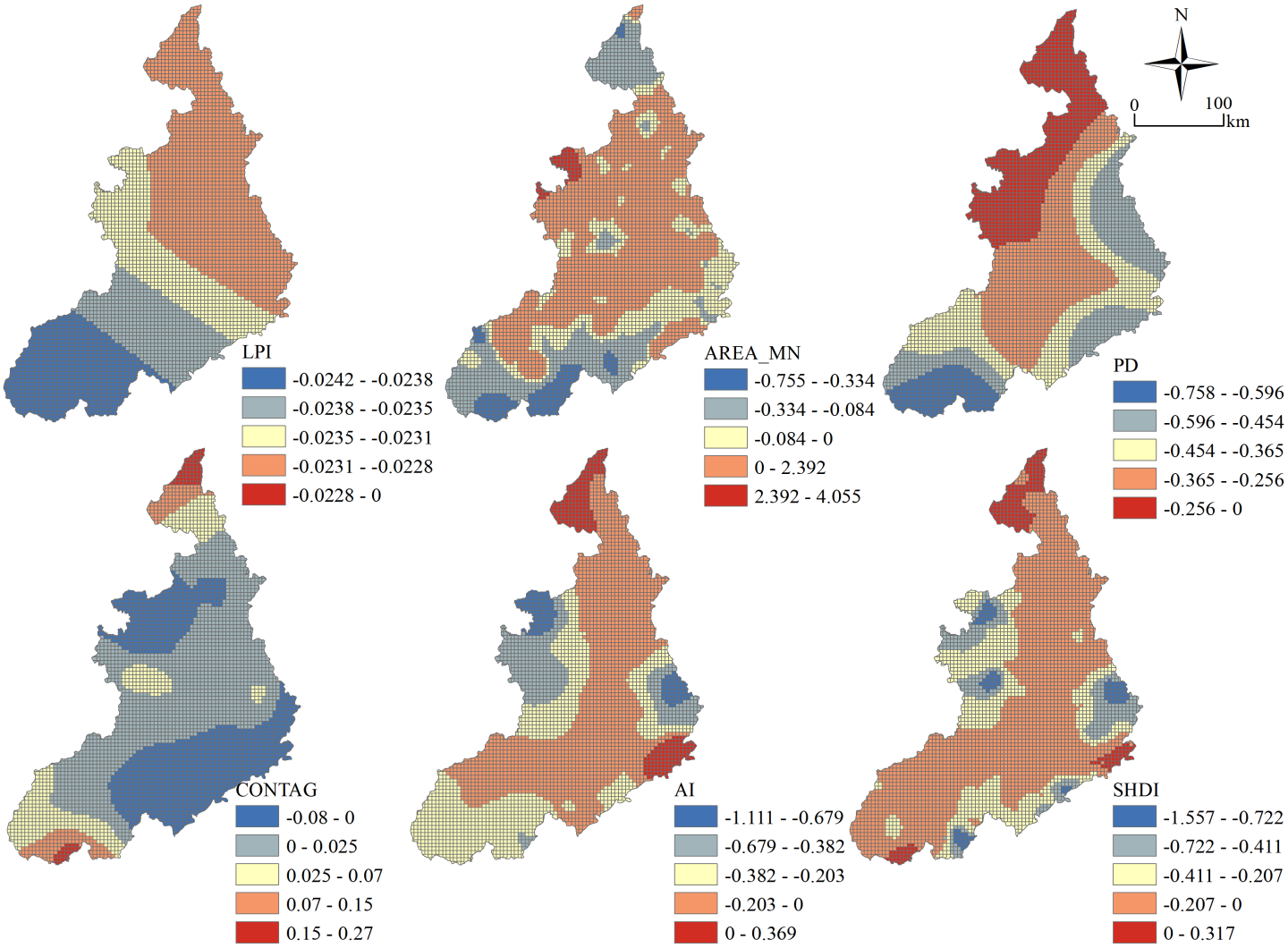


Figure 7

Spatial distribution of MGWR coefficients for landscape-level pattern indices

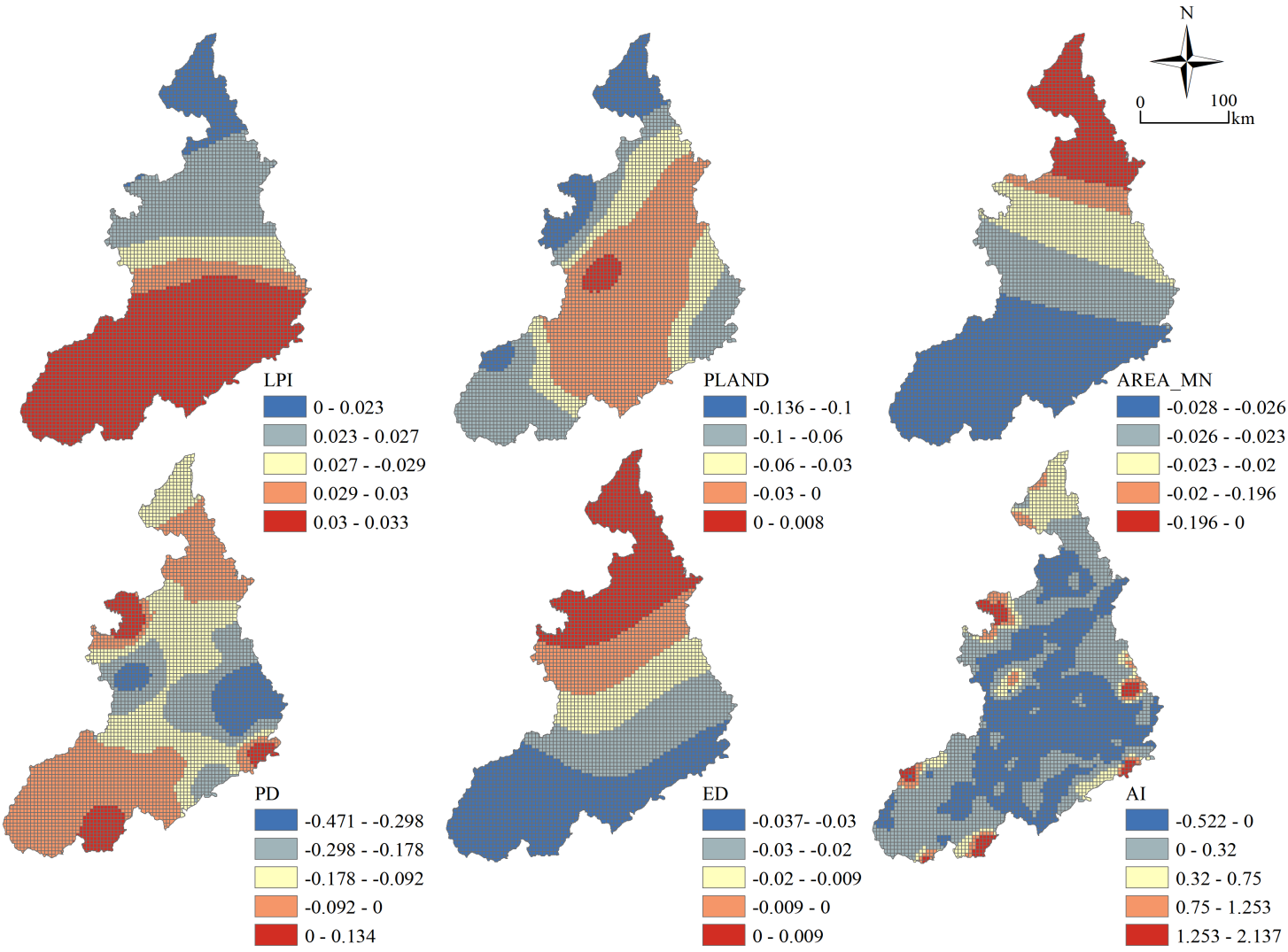


Figure 8

Spatial distribution of MGWR coefficients for farmland-related landscape indices

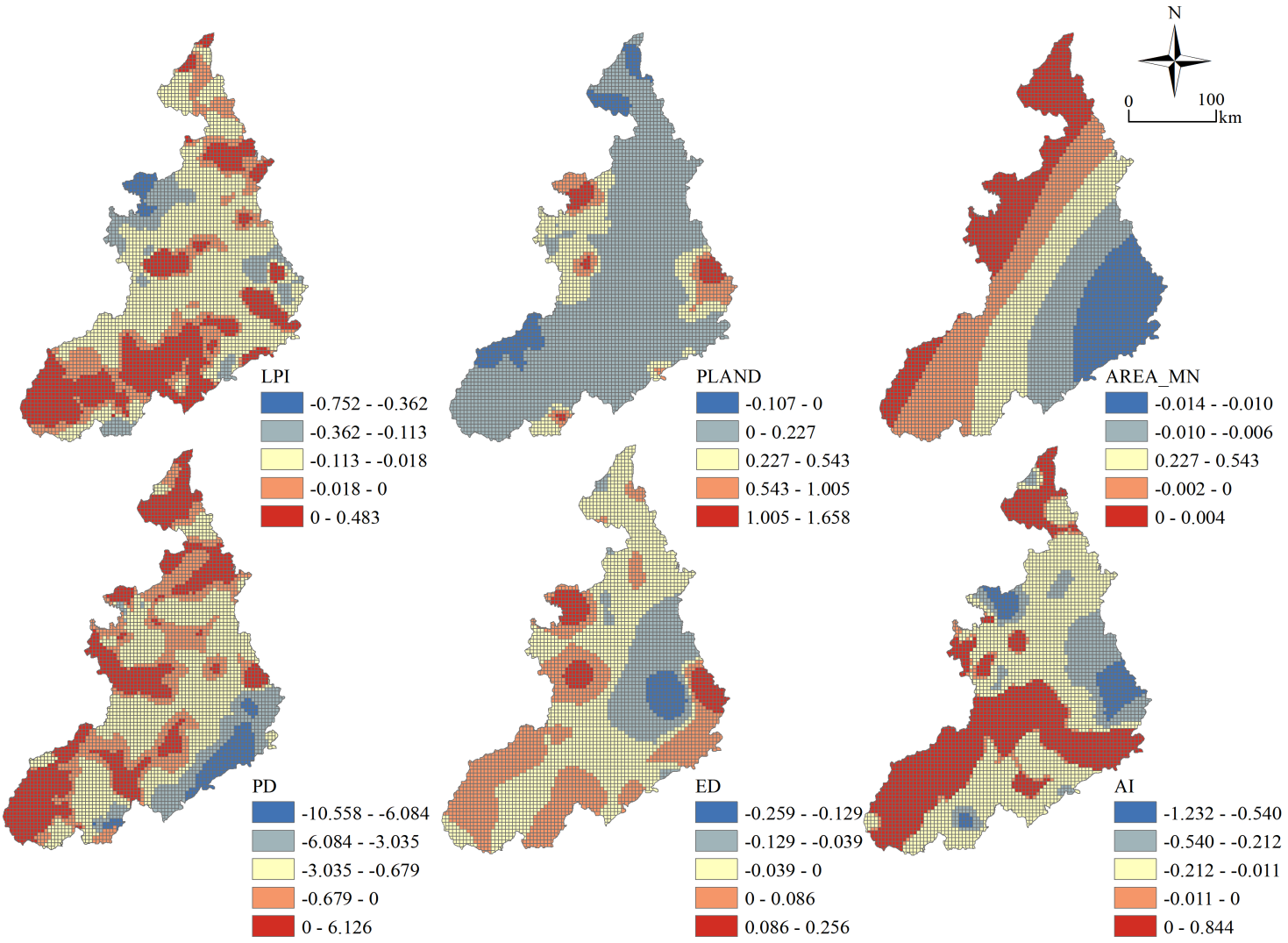


Figure 9

Spatial distribution of MGWR coefficients for forest-related landscape indices