Changes in Landscape Pattern Vulnerability and Its Driving Forces in the Songhua River Basin, Jilin Province: Postprint

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Abstract

Taking the Songhua River Basin in Jilin Province as the study area and three periods of Landsat TM/ETM imagery from 1995, 2005, and 2015 as data sources, this study investigates the landscape pattern, spatiotemporal distribution and changing characteristics of ecological vulnerability, and their driving forces in the basin. The main conclusions are as follows: Climate change varies among different periods in the basin. The dominant landscape types are cultivated land and forest land, while urban-rural land and grassland exhibit steady growth, and forest land, cultivated land, and water areas show a decreasing trend. The vulnerability of the basin is dominated by relatively low vulnerability zones and moderate vulnerability zones. Low vulnerability zones and moderate vulnerability zones are mainly distributed in the relatively developed middle and lower reaches of the basin, while high vulnerability zones are mainly distributed in the southeastern region of the basin and the desertification and forest-grassland degradation areas in the northwest of the lower reaches. The overall vulnerability of the basin is relatively stable, showing a slight upward trend and polarization. Vulnerability is closely related to human activities, has a certain correlation with topography, is not significantly affected by climate change, yet can still reflect certain issues.

Full Text

Abstract

The Songhua River Basin in Jilin Province was selected as the study area to investigate landscape patterns, spatiotemporal distribution of ecological vulnerability, and its driving forces using three Landsat TM/ETM+ images from 1995, 2005, and 2015 as data sources. The main conclusions are as follows: (1) Climate change in the drainage basin varied across different periods. The dominant landscapes were cultivated land and woodland, while the areas of urban and rural land and grassland steadily increased; conversely, the areas of woodland, cultivated land, and water bodies showed a decreasing trend. (2) Areas with low and moderate ecological vulnerability dominated the middle and lower reaches of the drainage basin, whereas areas with high ecological vulnerability were mainly distributed in the southeast of the basin, northwest desertified land in the lower reaches, and woodland and grassland patches. (3) The ecological vulnerability of the drainage basin remained relatively stable with slight increasing and polarizing trends. The distribution of ecological vulnerability was closely related to human activities and, to some extent, topographical conditions. The effect of climate change was not significant; however, it could still reflect some ecological problems.

Keywords: landscape pattern; vulnerability; spatiotemporal distribution; driving factor; land use; random forest models; Songhua River Basin; Jilin

2 Materials and Methods

2.1 Data Sources

Landsat TM/ETM+ images from 1995, 2005, and 2015 were used as the primary data source. Image preprocessing included radiometric calibration, atmospheric correction, and geometric correction. A digital elevation model (DEM) and GDP data were also incorporated into the analysis. All data were processed using Fragstats and ArcGIS software to calculate landscape metrics and analyze spatial patterns.

2.2 Landscape Pattern Indices

The landscape vulnerability assessment was based on a comprehensive index system. The Landscape Vulnerability Index (LAI) was calculated as the product of three components: Relative Patch Richness (RPR), Simpson' s Diversity Index (SIDI), and Shannon' s Evenness Index (SHEI). This multiplicative approach captures different dimensions of landscape vulnerability, including patch composition, diversity, and spatial distribution.

2.2.1 Landscape Status Index (LSI) The Landscape Status Index was calculated using the formula:

$$LSI = \sum U_i \times V_i$$

where U_i represents the landscape status value of patch type i, and V_i represents the vulnerability coefficient of landscape type i. The landscape status value U_i was determined based on three factors: naturalness (FN_i), fragmentation (FD_i), and disturbance intensity (DO_i), expressed as:

$$U_i = aFN_i + bFD_i + cDO_i$$

In this equation, FN_i denotes the naturalness index (higher values indicate more natural landscapes), FD_i represents the fragmentation degree (scored as 1 for low fragmentation, 2 for moderate fragmentation, and 3 for high fragmentation), and DO_i indicates the disturbance intensity. The coefficients a, b, and c were determined through expert scoring and weighted averaging.

2.2.3 Ecological Vulnerability Assessment The ecological vulnerability levels were classified based on Landscape Vulnerability Index (LVI) values: low vulnerability (LVI 0.05), relatively low vulnerability (0.05 < LVI 0.12), moderate vulnerability (0.12 < LVI 0.20), relatively high vulnerability (0.20 < LVI 0.28), and high vulnerability (LVI > 0.28). This classification system provides a quantitative framework for assessing and comparing vulnerability across different landscape types and time periods.

3 Results and Discussion

3.4 Ecological Vulnerability Assessment

The spatial distribution of ecological vulnerability in the Songhua River Basin showed distinct patterns. Areas with low and moderate vulnerability were predominantly located in the middle and lower reaches of the basin, characterized by stable agricultural landscapes. High vulnerability areas were concentrated in the southeastern mountainous regions, northwestern desertified lands, and fragmented woodland and grassland patches.

Correlation analysis revealed that ecological vulnerability was significantly associated with human activities such as urban expansion and agricultural intensification. Topographical factors, including elevation and slope, also influenced vulnerability patterns, though to a lesser extent. Climate change impacts were not statistically significant during the study period; however, localized ecological problems were evident, particularly in areas experiencing land degradation and habitat fragmentation.

The temporal analysis from 1995 to 2015 indicated that overall vulnerability remained relatively stable, though with a slight increasing trend and increasing polarization between vulnerable and stable areas. This suggests that while some regions benefited from conservation efforts, others experienced heightened vulnerability due to intensified land use pressures.

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Note: Figure translations are in progress. See original paper for figures.