Changes in Vegetation Ecological Quality and Their Driving Forces in Guangxi, 2000–2020: Postprint

Authors: Jianfei Mo, Zhou Xiyuan, Mo Weihua, Chen Yanli

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Abstract

To grasp the spatiotemporal variation characteristics and driving mechanisms of vegetation ecological quality in Guangxi, this study utilized the Ecological Quality Index (EQI) as the evaluation indicator. Based on multi-source data encompassing meteorology, topography, soil, and remote sensing, and employing methods including linear trend analysis, correlation analysis, and Geodetector, we analyzed the spatiotemporal variation characteristics and driving forces of vegetation ecological quality in Guangxi from 2000 to 2020. The results indicate: (1) Since 2000, the EQI in Guangxi has demonstrated a significant increasing trend, with notable improvement in regional vegetation ecological quality. The development of vegetation ecological quality has experienced evolutionary stages of slow growth, rapid growth, and significant enhancement. Spatially, the EQI in Guangxi exhibits a pattern of high values in peripheral regions and low values in the central area, with high-value zones gradually expanding from east to west and north. (2) The factors influencing the spatiotemporal evolution of vegetation ecological quality in Guangxi show significant differences. With increasing altitude, the overall change in vegetation ecological quality follows a trend of "increase—decrease—stability—fluctuation". Loam soils exhibit high vegetation ecological quality, while sandy soils show low quality. Forests and shrub-grasslands possess relatively high ecological quality, whereas cropland vegetation has lower quality. Vegetation ecological quality shows a significant positive correlation with climatic drivers, being jointly influenced by temperature and precipitation. Among these, areas where temperature serves as the primary driver (T) are the most extensive, followed by areas where precipitation is the primary driver (P). Areas with strong temperature-precipitation driving ([T+P]+) and weak driving ([T+P]-) are relatively small. (3) The driving forces of vegetation ecological quality change in Guangxi are collectively influenced by topography, soil, vegetation, climate, natural disasters, and human activities. The explanatory power of natural influencing factors follows the order:

vegetation > topography > soil > climate, with vegetation net primary productivity and vegetation coverage being the most crucial factors affecting the spatiotemporal differentiation of vegetation ecological quality. Interaction effects exist among natural factors influencing vegetation ecological quality change in Guangxi, all displaying nonlinear enhancement and two-factor enhancement relationships, with the most pronounced interactions occurring between topography and vegetation, soil and vegetation, and climate and vegetation factors. Natural disasters and human activities intensify the impacts on vegetation ecological quality change, wherein meteorological disasters such as drought and low-temperature chilling damage inhibit the improvement of vegetation ecological quality, while anthropogenic activities such as forestry ecological engineering promote its enhancement. These research findings provide scientific theoretical basis and technical support for rationally formulating vegetation ecological protection and restoration measures in Guangxi.

Full Text

Analysis of Vegetation Ecological Quality Change and Its Driving Forces in Guangxi from 2000 to 2020

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Authors: Mo Jianfei[1,2], Zhou Xiyuan[3], Mo Weihua[1,2*], Chen Yanli[1,2]
[1]Guangxi Institute of Meteorological Sciences, Nanning 530022, China
[2]Guangxi Ecological Meteorology and Satellite Remote Sensing Center, Nanning 530022, China
[3]Guilin Meteorological Bureau, Guilin 541001, Guangxi, China

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Abstract

To understand the spatiotemporal variation characteristics and driving mechanisms of vegetation ecological quality in Guangxi, this study employed the Ecological Quality Index (EQI) as an evaluation metric. Based on multi-source data including meteorology, terrain, soil, and remote sensing, we analyzed the spatiotemporal changes and driving forces of vegetation ecological quality in Guangxi from 2000 to 2020 using linear trend analysis, correlation analysis, and the geographical detector method. The results show: (1) Since 2000, the vegetation ecological quality index in Guangxi has exhibited a significant increasing trend, indicating substantial ecological improvement. The development of vegetation ecological quality has experienced evolutionary stages of slow growth, rapid growth, and significant enhancement. Spatially, the EQI demonstrates a pattern of high values in peripheral areas and low values in the central region, with high-value zones gradually expanding from the east toward the west and north. (2) The factors influencing the spatiotemporal evolution of vegetation ecological quality vary significantly across the region.

With increasing altitude, vegetation ecological quality shows an overall trend of "increase-decrease-stability-fluctuation." Loamy soils support higher vegetation ecological quality, while sandy soils yield lower quality. Forests and shrub-grasslands exhibit higher ecological quality, whereas farmland vegetation shows lower quality. Vegetation ecological quality is significantly positively correlated with climatic drivers, being jointly affected by temperature and precipitation. The area where temperature is the primary driver (T) is the largest, followed by the area where precipitation is the primary driver (P). Areas with strong temperature-precipitation co-driving ([T+P]+) and weak temperature-precipitation co-driving ([T+P]-) are relatively small. (3) The driving forces of vegetation ecological quality change in Guangxi result from the combined effects of terrain, soil, vegetation, climate, natural disasters, and human activities. The explanatory power of natural factors follows the order: vegetation > terrain > soil > climate, with vegetation net primary productivity and vegetation coverage being the most critical factors affecting spatiotemporal differentiation. Natural factors exhibit interactive effects on vegetation ecological quality changes, showing nonlinear enhancement and two-factor enhancement relationships, with the most pronounced interactions occurring between terrain and vegetation, soil and vegetation, and climate and vegetation factors. Natural disasters and human activities exacerbate the impacts on vegetation ecological quality changes, wherein meteorological disasters such as drought and low-temperature damage inhibit improvements, while anthropogenic activities such as forestry ecological engineering promote enhancement. These findings provide a scientific theoretical basis and technical support for formulating rational vegetation ecological protection and restoration measures in Guangxi.

Keywords: vegetation ecological quality; spatiotemporal evolution; driving force; remote sensing; Guangxi

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Introduction

Vegetation constitutes a crucial component of ecosystems and serves as an "indicator" for reflecting regional ecological environmental quality and its changes. Vegetation dynamics and their driving forces have long been a hot topic in ecological research both domestically and internationally (Jin et al., 2020). Guangxi, located in southern China, features a terrain that slopes from northwest to southeast, with complex topography and typical, widespread karst landforms. The region suffers from severe rocky desertification, making it one of China's ecologically fragile areas (Chen et al., 2019) and a key focus for ecological civilization construction and poverty alleviation. Rapid socioeconomic development and intensified human activities in recent years have complicated vegetation ecological changes in Guangxi. Conducting comprehensive monitoring of long-term vegetation changes and their driving forces is essential for understanding vegetation ecological evolution mechanisms and maintaining regional ecological security.

The Normalized Difference Vegetation Index (NDVI) and Net Primary Productivity (NPP) offer advantages in characterizing vegetation conditions. NDVI effectively reflects changes in vegetation cover, biomass, and ecosystem parameters (Zhao, 2003) and has been widely used in vegetation change and driving force studies. NPP serves as an effective indicator for assessing ecosystem function and ecological environmental quality (Liu et al., 2017; Wang et al., 2018). Using NDVI as an indicator, Wei et al. (2013) found that Guangxi's NDVI increased significantly from 1999 to 2010, with greater increases in southern and northwestern Guangxi, and that vegetation responded more sensitively to precipitation than temperature. Liao et al. (2018) reported that NDVI increased from 2007 to 2016, but the area of negative partial correlation between NDVI and precipitation/temperature exceeded that of positive correlation. Similar research (Zhang et al., 2019) indicated significant NDVI fluctuations from 2006 to 2016, with positive correlations between temperature, precipitation, and vegetation cover, and identified artificial afforestation as the main reason for NDVI increase in Guangxi.

Longer time series remote sensing studies show that Guangxi's NDVI increased from 2000 to 2018, with varying changes under different terrain conditions: NDVI first increased then decreased with rising elevation, and first increased to stability then decreased with increasing slope (Yang et al., 2021). Using NPP as an indicator, Zhou et al. (2014) reported a significant decline in Guangxi's vegetation NPP from 2001 to 2010, with significant correlations with temperature and precipitation, and identified slope, longitude, landform characteristics, latitude, and precipitation as the main factors affecting NPP spatial patterns. Research on a similar period (2000–2011) found an overall increasing trend in NPP, significant positive correlation with precipitation but not temperature, higher NPP at greater altitudes, and human activities as the main factor affecting NPP changes (Li et al., 2014). A longer-term study (2000–2015) indicated fluctuating declines in vegetation NPP, non-significant responses to temperature and precipitation changes, and substantial differences in NPP trends across soil types: NPP decreased in red soil, limestone soil, and skeletal soil areas but increased in latosol areas, showing an "increase-decrease-increase-decrease" pattern with altitude (Xiong et al., 2019).

In summary, studies using single remote sensing indicators show that since 2000, Guangxi's NDVI (Liao et al., 2018; Zhang et al., 2019; Yang et al., 2021; Xu et al., 2023) and vegetation coverage (He, 2018; Huang et al., 2022; Li, 2019) have increased significantly, while vegetation NPP has decreased significantly (Zhou et al., 2014; Rong et al., 2017; Xiong et al., 2019). These findings demonstrate that Guangxi's vegetation change characteristics and driving forces are influenced by data time series and remote sensing indicators, with substantial differences and limitations in research results. Vegetation ecological quality represents a comprehensive manifestation of vegetation geographical distribution, productivity, and ecological services (Ji et al., 2021). NDVI and NPP can only reflect one aspect of terrestrial ecosystem service functions or vegetation ecological quality (Qian et al., 2020). Therefore, using single remote sensing indicators to evaluate vegetation ecological quality changes and their driving factors may yield incomplete results.

The Ecological Quality Index (EQI) simultaneously considers both vegetation coverage and NPP, reflecting the comprehensive capacity of vegetation cover status and production capacity per unit area. This largely resolves discrepancies in vegetation ecological quality monitoring results caused by using single indicators such as NDVI, vegetation coverage, or NPP, and has proven applicable for national vegetation ecological quality monitoring and evaluation (Qian et al., 2020). EQI effectively reflects vegetation spatiotemporal change characteristics (Cao et al., 2022; Dai et al., 2022; Han et al., 2022). However, existing driving force research has focused mainly on meteorological factors such as temperature and precipitation, with less attention to vegetation, terrain, and soil factors. No studies using EQI as an indicator to investigate vegetation ecological quality changes and their driving forces in Guangxi have been reported. This study focuses on Guangxi vegetation, using MODIS NDVI remote sensing data and daily meteorological data from 2000 to 2020, with EQI as the evaluation indicator. Employing linear trend analysis, correlation analysis, and geographical detector methods, we analyze 21 years of spatiotemporal variation characteristics and influencing factors of vegetation ecological quality in Guangxi to: (1) characterize the complex and variable vegetation ecological changes in Guangxi; (2) explore the driving mechanisms of vegetation ecological evolution; and (3) provide scientific theoretical basis and technical support for rational development, utilization, and protection of Guangxi's plant resources and promotion of green ecological development.

1.1 Study Area Overview

Guangxi is located in South China, between 104°26 –112°04 E and 20°54 –26°24 N. It borders the Nanling Mountains in the north, the Beibu Gulf in the south, and the southeastern edge of the Yunnan-Guizhou Plateau in the second topographic step in the northwest, representing a transitional zone from the Yunnan-Guizhou Plateau to southeastern coastal hills. The terrain slopes gradually from western, northwestern, and northeastern Guangxi toward central and southeastern regions, forming a basin-like shape with high peripheries and a low middle. The landform is characterized by continuous mountains, undulating hills, narrow plains, numerous rivers, and widespread karst features. The climate belongs to the mid-subtropical and south-subtropical monsoon climate zones, with concurrent rainfall and heat, uneven spatiotemporal precipitation distribution, long hot summers with abundant rainfall, and short dry warm winters (Guangxi Climate Center, 2007). Influenced by alternating southwestern warm-humid air currents and northern modified cold air masses, meteorological disasters such as drought, torrential rain and flooding, and low-temperature cold (freezing) damage occur frequently. Vegetation types are diverse, including coniferous forests, broadleaf forests, shrublands, grasslands, and farmland cultivation vegetation.

Coniferous and broadleaf forests are mainly distributed in mountainous areas of northwestern and southeastern Guangxi, shrubs and grasses predominantly occur in karst rocky mountainous areas, and farmland cultivation vegetation is widely planted in plains, terraces, and hilly areas within Guangxi's basins. Soil types are rich, including red soil, yellow soil, yellow-brown soil, purple soil, limestone soil, paddy soil, and fluvo-aquic soil, among which limestone soil is mainly distributed in karst areas and paddy soil is primarily found in plains, deltas, basins, and intermountain valleys.

1.2 Data Sources and Processing

Research data primarily included vegetation ecological parameters, meteorology, terrain, soil, and basic geographic information. All raster data were unified to a spatial resolution of 250 m × 250 m and projected using CGCS2000_{{{GK}}{{Zone}}}{18}.

1.2.1 Vegetation Ecological Parameter Data We utilized MOD13Q1 vegetation index products provided by NASA, applying the Maximum Value Composition (MVC) method to generate monthly NDVI data. Cloud-contaminated pixels were processed using cubic spline interpolation (Spline) to reconstruct high-quality NDVI time series data. Fractional vegetation cover (FVC) for Guangxi from 2000 to 2020 was calculated using a pixel linear decomposition model (Su et al., 2018). Based on the principle of vegetation light energy utilization (Yan et al., 2015), we estimated vegetation net primary productivity (NPP) for Guangxi from 2000 to 2020 using reconstructed high-quality NDVI data combined with ground meteorological observation data. The calculation formula is as follows:

NPP GPP FPAR PAR

Where NPPij, GPPij, and Rij represent vegetation net primary productivity, gross primary productivity, and respiratory consumption ($\mathrm{gC \cdot m^{-2} \cdot month^{-1}}$) in month j of year i, respectively; ij is the actual light energy utilization efficiency in month j of year i; FPAR is the fraction of photosynthetically active radiation absorbed by vegetation, which varies with vegetation growth and was estimated using monthly NDVI in this study; PARij is the incident photosynthetically active radiation ($\mathrm{MJ \cdot m^{-2} \cdot month^{-1}}$) in month j of year i, calculated using the method recommended by the Food and Agriculture Organization of the United Nations. Solar total radiation was computed from sunshine hours at national meteorological stations, and PARij was then derived using the proportion of 0.48 for photosynthetically active radiation in total solar radiation.

1.2.2 Meteorological Data Meteorological data were obtained from the Guangxi Meteorological Information Center, including daily average temperature and precipitation from 92 meteorological stations in Guangxi from 2000 to 2020. Monthly and annual values were calculated and interpolated using the inverse distance weighting method to generate meteorological element raster data at 250 m × 250 m resolution.

1.2.3 Terrain Data Terrain data consisted of a 30 m resolution digital elevation model (DEM) for Guangxi, sourced from the Geospatial Data Cloud. After geometric correction, mosaicking, clipping, and projection transformation, we obtained altitude and slope data for Guangxi.

1.2.4 Soil Data Soil data included soil type and soil texture information from the Harmonized World Soil Database (HWSD), which was clipped and projected to obtain Guangxi soil type and texture data.

1.2.5 Vegetation Types Based on Landsat TM/ETM/OLI satellite remote sensing data and referencing the spectral characteristics of different vegetation types, we determined remote sensing classification characteristic parameters for various vegetation types. Using maximum likelihood classification (Sun, 2003) and decision tree hierarchical extraction methods, we obtained vegetation type information data for forest, shrub-grass, and farmland in Guangxi for the years 2000, 2005, 2010, 2015, and 2020.

1.3 Methods

1.3.1 Vegetation Ecological Quality Evaluation Method Based on vegetation net primary productivity and vegetation coverage, we constructed the vegetation ecological quality index using a weighted method as an evaluation indicator to quantitatively reflect the change characteristics of vegetation ecological quality in Guangxi from 2000 to 2020. The calculation formula is as follows (Qian et al., 2020):

Where Qi is the comprehensive vegetation ecological quality index for year i; FVCi is the annual average vegetation coverage for year i, obtained by averaging the 12 monthly vegetation coverage values; NPPi is the annual vegetation net primary productivity for year i, obtained by accumulating the 12 monthly values; NPPm is the historical maximum annual vegetation NPP for a certain period, representing the annual vegetation NPP under the best climate conditions in the corresponding spatial region; f1 and f2 are weight coefficients (f1 = 0.5, f2 = 0.5).

1.3.2 Calculation Method for Vegetation Dynamic Change Degree We calculated the vegetation dynamic change degree in Guangxi using a spatiotemporal change model with the following formula (Bi, 2006):

Where K is the vegetation dynamic degree (%); Ua and Ub represent the vegetation area (km^2) at the initial and final stages of the study period, respectively;

and T is the study period length (years).

1.3.3 Trend Analysis Method We employed a unary linear regression method to analyze the temporal trend of the vegetation ecological quality index in Guangxi from 2000 to 2020, using the trend rate to represent the rate of increase or decrease during this period. The trend rate calculation formula is as follows (Zhang et al., 2008):

slope

Where slope is the trend rate; Qi is the annual vegetation ecological quality index for year i; and n is the number of evaluation years. slope $>$ 0 indicates an increasing trend in vegetation ecological quality and ecological improvement in the study area during a certain period, while slope $<$ 0 indicates a decreasing trend and vegetation degradation.

1.3.4 Correlation Analysis Method Using GIS technology and correlation analysis, we examined the relationships between vegetation ecological quality changes and terrain, soil, and climate conditions in Guangxi. The vegetation ecological quality index spatial distribution map was matched with elevation and slope maps. Elevation was analyzed at 10 m intervals and slope at 1° intervals, with the average vegetation ecological quality index for different periods from 2000 to 2020 calculated for each interval to analyze terrain impacts. Similarly, the vegetation ecological quality index map was matched with soil type, soil texture, and vegetation type maps to calculate average indices for each soil type, texture type, and vegetation type across different periods.

Based on annual average vegetation ecological quality indices and corresponding temperature and precipitation data from 2000 to 2020, we used partial and multiple correlation analysis methods (Mu et al., 2012) to calculate pixel-scale correlation coefficients between interannual vegetation ecological quality changes and climate factors. T-tests and F-tests were applied to examine the significance of partial and multiple correlation coefficients, respectively. Following relevant research (Cao et al., 2014), correlations passing the 0.05 significance level were considered significant, while those passing the 0.01 level were considered highly significant, enabling analysis of climate impacts on vegetation ecological quality changes.

1.3.5 Driving Force Analysis Method The geographical detector is a statistical method for detecting spatial stratified heterogeneity and revealing its underlying driving forces (Wang et al., 2017). Its core principle assumes that if an independent variable significantly influences a dependent variable, their spatial distributions should be similar. The explanatory power is measured by the q-value, calculated as follows (Wang et al., 2010):

Where h = 1, 2, …, L represents the strata of the dependent variable (Y) and independent variable (X); Nh and N are the numbers of units within stratum h and the entire region, respectively; and σh^2 and σ^2 are the variances of Y values within stratum h and the entire region, respectively. The q-statistic ranges from [0, 1], with larger values indicating more pronounced spatial stratified heterogeneity and stronger explanatory power of independent variables on the dependent variable.

Using the data discretization method proposed by Wang et al. (2017), we discretized the dependent variable (vegetation ecological quality change) and independent variables. Factor detection and interaction detection were then applied to calculate the influence q-values of various natural factors on vegetation ecological quality changes and their interactions, thereby analyzing the driving forces of vegetation ecological quality changes.

2.1.1 Temporal Variation Characteristics

From 2000 to 2020, the annual vegetation ecological quality index in Guangxi showed a fluctuating increasing trend, with clear ecological improvement [Figure 1: see original paper]. The annual average vegetation ecological quality index ranged from 50 to 80, with a trend rate of 6.3/10 a ($P < 0.05$). The lowest value occurred in 2005 (62.72) and the highest in 2017 (77.75). The average annual vegetation ecological quality indices for the four periods of 2000–2005, 2006–2010, 2011–2015, and 2016–2020 were 66.29, 68.40, 71.45, and 76.82, respectively. These results demonstrate a gradual increase in the annual average vegetation ecological quality index, though the growth rate was slightly slower during 2006–2010, possibly related to severe drought and frequent low-temperature freezing disasters during this period. A jump growth began in 2011–2015, particularly showing a clear upward trend from 2013 onward. The 2016–2020 period saw a 14.62% increase compared to 2000–2005, indicating significant overall environmental improvement and a positive vegetation ecological trend.

FIGURE:1 Variation of Vegetation Ecological Quality Index in Guangxi from 2000 to 2020

2.1.2 Spatial Variation Characteristics

The spatial distribution of annual vegetation ecological quality in Guangxi from 2000 to 2020 showed significant heterogeneity [Figure 2: see original paper]. Since 2000, the annual average vegetation ecological quality index has exhibited a pattern of high values in peripheral areas and low values in the central region, with high-value zones gradually expanding from the east and south toward the west and north. The spatial distribution patterns during 2000–2005 and 2006–2010 were similar, with 78.21% and 82.89% of the region, respectively, showing high vegetation ecological quality indices (>70), mainly distributed in Wuzhou

City in the east and Fangchenggang City in the south. During 2011–2015, vegetation ecological quality continued to improve, with high-value zones expanding to Yulin, Qinzhou, and Chongzuo cities, accounting for 89.86% of the region. In 2016–2020, vegetation ecological quality improved significantly, with high-value zones extending to Baise and Hechi cities, representing 95.31% of the region, indicating an overall positive development trend.

A. 2000–2005; B. 2006–2010; C. 2011–2015; D. 2016–2020.

FIGURE:2 Distribution of Spatial Variation of Vegetation Ecological Quality in Guangxi in Each Period from 2000 to 2020

2.1.3 Spatiotemporal Change Trends

Based on the vegetation ecological quality index and using 2000 as a baseline, we calculated the vegetation change trend rate (Slope) for Guangxi from 2000 to 2020. Using the natural breaks method and considering actual vegetation ecological improvement conditions, Slope values were divided into six categories: significantly deteriorated (Slope $\leq$ -1.0), deteriorated (-1.0 $<$ Slope $\leq$ -0.5), slightly deteriorated (-0.5 $<$ Slope $\leq$ 0.0), slightly improved (0.0 $<$ Slope $\leq$ 0.5), improved (0.5 $<$ Slope $\leq$ 1.0), and significantly improved (Slope $>$ 1.0). F-tests were applied for significance testing [Figure 3: see original paper]. From 2000 to 2020, 98.83% of Guangxi showed an improving trend in vegetation ecological quality, with 88.71% passing the significance test for increase, indicating substantial ecological improvement, mainly distributed in central-southern Laibin, southern Nanning, and central-southern Qinzhou. Only 1.17% of the region showed a decreasing trend, with 0.45% passing the significance test for decrease, primarily located in urban development zones of Nanning, Liuzhou, Wuzhou, and Yulin cities.

FIGURE:3 Spatial Variation Trend (A) and Significance Test (B) of Vegetation Ecological Quality in Guangxi from 2000 to 2020

2.2.1 Terrain Impacts on Vegetation Ecological Quality

The variation trends of average annual vegetation ecological quality index with terrain environment in Guangxi during different periods from 2000 to 2020 are shown in [Figure 4: see original paper]. Regarding altitude, the index increased most rapidly from 0–200 m, showed a slow increasing trend from 200–400 m, decreased from 400–800 m, remained almost unchanged from 800–1200 m, slowly declined from 1200–1600 m, and exhibited strong fluctuation from 1600–2000 m. Regarding slope, vegetation ecological quality showed a clear increasing trend with slope from 0°–15°, a slow increase from 15°–25°, a slight decrease from 25°–45°, remained almost unchanged from 45°–60°, and showed an “increase-decrease-increase” fluctuation pattern from 60°–80°. Across different periods, vegetation ecological quality improved gradually within the altitude range of 0–800 m and slope range of 0°–25°. However, in the 1200–1600 m altitude range, the indices for 2006–2010 and 2011–2015 were lower than for 2000–2005, possibly related to complex terrain and natural disasters. During 2016–2020, vegetation ecological quality improved substantially across all terrain environments.

A. Altitude; B. Slope.

FIGURE:4 Variation Trend of Vegetation Ecological Quality Index with Topography in Guangxi in Different Periods from 2000 to 2020

2.2.2 Soil Impacts on Vegetation Ecological Quality

The variation trends of average annual vegetation ecological quality index with soil environment in Guangxi during different periods from 2000 to 2020 are shown in [Figure 5: see original paper]. Among soil types, yellow soil showed the highest average vegetation ecological quality index (75.6), followed by yellow-red soil (75.0), with limestone soil and purple soil being similar (70.1), and fluvo-aquic soil and paddy soil being relatively low (64.9 and 55.3, respectively). Regarding soil texture, loam showed the highest average vegetation ecological quality index (68.5), followed by clay (65.1), with sand being the lowest (62.4). Across periods, all soil texture types except sandy loam and silty clay showed increasing trends from 2006–2010 compared to 2000–2005. During 2016–2020, vegetation ecological quality improved substantially across all soil textures.

A. Soil type; B. Soil texture.

FIGURE:5 Variation Trend of Vegetation Ecological Quality Index with Soil Environment in Guangxi in Different Periods from 2000 to 2020

2.2.3 Vegetation Type Impacts on Vegetation Ecological Quality

Using Guangxi vegetation type information for 2000, 2005, 2010, 2015, and 2020, we calculated the dynamic degree and average ecological quality index for different vegetation types during 2000–2005, 2006–2010, 2011–2015, and 2016–2020 . The results reveal significant differences in dynamic changes and ecological quality among forests, shrub-grasslands, and farmland vegetation. Regarding dynamic changes, both forests and shrub-grasslands showed positive dynamic degrees from 2000 to 2020, with forests having the largest dynamic degree (average annual growth rate of 1.30%), representing the dominant factor in vegetation area evolution, followed by shrub-grasslands (average annual growth rate of 0.56%) showing a yearly increasing trend. Farmland vegetation showed negative dynamic degrees, indicating a decreasing trend with an average annual reduction rate of 2.64%, most pronounced after 2010. Regarding ecological quality, forests exhibited the best average quality (74.38), followed by shrub-grasslands (72.19), with farmland vegetation being the lowest (64.93). Across different periods, farmland vegetation showed the fastest average annual growth rate from 2000–2010, followed by forests, with shrub-grasslands being the slowest. From 2011–2020, forests showed the fastest growth rate, followed by shrub-grasslands, with farmland being the slowest [Figure 6: see original paper].

TABLE:1 Variation of Vegetation Ecological Quality Index (EQI) of Different Vegetation Types in Guangxi from 2000 to 2020

FIGURE:6 Variation of Vegetation Ecological Quality Index of Different Vegetation Types in Guangxi from 2000 to 2020

2.2.4 Climate Impacts on Vegetation Ecological Quality Changes

From 2000 to 2020, the annual average temperature in Guangxi ranged from 20.25–21.77 °C, with a multi-year average of 20.96 °C, showing an increasing trend. Annual precipitation ranged from 1224.05–1920.32 mm, with a multi-year average of 1547.51 mm, also showing an increasing trend [Figure 7: see original paper]. Temperature and precipitation changes in Guangxi showed clear positive correlations with the vegetation ecological quality index [Figure 8: see original paper]. The partial correlation coefficient between temperature and vegetation ecological quality index ranged from -0.69 to 0.92, with an average of 0.32. Positive and negative correlation areas accounted for 94.26% and 5.74% of the total area, respectively. Significantly positive correlation areas comprised 39.90%, mainly distributed in Guilin, Liuzhou, eastern and western Hechi in northeastern Guangxi, northern Baise in northwestern Guangxi, northeastern Qinzhou and eastern Fangchenggang in southern Guangxi, and northeastern Laibin in central Guangxi. Significantly negative correlation areas accounted for only 0.24%, mainly distributed in southern Wuzhou.

The partial correlation coefficient between precipitation and vegetation ecological quality index ranged from -0.64 to 0.89, with an average of 0.34. Positive and negative correlation areas accounted for 96.57% and 3.43% of the total area, respectively. Significantly positive correlation areas comprised 44.38%, mainly distributed in southeastern and northwestern Baise, most of Chongzuo, Nanning, and Wuzhou, southeastern Hechi, southeastern and northeastern Guilin, northern Hezhou, and northeastern Qinzhou. Significantly negative correlation areas accounted for only 0.04%.

The multiple correlation coefficient between temperature-precipitation and vegetation ecological quality index ranged from 0.00 to 0.92, with an average of 0.49. Areas with strong multiple correlations (coefficient > 0.4) covered 73.19% of the total area, with significant areas comprising 44.14%, mainly distributed in northeastern Liuzhou, eastern Hechi, southwestern Guilin, northwestern and southeastern Baise, western Chongzuo, northwestern Nanning, eastern Qinzhou, and central Wuzhou. The remaining areas were mostly non-significant, accounting for 55.86%.

FIGURE:7 Variation Trend of Annual Average Temperature and Annual Precipitation in Guangxi from 2000 to 2020

A. Partial correlation with temperature; B. Significance of partial correlation with temperature; C. Partial correlation with precipitation; D. Significance of partial correlation with precipitation; E. Complex correlation with temperature and precipitation; F. Significance of complex correlation with temperature and precipitation.

FIGURE:8 Spatial Distribution of Correlation between Vegetation Ecological Quality and Climate and Its Significance in Guangxi

Based on the correlation between vegetation ecological quality changes and climate factors and their significance tests, we constructed a climate-driven zoning index for vegetation ecological quality evolution in Guangxi using a quantitative factor change-driven zoning method . Temperature-precipitation strong driving ([T+P]+): Both R1 and R2 satisfy $|t| > t_{0 \cdot 01}$, and R3 satisfies $F > F_{0 \cdot 05}$; Temperature primary driving (T): R1 satisfies $|t| > t_{0 \cdot 01}$, and R3 satisfies $F > F_{0 \cdot 05}$; Precipitation primary driving (P): R2 satisfies $|t| > t_{0 \cdot 01}$, and R3 satisfies $F > F_{0 \cdot 05}$; Temperature-precipitation weak driving ([T+P]-): Both R1 and R2 satisfy $|t| \leq t_{0 \cdot 01}$, and R3 satisfies $F > F_{0 \cdot 05}$; Non-climate driving (NC): R3 satisfies $F \leq F_{0 \cdot 05}$.

TABLE:2 Climate-Driven Zoning Index of Vegetation Ecological Quality Change in Guangxi

Note: R1 is the T-significance test of the partial correlation between vegetation ecological quality and temperature; R2 is the T-significance test of the partial correlation between vegetation ecological quality and precipitation; R3 is the F-significance test of the compound correlation between vegetation ecological quality and temperature and precipitation.

According to the driving force zoning indicators and using GIS technology, we delineated the driving force zones for vegetation ecological quality evolution in Guangxi [Figure 9: see original paper]. From 2000 to 2020, the driving forces were mainly divided into climate-driven (44.14%) and non-climate-driven (55.86%) categories. The temperature primary driving (T) zone had the largest area (17.86%), mainly distributed in Sanjiang, Liujiang, and Rongshui counties in Liuzhou, most of Guilin, Leye County in Baise, Zhaoping County in Hezhou, and other areas. These regions are located in the mountainous areas at the edge of the Yunnan-Guizhou Plateau, with abundant precipitation (annual average of 1633.2 mm, 5.54% higher than the regional average) but complex terrain (average altitude of 472.1 m and average slope of 20.7°), making vegetation ecological quality changes more sensitive to temperature. The precipitation primary driving (P) zone ranked second (13.64%), concentrated in Longlin, Xilin, Tiandong, and Tianyang counties in Baise, Longzhou County in Chongzuo, Wuming District in Nanning, Fuchuan County in Hezhou, Pingle County in Guilin, and Teng and Cangwu counties in Wuzhou. These areas are located in Guangxi's hilly region (average altitude of 365.2 m and average slope of 18.7°) with sufficient heat (annual average temperature of 21.3 °C) but relatively low precipitation (annual average of 1422.9 mm, 8.05% lower than the regional average) and high meteorological drought risk, making vegetation ecological quality changes more sensitive to precipitation. Temperature-precipitation strong driving ([T+P]+) and weak driving ([T+P]-) zones covered smaller areas (7.59% and 5.05%, respectively), with climate conditions intermediate between T and P types. The [T+P]+ type was mainly concentrated in Yizhou District in Hechi, Liujiang and Liucheng counties in Liuzhou, Gongcheng and Pingle counties and Quanzhou County in Guilin, Longlin and Tianlin counties in Baise, Wuxuan County in Laibin, Pubei County in Qinzhou, and Longxu District in Wuzhou. The [T+P]- type was scattered in Rong'an County in Liuzhou and Xingbin District in Laibin. Most remaining areas belonged to the non-climate driving (NC) zone, primarily characterized by karst landforms with complex terrain, shrub-dominated vegetation, thin limestone soil layers, barren land, severe rocky desertification, and vulnerability to natural disasters, representing a key focus area for ecological restoration in Guangxi.

FIGURE:9 Distribution of Driving Forces of Vegetation Ecological Change in Guangxi

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2.3 Driving Force Analysis of Vegetation Ecological Quality Change in Guangxi

Based on the analysis of driving factors for vegetation ecological quality changes in Guangxi, we used data discretization methods to classify terrain, soil, vegetation, and climate factors. Terrain factors included elevation (X1) classified into six categories: <200 m, 200–400 m, 400–800 m, 800–1200 m, 1200–1600 m, and >1600 m; and slope (X2) classified into five categories: <15°, 15°–25°, 25°–45°, 45°–60°, and >60°. Soil factors included soil type (X3) classified into eight categories: yellow soil, red soil, yellow-red soil, clay, limestone soil, purple soil, fluvo-aquic soil, and paddy soil; and soil texture (X4) classified into nine categories: sandy loam, sandy clay loam, clay, loam, silt loam, loamy sand, sand, silty clay loam, and silty clay. Vegetation factors included vegetation type (X5) classified into four categories: forest, shrub-grass, farmland, and others; annual average vegetation coverage (X6) classified into five categories: <30%, 30%–45%, 45%–60%, 60%–75%, and >75%; and annual average vegetation net primary productivity (X7) classified into five categories: <600 $gC \cdot m^{-2}$, 600–800 $gC \cdot m^{-2}$, 800–1000 $gC \cdot m^{-2}$, 1000–1200 $gC \cdot m^{-2}$, and >1200 $gC \cdot m^{-2}$. Climate factors included annual average precipitation (X8) classified into six categories: <1200 mm, 1200–1400 mm, 1400–1600 mm, 1600–1800 mm, 1800–2000 mm, and >2000 mm; and annual average temperature (X9) classified into five categories: <19 °C, 19–20 °C, 20–21 °C, 21–22 °C, and >22 °C. Using annual average vegetation ecological quality index as the dependent variable and terrain, soil, vegetation, and climate factors as independent variables, we generated equally spaced (0.025°) sampling points using ArcGIS fishnet tools, extracted information from raster data for dependent and independent variables, and analyzed the driving mechanisms of vegetation ecological quality changes in Guangxi during different stages from 2000 to 2020 using geographical detectors.

2.3.1 Single-Factor Driving Force Detection Results Single-factor detection results for vegetation ecological quality changes in Guangxi indicate significant differences in the influence of various driving factors on the spatiotemporal distribution of vegetation ecological quality. The average q-values for ecological environmental factors followed the order: vegetation > terrain > soil > climate. From the perspective of single-factor explanatory power, annual vegetation net primary productivity and vegetation coverage both exceeded 70%, representing the most important factors affecting spatiotemporal differentiation of vegetation ecological quality in Guangxi. Elevation, slope, and vegetation type showed explanatory power between 20%–60%, representing secondary factors. Soil type, soil texture, annual precipitation, and temperature showed explanatory power below 10%, indicating minor impacts on spatial differentiation characteristics. Across different periods, the q-values for single terrain, soil, and climate factors showed decreasing trends, while vegetation factors showed increasing trends, indicating that the explanatory power of single terrain, soil, and climate factors on vegetation ecological quality spatial distribution gradually weakened, while that of vegetation factors gradually strengthened.

TABLE:3 q Values of Single Impact Factor

2.3.2 Factor Interaction Detection Results Interaction detection results for vegetation ecological quality changes in Guangxi demonstrate that the formation of spatiotemporal differentiation characteristics is not influenced by single factors alone but results from the combined effects of multiple factors. Interactions among influencing factors showed nonlinear enhancement and two-factor enhancement relationships, with no cases of independence or weakening. Regarding explanatory power among different factor types, interactions between terrain and vegetation, soil and vegetation, and climate and vegetation were most pronounced, with average explanatory power exceeding 60%. The strongest interactions included slope with vegetation net primary productivity (q = 0.8843), elevation with vegetation net primary productivity (q = 0.8750), temperature with vegetation net primary productivity (q = 0.8611), soil type with vegetation net primary productivity (q = 0.8523), soil texture with vegetation net primary productivity (q = 0.8520), and precipitation with vegetation net primary productivity (q = 0.8516), all exceeding 80% explanatory power. Interactions of elevation with vegetation coverage (q = 0.7891), temperature with vegetation coverage (q = 0.7861), soil type with vegetation coverage (q = 0.7849), soil texture with vegetation coverage (q = 0.7848), and precipitation with vegetation coverage (q = 0.7828) were secondary, with 60%–

80% explanatory power. The weakest interactions were soil type with precipitation (q = 0.0955), soil type with temperature (q = 0.0935), soil texture with temperature (q = 0.0836), and soil texture with precipitation (q = 0.0692), all below 10% explanatory power. Regarding interactions among similar factor types, vegetation factor interactions were most pronounced, with vegetation coverage and vegetation net primary productivity (q = 0.9288), vegetation type and vegetation net primary productivity (q = 0.8632), and vegetation type and vegetation coverage (q = 0.7917) showing the strongest interactions, exceeding 70% explanatory power. Elevation and slope (q = 0.4839) and soil type and soil texture (q = 0.1180) showed moderate interactions (10%–50% explanatory power), while precipitation and temperature (q = 0.0722) showed the weakest interaction (<10%).

TABLE:4 q Values of Interaction Factors

Note: * represents a non-linear enhancement relationship; no * represents a two-factor enhancement relationship.

Discussion

Spatiotemporal variation characteristics of vegetation ecological quality differ based on evaluation indicators. This study used EQI, constructed from both vegetation coverage and net primary productivity, as the evaluation indicator. Results show that Guangxi's vegetation ecological quality index increased fluctuatingly from 2000 to 2020, with clear ecological improvement, consistent with national-scale assessments using the comprehensive vegetation ecological quality index QI (Qian, 2020). This differs from assessments using NPP alone (Zhou et al., 2014; Rong et al., 2017; Xiong et al., 2019). The main reason is that this study, based on vegetation ecological principles, incorporated both vegetation productivity (representing intrinsic and extrinsic factors determining vegetation distribution and quantity) and vegetation coverage (representing vegetation's economic contribution to ecological processes or balance). This comprehensive vegetation ecological quality model provides more objective and complete results than single-factor evaluations. Additionally, this study reveals substantial spatial heterogeneity in vegetation ecological quality improvement in Guangxi, with EQI showing a peripheral-high, central-low pattern consistent with vegetation coverage (Wang et al., 2017; Yang et al., 2021) and NPP distribution patterns (Rong et al., 2017; Xiong et al., 2019), closely related to Guangxi's basin-like topography with high peripheries and low center. EQI uses vegetation coverage to represent ecological function and NPP to represent production function, with weight coefficients adjustable according to study region and vegetation type, making it highly applicable across China's diverse climate gradients and vegetation ecosystem types, though localization of parameters such as weights requires further research.

Vegetation ecological quality is significantly affected by meteorological disasters and human activities. Extreme meteorological disasters such as drought, flooding, and extreme temperature changes can reduce forest coverage and quality (Wang et al., 2012). For example, the 2008 low-temperature rain-snow-freezing disaster caused extensive forest damage and severely impacted the ecological environment in Guangxi (Wang et al., 2008). This study found lower EQI values during 2000–2010, possibly because severe regional droughts in 2004, 2005, 2006, and 2009 (Chen et al., 2019) reduced vegetation greenness and productivity, affecting ecological quality. These results align with actual disaster conditions. Human activity impacts on vegetation EQI cannot be ignored either. Since 1999, the state has implemented multiple programs for returning farmland to forest and rocky desertification control, increasing investment in forest and grassland vegetation protection (Ma et al., 2014). Rocky desertification control projects centered on forestry ecological construction have significantly reduced rocky desertification, with Guangxi achieving the largest reduction in rocky desertification area among eight provincial regions in 2012, and the region's forest coverage rate reaching 61.4%, ranking third nationally (Huang et al., 2013). Human activities have increased vegetation coverage and productivity, thereby improving ecological quality. This study also found positive dynamic degrees for forests and shrub-grasslands (increasing area) and negative dynamic degrees for farmland vegetation (decreasing area), with EQI showing jump growth from 2013 and clear ecological improvement. This indicates increased forest and shrub-grassland areas, decreased farmland area, and mutual transformation among vegetation types. These changes may be related to national rocky desertification control policies of "returning farmland to forest and grassland," urbanization and construction projects occupying or converting farmland, and rural labor migration leading to farmland abandonment. This study's detection of driving forces for vegetation ecological changes in Guangxi also shows that the explanatory power of terrain, soil, and climate factors on spatiotemporal differentiation gradually weakened, while that of vegetation factors strengthened, indicating that human activities reduced the influence of terrain, soil, and climate on vegetation ecological quality spatial differentiation. Therefore, future ecological protection in Guangxi should focus on the impacts of natural disasters and human activities on vegetation, while also considering synergistic effects among multiple natural factors to explore their influences from multiple perspectives and dimensions for rational vegetation ecological protection and restoration measures.

Terrain, soil, vegetation, and climate show substantial spatial differences in their impacts on vegetation ecology. Terrain encompasses multidimensional variables such as elevation and slope, affecting vegetation growth through water, heat, and soil conditions (Deng et al., 2020). This study found lower and more volatile EQI in areas with elevation <400 m and slope <25°, possibly because these are densely populated areas with frequent human activity and represent transition zones between plains and hills with unstable vegetation types and frequent conversion from farmland to shrub-grassland or forest, leading to more obvious EQI changes—similar conclusions were reached regarding NDVI variation with terrain in Guangxi (Yang et al., 2021). In areas with 1600 m < elevation <2000 m and 60° < slope <80°, EQI also showed strong fluctuations with elevation and slope, possibly related to landforms including both karst and hilly-mountainous types. Karst areas (rocky mountainous areas) have shrub-grass dominated vegetation with relatively low EQI, while hilly-mountainous areas have woody and liana plants with relatively high EQI. Additionally, these areas are mostly mountain peaks with steep slopes where most vegetation has low adhesion, making them prone to soil erosion and resulting in poor EQI stability.

Regarding soil, different soil types, textures, and fertility levels affect vegetation growth rates and conditions. This study found higher EQI in loam and lower EQI in sand. Previous research also indicates that loam has good aeration, water permeability, and water-fertilizer retention, suitable for vegetation growth, while sand has high soil temperature, poor organic matter accumulation, and low humus content, which is unfavorable for vegetation growth. Climate-wise, temperature and precipitation have been confirmed as important drivers of vegetation growth, though response patterns vary with study period, remote sensing parameters, and methods. For Guangxi vegetation, Yang et al. (2021) found that vegetation responded more strongly to temperature on residential and unused land but more strongly to precipitation on forest land. Li et al. (2014) found that NPP was positively correlated with precipitation but not significantly with temperature, while Rong et al. (2017) believed NPP was negatively correlated with precipitation but positively correlated with temperature at annual scale, and Xiong et al. (2019) suggested NPP showed no significant response to temperature and precipitation changes. These findings indicate substantial differences in how different vegetation types respond to precipitation and temperature (Wang et al., 2017), and the relative importance of these factors requires further research (Wei et al., 2013; Zhang et al., 2019). This study used partial correlation analysis to examine response characteristics, finding strong spatial heterogeneity in Guangxi vegetation EQI under combined temperature and precipitation effects, with significant positive correlations for both. Vegetation EQI was more sensitive to temperature in high-altitude, precipitation-rich mountainous areas, and more sensitive to precipitation in low-altitude, relatively dry hilly areas. The possible reason is that in mountainous areas with abundant precipitation, sufficient water supply weakens the direct effect of precipitation, while higher altitude leads to greater temperature variation that affects photosynthesis of different vegetation types, making EQI more temperature-sensitive. In hilly areas with sufficient heat, stable temperature weakens the direct temperature effect, while water shortage inhibits vegetation growth, making EQI more precipitation-sensitive. These conclusions are consistent with previous findings that temperature affects vegetation more than precipitation in semi-humid and humid regions, while precipitation affects vegetation more than temperature in semi-arid regions (Hua et al., 2017; Zhang et al., 2021).

Driving forces for vegetation ecological quality spatiotemporal evolution show certain coupling relationships. This study's climate-driven zoning results for Guangxi vegetation EQI changes indicate large areas where temperature or precipitation are primary drivers, while single-factor detection shows temperature and precipitation have minor impacts on EQI spatial differentiation. Interaction detection results further demonstrate that compared with single ecological factors, synergistic effects between climate and ecological factors enhance their explanatory power for EQI spatiotemporal differentiation, with interactions between temperature, precipitation, vegetation coverage, and NPP all exceeding 70% explanatory power. Related studies also show that vegetation responses and adaptations to combined water-heat conditions greatly affect vegetation eco-physiological processes, material accumulation and allocation, and ecosystem structure and function (Butler et al., 2012; Lü et al., 2015). Temperature can directly affect soil temperature, thereby influencing plant water-fertilizer absorption and transport and consequently vegetation growth (Kang et al., 2020). However, this study found weak interactions between temperature, precipitation, and soil type/texture, suggesting that in subtropical regions, higher temperatures may increase soil temperature, which is unfavorable for water-fertilizer absorption, inhibits vegetation growth, and weakens explanatory power for vegetation ecological quality spatial differentiation. This differs from semi-humid and semi-arid regions where temperature and soil type interactions are strongest, as suitable temperatures facilitate soil nutrient absorption, promote vegetation growth, and enhance explanatory power (Wang et al., 2021).

Overall, since 2000, vegetation ecological quality changes in Guangxi have resulted from combined driving forces of terrain, soil, vegetation, climate, natural disasters, and human activities. Although geographical detectors lack clear standards for spatial zoning of influencing factors, this study's zoning was based on vegetation ecological quality change driving factor analysis, providing certain objectivity to factor explanatory power. However, this study only quantitatively analyzed the driving mechanisms of natural factors on Guangxi vegetation ecological quality spatiotemporal differentiation from terrain, soil, vegetation, and climate perspectives, without quantitatively evaluating climate impact rates, meteorological disaster damage assessment, or human activity contribution rates. Further research should develop technical methods for evaluating contributions of meteorological conditions, meteorological disasters, and human activities to vegetation ecological quality changes based on meteorological and ecological models.

Conclusions

This study analyzed spatiotemporal distribution characteristics and driving forces of vegetation ecological quality in Guangxi from 2000 to 2020 using the ecological quality index, yielding the following conclusions:

1. Since 2000, Guangxi's vegetation ecological quality index has shown a significant increasing trend, with clear regional ecological improvement. Vegetation ecological quality development has experienced evolutionary

stages of slow growth, rapid growth, and significant enhancement. Spatially, the vegetation ecological quality index exhibits a peripheral-high, central-low pattern, with high-value zones gradually expanding from east to west and north.

2. Factors influencing the spatiotemporal evolution of vegetation ecological quality in Guangxi vary significantly. With increasing altitude, vegetation ecological quality shows an overall trend of "increase-decrease-stability-fluctuation." Among soil types, loamy soils support higher vegetation ecological quality, while sandy soils yield lower quality. Among vegetation types, forests and shrub-grasslands show positive dynamic degrees and increasing areas with higher ecological quality, while farmland vegetation shows negative dynamic degrees and decreasing areas with lower quality. Under different climate characteristics, vegetation ecological quality is significantly positively correlated with both temperature and precipitation, jointly affected by these factors. The area where temperature is the primary driver is the largest, followed by precipitation as the primary driver, while areas with strong and weak temperature-precipitation co-driving are relatively small.

3. Driving forces of vegetation ecological quality changes in Guangxi result from combined effects of terrain, soil, vegetation, climate, natural disasters, and human activities. The explanatory power of natural factors follows the order: vegetation > terrain > soil > climate, with vegetation net primary productivity and vegetation coverage being the most critical factors affecting spatiotemporal differentiation. Natural factors exhibit interactive effects on vegetation ecological quality changes, showing nonlinear enhancement and two-factor enhancement relationships, with the most pronounced interactions between terrain and vegetation, soil and vegetation, and climate and vegetation. Natural disasters and human activities exacerbate impacts on vegetation ecological quality changes, wherein meteorological disasters such as drought and low-temperature damage inhibit improvement, while anthropogenic activities such as forestry ecological engineering promote enhancement.

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