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# Simulation of Vegetation Growth Dynamics and Climate Driving Mechanisms in the Qinling-Daba Mountains Driven by Climate Scenarios (Postprint)

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**Date:** 2026-02-27T22:08:33+00:00

## Abstract

The Qinling-Daba Mountains are located at the intersection of China' s north-south climate transition zone and the warm temperate-subtropical ecological transition zone. As a region sensitive to climate change, studying the coupling relationship between its vegetation and climate helps reveal the evolution mechanisms of ecosystems under climate change. Based on MODIS data and climate factor data from 2001 to 2023, this study utilizes a multiple linear regression model to predict the Kernel Normalized Difference Vegetation Index (kNDVI) under three Shared Socioeconomic Pathways (SSPs) climate scenarios for 2024–2100. Combined with Theil-Sen and Mann-Kendall methods, the spatiotemporal variation trends of vegetation were analyzed, and path analysis was used to reveal the driving mechanisms of climate factors.

The results indicate that: (1) Temperature is the dominant factor for vegetation change, accounting for 67.27% of the area, with positive effect regions concentrated in the Qinling-Daba Mountains, while the impacts of evapotranspiration and precipitation exhibit significant spatial heterogeneity. (2) From 2001 to 2023, the growth rate of vegetation kNDVI characterized a "fast then slow" pattern, with degraded areas concentrated in low-altitude urbanized regions and high-altitude water-heat limited zones. (3) Future scenario simulations show that under the low-carbon pathway (SSP119) scenario, vegetation changes tend to stabilize, while the high-carbon pathway (SSP585) scenario presents polarization, where the direct inhibitory effect of evapotranspiration coexists with the indirect promotion effect driven by high temperatures. (4) The replenishment efficiency of precipitation for vegetation weakens with climate extremes, while the direct driving intensity of temperature significantly enhances as emission scenarios rise. (5) Significant spatial differentiation exists in regional vegetation response, necessitating the implementation of differentiated ecological restoration strategies for high-altitude vulnerable zones, low-altitude human activity interference belts, and evapotranspiration-sensitive areas in the central and eastern regions. By revealing the nonlinear response of vegetation to climate change in the Qinling-Daba Mountains and confirming the ecological stability advantages of SSP119, this study provides a spatial optimization path for vegetation protection and carbon sink function enhancement under regional carbon neutrality goals.

## Full Text

## Preamble

## Vegetation Growth Dynamic Simulation and Climate Driving Mechanisms in the Qinling-Daba Mountains Under Climate Scenarios

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The Qinling-Daba Mountains are located at the intersection of China' s north-south climate divide and the ecological transition zone between the warm temperate and subtropical zones. As a region sensitive to climate change, studying the coupling relationship between vegetation and climate in this area is essential for revealing ecosystem evolution mechanisms under changing environmental conditions. Based on MODIS data and climate factor datasets, this study utilizes a multiple linear regression model to predict the Kernel Normalized Difference Vegetation Index (kNDVI) under three Shared Socioeconomic Pathways (SSP119, SSP245, and SSP585). Combined with Theil-Sen slope estimation and the Mann-Kendall test, we analyzed the spatiotemporal trends of vegetation and employed path analysis to reveal the driving mechanisms of climate factors.

The results indicate that: 1. Temperature is the dominant factor driving vegetation changes, accounting for 67.27% of the total area. Regions showing positive effects are concentrated in the Qinling and Daba Mountains, while the impacts of evapotranspiration and precipitation exhibit significant spatial heterogeneity. 2. The growth rate of kNDVI is characterized by an "initial rapid increase followed by a slowdown." Degraded areas are primarily concentrated in low-altitude urbanized zones and high-altitude regions limited by hydrothermal conditions. 3. Future scenario simulations show that vegetation changes tend to stabilize under the low-carbon pathway (SSP119). In contrast, the high-carbon pathway (SSP585) exhibits polarization, where the direct inhibitory effect of evapotranspiration competes with the indirect promotional effect driven by high temperatures. 4. The replenishment efficiency of precipitation for vegetation weakens as climate extremes increase, while the direct driving intensity of temperature significantly strengthens under higher emission scenarios. 5. There is significant spatial differentiation in regional vegetation responses. Differential ecological restoration strategies should be implemented for high-altitude vulnerable areas, low-altitude zones disturbed by human activity, and evapotranspiration-sensitive areas in the central and eastern regions.

By revealing the nonlinear response of vegetation in the Qinling-Daba Mountains to climate change, this study confirms the ecological stability advantages of the SSP119 scenario. These findings provide a spatial optimization path for vegetation protection and the enhancement of carbon sink functions under regional carbon neutrality goals.

### 关键词

kNDVI; Qinling-Daba Mountains; Climate factors; Multiple linear regression model; Trend analysis

Vegetation serves as the core of terrestrial ecosystems, maintaining close links with the atmosphere, soil, and water through photosynthesis and respiration. It is not only a sensitive indicator of environmental change but also directly or indirectly influences the carbon sources of terrestrial ecosystems. Researching the characteristics of vegetation change and its relationship with geographic and climatic factors is of great significance. Such studies help explore future development trends of vegetation and its response to regional environmental evolution, while also revealing the resilience and sensitivity of ecosystems under different climate scenarios.

The International Coupled Model Intercomparison Project (CMIP), initiated and organized by the Working Group on Coupled Modelling (WGCM) of the World Climate Research Programme (WCRP) in 1995, has organized several phases of comparison. The Shared Socioeconomic Pathways (SSPs) adopted by the CMIP6 models reflect the correlation between radiative forcing and socioeconomic development, embodying the integrated effects of climatic and socioeconomic factors. Under the influence of global climate change, the response of vegetation to climate change has become a focal point and core issue for scholars worldwide. In domestic and international research on dynamic vegetation changes, the selection of influencing factors primarily focuses on key variables such as precipitation [?, ?, ?, ?], temperature [?, ?, ?, ?], and solar radiation [?, ?]. Methodologically, researchers frequently employ correlation analysis, regression analysis, and trend analysis. In previous modeling efforts, climate factors often only included temperature and precipitation, while evapotranspiration—a key factor in surface water retention—has rarely been incorporated into modeling analyses.

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Despite its importance, few studies have integrated evapotranspiration into modeling analyses. Furthermore, research regarding the coupling mechanisms between vegetation changes and multiple climate factors across different regions within a study area—specifically through the establishment of simulation models to explore spatial characteristics at the pixel scale—remains relatively scarce. Most multi-scenario predictive analyses have focused on the field of land-use change. The climate simulation capabilities of CMIP6 have been widely recognized by the academic community. Based on the aforementioned literature review and analysis, research on the simulation and prediction of vegetation dynamic changes under CMIP6 scenarios in specific regions such as the Qinling-Daba Mountains is still relatively limited. Moreover, few studies have established coupling models between vegetation change and climate factors at a pixel-by-pixel spatial scale to conduct predictive analyses under future multi-scenarios, thereby exploring the interactive characteristics of vegetation change and multiple climate factors across different regions.

Existing research relies heavily on the traditional Normalized Difference Vegetation Index (NDVI) for monitoring [**?**, **?**]. However, its nonlinear response and saturation effects in complex terrain areas can easily lead to biases in ecological parameter estimation. In 2021, Camps-Valls proposed a new Kernel Normalized Difference Vegetation Index (kNDVI). This index outperforms traditional NDVI in various application scenarios and exhibits stronger robustness across spatial and temporal scales. There is currently limited research applying kNDVI to the field of vegetation change trend modeling. Based on the above analysis, it is crucial to construct a vegetation dynamic analysis model that couples kNDVI with multiple climate factors to explore regional vegetation evolution and future development trends.

Therefore, to address these issues, this study utilizes meteorological datasets and kNDVI time-series data from 2000 to 2020, focusing on the Qinling-Daba Mountains as the research area. A pixel-based simulation model relating vegetation to potential evapotranspiration, precipitation, and temperature was established using a multiple linear regression model. Furthermore, the low-carbon pathway (SSP119), intermediate pathway (SSP245), and high-carbon pathway (SSP585) from CMIP6 were selected to predict vegetation coverage pixel-by-pixel from 2021 to 2100. This study explores the characteristics of the interaction between long-term vegetation changes and multiple climate factors within the region, as well as the response and dynamic evolution characteristics of vegetation to climate change under multiple scenarios. Simultaneously, it further reveals the resilience and sensitivity of the ecosystem under different climate scenarios, providing a new perspective for the study of vegetation change in the Qinling-Daba Mountains.

## 1.1 研究区概况

The Qinba Mountains ([Figure 1: see original paper]) are located in central China, stretching approximately 1000 km from east to west and covering an area of $300,000$ km$^2$. The region is composed of the Qinling Mountains, the Hanjiang River Valley Basin, and the Daba Mountains. Driven by significant topographic gradients, the Qinba Mountains facilitate the vertical differentiation of water and heat, resulting in a convergence zone for biodiversity. Note: This map was produced based on the standard map GS(2024)0650 from the Standard Map Service website of the Ministry of Natural Resources; the boundaries of the base map have not been modified. The same applies hereafter.

This region serves as a natural laboratory for studying sensitive responses to climate change and the multidimensional zonality of ecosystems in China. The northern part of the Qinba Mountains is characterized primarily by a warm-temperate semi-humid to semi-arid monsoon climate, while the southern part features a subtropical monsoon climate. Influenced significantly by altitude, the average annual temperature ranges from 12 to 16 °C, and annual precipitation varies between 709 and 1500 mm, increasing from north to south with an uneven distribution. The Qinba Mountains possess a rich variety of vegetation types, serving as a critical hub in China’ s geo-ecological pattern and representing one of the country’ s ecologically fragile regions [?, ?].

### 1.2.1 数据来源

The kNDVI data used in this study were calculated and obtained from the MOD13A3 dataset. Monthly data for historical and future multi-scenario potential evapotranspiration, precipitation, and temperature were all sourced from the National Tibetan Plateau Data Center (TPDC).

### 1.2.2 数据预处理

After performing projection and format conversion on the MOD13A3 dataset, the kernel Normalized Difference Vegetation Index (kNDVI) was calculated using MATLAB. To facilitate predictive modeling, the evapotranspiration, precipitation, and temperature data were batch-processed and normalized alongside the kNDVI data to a range of $[0, 1]$. Monthly averages for each year were calculated to analyze the characteristics of the vegetation growing season. All raster datasets were standardized to a uniform spatial resolution with a grid dimension of $1323 \times 1232$ pixels, using the WGS 1984 Albers geographic coordinate system. Following the simulation and prediction phases, the data were further clipped to the specific extent of the Qinling-Daba Mountains for detailed regional analysis.

### 1.3 研究方法

## Modeling and Prediction of kNDVI Coupled with Climatic Factors

The MOD13A3 dataset is utilized to calculate the Kernel Normalized Difference Vegetation Index (kNDVI). The calculation formula is as follows:

$$kNDVI = \tanh\left(\left(\frac{NIR - Red}{2\sigma}\right)^2\right)$$

In this expression, $NIR$ represents the near-infrared band, $Red$ represents the red band, and $\sigma$ is a length-scale parameter that determines the sensitivity of the kernel.

### 1.1 Research Background and Objectives

Vegetation indices are critical indicators for monitoring ecosystem health and carbon sequestration capacity. While the traditional Normalized Difference Vegetation Index (NDVI) is widely used, it often suffers from saturation effects in high-biomass regions and sensitivity to soil background noise. The kNDVI, based on machine learning kernel methods, provides a non-linear alternative that effectively addresses these limitations, offering higher sensitivity to vegetation structural changes.

The primary objective of this study is to establish a predictive model that couples kNDVI with key climatic factors (such as temperature, precipitation, and solar radiation). By integrating multi-source remote sensing data with meteorological observations, we aim to analyze the spatiotemporal response of vegetation to climate change and improve the accuracy of vegetation growth forecasting.

### 1.2 Data Processing and Methodology

The MOD13A3 product provides monthly vegetation index data at a 1km spatial resolution. To ensure data quality, we perform preprocessing steps including coordinate transformation, atmospheric correction, and the removal of cloud-contaminated pixels.

The modeling process involves the following steps: 1. **Feature Extraction**: Extracting monthly mean temperature, cumulative precipitation, and potential evapotranspiration as independent variables. 2. **Correlation Analysis**: Quantifying the lag effects and sensitivity of kNDVI to different climatic drivers across various biomes. 3. **Model Construction**: Utilizing machine learning algorithms (such as Random Forest or Long Short-Term Memory networks) to capture the complex, non-linear relationships between climate inputs and kNDVI outputs.

### 1.3 Preliminary Results and Discussion

Initial results indicate that kNDVI exhibits a stronger correlation with biomass and Gross Primary Productivity (GPP) compared to traditional NDVI, particularly in forested areas. The coupling model demonstrates that precipitation is the dominant factor driving kNDVI variations in arid and semi-arid regions, while temperature

kNDVI = tanh é

NIR - red

In the equation, $\sigma$ represents the length scale parameter specified for each particular application.

The formula for the Kernel Normalized Difference Vegetation Index (kNDVI) is as follows:

$$kNDVI = \tanh\left(\left(\frac{NIR - Red}{2\sigma}\right)^2\right)$$

In this expression, $\sigma$ is a parameter representing the sensitivity of the index to sparse or dense vegetation areas; $NIR$ denotes the near-infrared band, and $Red$ denotes the red band. tanh represents the hyperbolic tangent function. A reasonable choice for the parameter is to take the average value of 0.5.

kNDVI = tanh ( ) NDVI 2 (2 )

A multiple linear regression model was constructed using MATLAB, incorporating independent variables (evapotranspiration, precipitation, and temperature) and a dependent variable to investigate the coupling relationship between historical environmental factors and the Kernel Normalized Difference Vegetation Index (kNDVI). The model is expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon$$

where $y$ represents the kNDVI value, $x_1, x_2, \dots, x_n$ represent the various environmental driving factors, $\beta_0$ is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ are the regression coefficients for each respective variable, and $\epsilon$ denotes the random error term.

Y = k 1 X 1 + k 2 X 2 + k 3 X 3 + b (3 )

In the formula: $Y$ represents the interannual mean of the kNDVI time series from 2001 to 2023.

represents the evapotranspiration data; represents the precipitation data;

data; $k_i$ $(i = 1, 2, 3)$ are the regression coefficients; $b$ is the intercept.

The coefficient values were calculated pixel-by-pixel using kNDVI and historical climate data. Finally, kNDVI was predicted based on evapotranspiration, precipitation, and temperature data under the different climate scenarios: SSP119, SSP245, and SSP585.

### 1.3.2 趋势分析

Theil-Sen Median analysis is a non-parametric trend estimation method used to calculate the variation trends of kNDVI within the study area. This approach effectively minimizes the influence of outliers and serves as a robust method suitable for long-term time series trend calculations [?, ?]. Its formula is expressed as:

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i$$

$\beta =$ Median æ

kNDVI - Let $kNDVI$ represent the time-series dataset, where the calculated slope represents the vegetation change trend.

When $\beta > 0$, it indicates that the kNDVI exhibits an upward trend; conversely, when $\beta < 0$, it indicates that

the kNDVI exhibits a downward trend. The Mann-Kendall (MK) significance test is employed to evaluate the significance of these trend changes. As a non-parametric statistical test, it is particularly well-suited for analyzing

time-series variables [?, ?]. A significance level of $\alpha = 0.05$ was selected to determine the significance of the observed trends.

Based on the aforementioned trend analysis methods, the characteristics of the trends are classified into specific types, as shown in (Classification of TS-MK trend analysis types), such as "Extremely Significant Increase."

Z| $ $2.58

1.96≤| Z |<2.58

without significantly increasing

Z |<1.96

without significantly reducing

Z |<1.96

1.96≤| Z |<2.58

significantly reduced

Z |$ $2.58

The Theil-Sen estimator is used as the statistical test value.

### 1.3.3 通径分析

Path analysis decomposes the correlation between independent and dependent variables into direct and indirect effects, thereby revealing the mutual relationships among independent variables, mediating variables, and dependent variables. The specific principles are as follows:

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Based on the simple correlation coefficients $r_{x_i x_j}$ $(i, j \leq n)$ between each pair of independent variables,

and the simple correlation coefficients between each independent variable and the dependent variable, a normal matrix can be established through numerical transformation of the linear regression equation.

In the formula: $n$ represents the number of variables. By solving the matrix equation, the path coefficients can be obtained.

The direct path coefficient represents the direct effect of the variable; the indirect path coefficient of the variable on the dependent variable represents its indirect effect. Centered on the primary theme of "climate driving and trend prediction," this study constructs a multiple linear regression model to quantify the contributions of climate factors. By combining multi-scenario simulations of the spatiotemporal differentiation patterns of vegetation and analyzing the relationships between factors and trends, we have developed a "data denoising and change attribution" framework. This framework provides systematic support for analyzing the feedback relationship between climate and vegetation. The detailed research workflow is illustrated in [Figure 1: see original paper].

## 2.1 秦巴山区气候因子对植被的影响

It can be observed that, overall, vegetation changes in the Qinling-Daba Mountains are positively correlated with climatic factors, with the affected area accounting for 70.41% of the total region. Among the dominant influencing factors in various locations, the ranking of the affected area from largest to smallest is temperature >

evapotranspiration > precipitation. Temperature influences a total area of 67.27%, of which the area exhibiting a

positive influence accounts for 51.34%. This indicates that temperature is the most significant dominant factor across the largest portion of the Qinling-Daba Mountains, further confirming its leading role in driving vegetation changes in the region. Evapotranspiration affects 22.92% of the total area, with relatively balanced positive and negative influences accounting for 10.09% and 12.83%, respectively. Precipitation affects 9.81% of the total area, with the smallest proportion of negative influence at 0.83%. From a spatial perspective [FIGURE:N], the regional differentiation of climatic influences across the Qinling-Daba Mountains is distinct. Temperature-influenced zones are primarily concentrated in the central Qinling and Daba Mountains. Evapotranspiration-influenced zones are mainly located in the eastern parts of the region, including the Wudang Mountains, Funiu Mountains, and the western Nanyang Basin. Precipitation-influenced zones are primarily concentrated in the western Qinling-Daba Mountains, the Min Mountains, the Minjiang River Basin, and the Jiuding Mountain area. kNDVI refers to the Kernel Normalized Difference Vegetation Index; SSP119 represents the low-carbon pathway; SSP245 represents the intermediate pathway; and SSP585 represents the high-carbon pathway. The same applies hereafter. Area and proportion of influencing factors in the Qinling-Daba Mountains.

"+" indicates a positive influence; "-" indicates a negative influence. In the western Qinling-Daba Mountains and the Min Mountains, although the influence of precipitation is concentrated, both positive and negative impacts from the three climatic factors are distributed and intermingled. The complexity of these interactions increases from north to south, making this region the most ecologically complex and vulnerable. The central Qinling and Daba Mountains are primarily characterized by a mix of positive and negative temperature influences; negative influence zones are distributed across the northern Qinling, Micang Mountains, and the "Daba Mountain Arc" area. Some areas along the west-to-east axis of the north-central region (including the Qinling Mountains and their northern slopes) show a negative correlation with evapotranspiration. It is evident that the central Qinling Mountains are more complexly affected by climatic factors than the Daba Mountains. The eastern Wudang and Funiu Mountains are mainly positively correlated with evapotranspiration, while their peripheral areas show a positive correlation with precipitation—a phenomenon that becomes increasingly prominent from south to north.

## 2.2 秦巴山区植被时间变化特征

To test the explanatory power of the model constructed based on evapotranspiration, precipitation, and temperature for future kNDVI in the Qinba Mountains, the model was used to predict the vegetation kNDVI for 2023. The accuracy was verified using MATLAB [FIGURE:N]. The results demonstrate that the simulated values are highly consistent with the actual values, confirming the reliability of the predictions. Data analysis shows a high correlation coefficient ($R$), a Symmetric Mean Absolute Percentage Error (SMAPE) of 87.90%, and a high overall accuracy (with a residual error of approximately 12.10%). These findings indicate that this model provides a high-precision tool for monitoring vegetation dynamics and conducting future multi-scenario simulations in the Qinba Mountains. It is suitable for assessing the impacts of climate change and human activities on local vegetation changes.

From 2000 to 2022, the kNDVI in the Qinba Mountains exhibited significant growth, generally following a "fast then slow" pattern [FIGURE:N]. This indicates a substantial improvement in the vegetation within the Qinba Mountains, suggesting that past vegetation protection measures have been effective. However, over time, the growth rate has tended to stabilize, gradually approaching a state of ecosystem equilibrium.

Under various scenarios, the kNDVI in the Qinba Mountains generally maintained the high levels observed in 2022, with an upward trend in some cases, indicating that vegetation cover is stable in the short term with no significant decline. In this context, ubRMSE represents the Unbiased Root Mean Square Error; MAE is the Mean Absolute Error; SMAPE denotes the Symmetric Mean Absolute Percentage Error; and WAPE refers to the Weighted Absolute Percentage Error.

The accuracy verification of the predicted values reveals distinct differences in the kNDVI trend lines, illustrating the high sensitivity of the Qinba Mountains to climate change. Regarding the growth trends across different scenarios, the overall growth trend of kNDVI in the SSP1-1.9 scenario is relatively flat compared to other scenarios, characterized by smaller fluctuations and a narrower error band, remaining basically between 0.500 and 0.503. Internally, the SSP1-1.9 scenario shows a "decrease-increase-decrease" trend. In the SSP2-4.5 scenario, kNDVI growth is significant, exhibiting a "decrease-increase-stabilize" pattern with values ranging roughly from 0.498 to 0.510. Compared to the SSP1-1.9 scenario, the kNDVI in SSP2-4.5 is initially lower but overtakes it around 2030, showing a more pronounced growth trend and greater fluctuations. In the SSP5-8.5 scenario, a steady growth trend is observed, with values ranging approximately from 0.498 to 0.518. Among the three scenarios, SSP5-8.5 exhibits the most significant growth trend, the widest error band, and the most intense fluctuations. At most time points, the kNDVI in this scenario is higher than in others, indicating that vegetation growth is greatest under high-emission scenarios, though this is accompanied by substantial uncertainty.

### 2.3 秦巴山区植被时空演变趋势

Trend analysis and significance testing were used to generate the vegetation change trend characteristic maps (Figure [FIGURE:N]) and statistical tables (Table [TABLE:N]) for the Qinling-Daba (Qinba) Mountains under various scenarios. In 2023, the area showing an increasing trend in vegetation was $300,682\ \mathrm{km}^2$ (96.69%), while the area showing a decreasing trend was $10,284\ \mathrm{km}^2$ (3.32%). The area of increasing trends far exceeds that of decreasing trends. Spatially,

Gao Jintao et al.: Simulation of Vegetation Growth Dynamics and Climate Driving Mechanisms in the Qinba Mountains Driven by Climate Scenarios. Regarding the temporal variation characteristics of kNDVI in the Qinba Mountains, most regions showed a highly significant or significant increase in kNDVI over the years. Areas exhibiting highly significant and significant decreases are primarily distributed near the Minjiang River basin in the southwest, Hanzhong and Ankang in the central region, Shiyan in the east, and the Zhengzhou-Luoyang area in the northeast. Regions with non-significant increases are mainly located in the Aba Tibetan and Qiang Autonomous Prefecture in the southwest and the Qinling Mountains in the north-central region. Overall, except for localized urban areas with intense human activity, vegetation cover in most parts of the Qinba Mountains has significantly increased and improved in the past.

Among the various scenarios, the SSP119 scenario shows a reduction in areas with highly significant increases in kNDVI compared to both historical and other scenarios. The non-significant change types account for 92.04%, indicating that the ecological environment is relatively stable under low-emission conditions.

Classification area and proportion of kNDVI change trends under historical and future climate scenarios: highly significant increase, non-significant increase, non-significant decrease, and highly significant decrease. Spatially, the non-significant decrease areas are concentrated west of Taibai Mountain in the Qinling range and east of Tianshui, between the Qinling and Daba Mountains, and around Zhengzhou and Luoyang in the northeast. The southwest, southern Minshan, and Jiudingshan regions contain both highly significant increase and decrease areas. Highly significant and significant increase areas are mainly distributed in valleys and the river valleys through which the Minjiang flows, mostly at lower altitudes. Highly significant and significant decrease areas are primarily distributed on mountain peaks. Under this scenario, the Minshan, Minjiang basin, and Jiudingshan regions exhibit significant vertical zonality in vegetation changes due to large vertical gradients and complex hydrothermal conditions.

Compared to the historical background, the areas of highly significant and significant decrease have expanded in the Minshan and Jiudingshan regions, though they remain generally balanced and stable. Using approximately [YEAR] as a node, the trends exhibit a "increase followed by deceleration" characteristic. The highly significant and significant increase areas remained relatively balanced between [YEARS], while the non-significant decrease areas followed a "decrease-increase-decrease" pattern, showing smaller fluctuations compared to other trend types.

The kNDVI values in the non-significant change areas were higher than those in the significant and highly significant change areas at all time points.

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Under the SSP245 scenario, the kNDVI change trends in the Qinba Mountains are dominated by highly significant increases, non-significant increases, and highly significant decreases, accounting for 54.54%, 15.18%, and 13.54%, respectively. Spatially, the Qinba Mountains west of the Jialing River show highly significant growth, except for Jiudingshan, which shows a highly significant decrease. The areas east of the Jialing River exhibit more complex changes: the southern Daba Mountains primarily show increases, while the southern foothills of the Qinling Mountains and the Hanjiang Plain primarily show decreases. Non-significant changes are mainly found in the Funiu Mountains in the northeast, the junction of the western Qinling and Minshan, the Huicheng Basin, the Jialing River basin, and the Hanzhong Basin. The highly significant decrease zones in the southern Daba Mountains are distributed in strips along the "Daba Mountain Arc" valleys. Temporally, the highly significant change areas exhibit a "slow-increase-slow" pattern; the significant and non-significant increase areas show a "decrease-increase-slow" pattern, beginning to grow in [YEAR] before leveling off. The decrease areas show a continuous decline during [YEARS].

Under the SSP585 scenario, the kNDVI change trends in the Qinba Mountains are primarily characterized by highly significant increases and highly significant decreases. Compared to the SSP245 scenario, the proportion of highly significant increases rose from 54.54% to 59.04%, and highly significant decreases rose from 13.54% to 23.94%, indicating a polarization of non-significant change areas. Spatially, the areas of highly significant and significant decrease have expanded markedly. Simultaneously, the spatial differentiation of highly significant increases and decreases along the peaks and valleys of the "Daba Mountain Arc" has become more pronounced. Under the SSP585 scenario, areas with significant vegetation improvement are concentrated in high-altitude mountain ranges such as Minshan, Qinling, Daba, Wudang, and Funiu. Conversely, areas with significant degradation are mostly distributed in the Minjiang, Jialing, and Hanjiang basins, as well as in low-altitude regions like valleys and plains. This suggests that although vegetation improves in some high-altitude areas under SSP585, the overall ecological environment tends to deteriorate. Temporally, the increase areas show an overall upward trend from [YEAR] to [YEAR], while the decrease areas are characterized by continuous reduction.

### 3.1 气候因子空间分异

Based on the spatial distribution of the strongest influencing factors derived for the Qinling-Daba Mountains, and in conjunction with [FIGURE:N] and existing research [?], it is evident that the response of vegetation to climate change is regulated by topography. For instance, research by Xiong Xueting et al. [?] on the Sanjiangyuan region of the Qinghai-Tibet Plateau demonstrates that altitude exerts the greatest influence within topographic regulation; this is consistent with the spatial distribution patterns of the strongest climatic factors identified in this study. Furthermore, the spatial distribution characteristics of temperature and precipitation are fundamentally consistent with the findings of Fan Yi et al. [?] and Fu Shasha et al. [?]. While previous studies have primarily focused on temperature and precipitation, this research identifies the spatial distribution patterns of evapotranspiration as a dominant influencing factor, in addition to those of temperature and precipitation.

The distribution of evapotranspiration is primarily concentrated in the Wudang and Funiu Mountains in the eastern Qinling-Daba region, the western Nanyang Basin, and the southern Min Mountains, showing a gradual decrease from south to north. Correlating [FIGURE:N] with the distribution of China' s three topographic steps, these areas are situated precisely at the transition zones between these steps. The Wudang and Funiu Mountains in the eastern Qinling-Daba region and the western Nanyang Basin are located near the transition zone from the first to the second step, while the western Hanzhong Basin and eastern Min Mountains are near the transition from the second to the third step. Furthermore, the complexity of climatic factors influencing vegetation change is higher at the junction of the first and second steps than at the junction of the second and third steps. This further illustrates that the impact of climatic factors on vegetation change exhibits significant regional differentiation.

## 3.2 气候因子对

Analysis of the mechanisms underlying kNDVI changes and future multi-scenario predictive analysis are based on climate factor simulations from the Sixth Assessment Report (AR6). These pathways are used to infer greenhouse gas emissions resulting from different climate change adaptation and mitigation policies. The results of the path analysis regarding the driving mechanisms of climate factors on kNDVI changes are shown in [FIGURE:N]. During the historical period,

Gao Jintao et al.: Simulation of Vegetation Growth Dynamics and Climate Driving Mechanisms in the Qinling-Daba Mountains under Climate Scenarios. (Note: ET represents evapotranspiration; years). The direct path coefficient of temperature is significantly higher than those of other factors, indicating that it plays a dominant positive driving role in vegetation growth. The direct path coefficient of precipitation is positive, representing a secondary promoting effect, while the direct effect of evapotranspiration is negative, significantly inhibiting vegetation growth.

In future multi-scenario simulations, the driving patterns of meteorological factors exhibit significant differences. The direct path coefficients for the evapotranspiration factor range from SSP119 to SSP585, indicating a significant inhibition of vegetation growth. However, evapotranspiration exerts a significant indirect positive effect by regulating temperature, suggesting that under high carbon emission scenarios, it may indirectly promote vegetation growth through an enhanced evapotranspiration-temperature positive feedback mechanism. The direct driving effect of precipitation shows a decreasing trend, with direct path coefficients from SSP119 to SSP585 suggesting that future climate extremes may weaken the efficiency of precipitation in replenishing moisture for vegetation. Across the various scenarios, the direct path coefficients for the temperature factor indicate a high promoting effect on vegetation growth under the SSP585 scenario, far exceeding the inhibitory effect of evapotranspiration. Furthermore, the indirect path coefficient of temperature on evapotranspiration reaches a level that further indirectly inhibits vegetation growth. The path analysis for the historical period, based on observational data, reveals the actual ecological feedback pathways between meteorological factors and kNDVI.

In contrast, the analysis of future scenarios focuses on the relative contributions of meteorological factors within the model framework, utilizing predicted values to reveal potential impact patterns of climate change on vegetation.

### 3.3 植被退化区识别

From 2000 to 2020, the overall vegetation cover in the Qinling-Daba Mountains showed an upward trend. Spatially, the vast majority of the region exhibited an increasing trend, which is fundamentally consistent with the conclusions of existing studies [?, ?, ?, ?]. According to previous research [?, ?], this improvement is related to the implementation of the "Grain for Green" program (returning farmland to forests and grasslands) and the intensification of ecological protection efforts in recent years, which have enhanced the regional vegetation cover level to a certain extent.

Amidst this broad increasing trend, a small portion of the region showed a decreasing trend [FIGURE:N]. Combined with [FIGURE:M], it can be observed that these areas are primarily distributed in the urban centers of various prefectural-level cities or counties (such as Zhengzhou, Luoyang, Hanzhong, and Shiyan). This decline is associated with rapid urban expansion, where peripheral areas have transitioned from non-urban land to urban construction land. In the southwest, represented by the Jiuding Mountain area, the kNDVI shows non-significant changes or even degradation. This may be attributed to the high altitude and complex topography of the region, which constrains hydrothermal conditions and creates a climate unsuitable for vegetation root growth [?, ?], resulting in a fragile ecological environment in that area.

## 4 结论

Climate factors exert a generally positive influence on vegetation changes in the Qinba Mountains, with positive impact areas accounting for 70.41% of the total region. When ranked by the area where they act as the dominant factor, the order is temperature followed by precipitation. Specifically, temperature accounts for 67.27% of the area, with 51.34% showing a positive influence, making it the primary dominant factor.

[TABLE:N] [FIGURE:N] Statistics of areas with significant and highly significant decreases in kNDVI and their temporal changes show significant decreases from 2001 to 2023. Spatially, the influence of temperature is mainly concentrated in the Qinling and Daba Mountains. Evapotranspiration effects are primarily centered around the Wudang Mountains and Funiu Mountains in the eastern Qinba Mountains, as well as the western Nanyang Basin and southern Minshan region. Precipitation influences are mainly concentrated in the western Qinba Mountains, the Minshan region, and the western Nanyang Basin.

Gao Jintao et al.: Simulation of Vegetation Growth Dynamics and Climate Driving Mechanisms in the Qinba Mountains Driven by Climate Scenarios. The spatial distribution of climate factors is significantly influenced by topography, exhibiting clear regional differentiation. The kNDVI in the Qinba Mountains is high, and the overall trend of vegetation coverage shows a significant increase. The growth rate of kNDVI follows a "fast then slow" pattern, indicating that vegetation conditions have been significantly improved. Areas showing a decrease are primarily concentrated in flat terrains such as river valleys or basins experiencing rapid urban development, as well as southwestern regions including the Aba Tibetan and Qiang Autonomous Prefecture and the Jiuding Mountain area.

In the predictions across various scenarios, the trends sequentially exhibit characteristics of "stability followed by differentiation," with evapotranspiration identified as the key factor inhibiting vegetation growth. The interaction of climate factors demonstrates significant scenario dependency. Path analysis indicates that while evapotranspiration directly inhibits vegetation growth, it indirectly promotes growth under the SSP5-8.5 scenario by enhancing the positive feedback mechanism of temperature (with an indirect path coefficient of 0.342). The direct driving effect of temperature strengthens significantly as emission intensity increases (with a path coefficient of 0.615 under SSP5-8.5), far exceeding the inhibitory effect of evapotranspiration. Conversely, the replenishment efficiency of precipitation for vegetation gradually weakens as climate extremes intensify, with its direct path coefficient decreasing from 0.184 under SSP1-1.9 to 0.072 under SSP5-8.5. These findings reveal the deep regulatory role of non-linear mutual feedback mechanisms between climate factors on vegetation dynamics.

References

## References

Piao Shilong, Fang Jingyun. Seasonal changes in vegetation activity in response to climate changes in China between 1982 and 1999[J]. Acta Geographica Sinica, 2003, 58(1): 119-125. Meng Dan, Li Xiaojuan, Gong Huili, et al. Analysis of spatial-temporal change of NDVI and its climatic driving factors in the Beijing-Tianjin-Hebei metropolis circle from 2001 to 2013[J]. Journal of Geo-Information Science, 2015, 17(8): 1001-1007. Sun Gaopeng, Liu Xianfeng, Wang Xiaohong, et al. Changes in vegetation coverage and its influencing factors across the Yellow River Basin during 2001–2020[J]. Journal of Desert Research, 2021, 41(4): 205-212. Huang Haoben, Xu Hailiang, Lin Tao, et al. Spatio-temporal variation characteristics of NDVI and its response to climate change in the Altay region of Xinjiang from 2001 to 2020[J]. Acta Ecologica Sinica, 2022, 42(7): 2798-2809. Piao S, Liu Q, Chen A, et al. Plant phenology and global climate change: Current progresses and challenges[J]. Global Change Biology, 2019, 25(6): 1922-1940.

Zhou Yuke. Detecting Granger effect of vegetation response to climatic factors on the Tibetan Plateau[J]. Progress in Geography, 2019, 38(5): 718-730. Lü Yang, Dong Guotao, Yang Shengtian, et al. Spatio-temporal variation in NDVI in the Yarlung Zangbo River Basin and its relationship with precipitation and elevation[J]. Resources Science, 2014, 36(3): 603-611. Zheng Hailiang, Fang Shifeng, Liu Chengcheng, et al.

Dynamics of monthly vegetation activity and its responses to climate change in the Qinghai-Tibet Plateau[J]. Journal of Geo-Information Science, 2019, 21(2): 201-214. He Baozhong, Ding Jianli, Zhang Zhe, et al. Experimental analysis of spatial and temporal dynamics of fractional vegetation cover in Xinjiang[J]. Acta Geographica Sinica, 2016, 71(11): 1948-1966. Zhang Chenhua, Li Shuheng, Bai Hongying, et al. Multi-scale periodic variation of NDVI in July and its response to climatic factors in the Taibai Mountain area[J]. Resources Science, 2019, 41(11): 2131-2143. Chen Yanli, Luo Yongming, Mo Weihua, et al. Differences between MODIS NDVI and MODIS EVI in response to climatic factors[J]. Journal of Natural Resources, 2014, 29(10): 1802-1812. Zhou Tianjun, Zou Liwei, Chen Xiaolong. Commentary on the Coupled Model Intercomparison Project Phase 6 (CMIP6)[J]. Advances in Climate Change Research, 2019, 15(5): 445-456. Weng Yuwei, Cai Wenjia, Wang Can. The application and future directions of the Shared Socioeconomic Pathways (SSPs)[J]. Advances in Climate Change Research, 2020, 16(2): 215-222. Intergovernmental Panel on Climate Change (IPCC). Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

climate change[R]. Geneva: IPCC, 2023.

[15] Testa S, Soudani K, Boschetti L, et al. MODIS - derived EVI, NDVI

and WDRVI time series to estimate phenological metrics in French deciduous forests[J]. International Journal of Applied Earth Observation and Geoinformation, 2018, 64: 132-144.

Zou Xiang, Zhang Yuting, Xu Lu. Spatiotemporal patterns of vegetation cover and its responses to climatic factors in Hulun Buir from 2000 to 2022[J]. Arid Land Geography, 2025, 48(6): 963-972. Xiong Xueting, Li Chuanhua, Chen Jiahao. Topographic regulatory role of vegetation response to climate change[J]. Acta Geographica Sinica, 2023, 78(9): 2256-2270. Cui Xiaolin, Bai Hongying, Wang Tao. Difference in NDVI with altitudinal gradient and temperature in the Qinling area[J]. Resources Science, 2013, 35(3): 618-626. Zhang Fei, Li Jian, Li Huirong, et al. Spatiotemporal characteristics of net primary productivity and its response to influencing factors in Xilin Gol League grassland from 2001 to 2024[J]. Arid Land Geography, 2025, 48(9): 1555-1566. Cai Yifei, Chen Linshu, Lü Shixuan, et al. Impact of vegetation change on evapotranspiration components in the Loess Plateau based on Google Earth Engine[J]. Scientia Geographica Sinica, 2023, 43(9): 1649-1658. Li Jiaxuan, Li Huipeng, Bai Lu, et al. Dynamics of evapotranspiration and its relationship with drought in a grain-forage compound ecosystem on the Loess Plateau[J]. Pratacultural Science, 2024, 41(9): 2025-2034. Jiang Yinghui, Jiao Limin, Zhang Boen. Scale effects of the spatial correlation between urban land surface temperature and

NDVI[J]. Progress in Geography, 2018, 37(10): 1362-1370. Ma Bingxin, He Caixia, Jing Juanli, et al. Attribution of vegetation dynamics in southwest China from 1982 to 2019[J]. Acta Geographica Sinica, 2023, 78(3): 714-728. Chen Chunbo, Li Gangyong, Peng Jian. Spatiotemporal characteristics of Xinjiang grassland NDVI and its response to climate change from 1981 to 2018[J]. Acta Ecologica Sinica, 2023, 43(4): 1537-1552. Wu Wanmin, Liu Tao, Chen Xin. Seasonal changes of NDVI in the arid and semi-arid regions of northwest China and its influencing factors[J]. Arid Zone Research, 2023, 40(12): 1969-1981. Zhao Jiapei, Guo Enliang, Wang Yongfang, et al.

Ecological drought monitoring of Inner Mongolia vegetation growing season based on kernel temperature vegetation drought index (kTVDI)[J]. Chinese Journal of Applied Ecology, 2023, 34(11): 2929-2937. Li Dan, Zhuang Yilin, Wu Xiuqin. Simulation and prediction of vegetation dynamic in Karst Faulted Basin from 2020 to 2050 in climate scenarios[J]. Acta Geoscientica Sinica, 2021, 42(3): 435-443. Fu Shasha, Peng Wei, Shao Aimei, et al. Variation in the NDVI characteristics during the summer and the climatic factor responses in the Qinling-Daba Mountains[J]. Arid Zone Research, 2023, 40(10): 1563-1574. Niu Tongli, Xiong Lihua, Chen Jie, et al. Land use simulation and multi-scenario prediction of the Yangtze River Basin based on PLUS model[J]. Engineering Journal of Wuhan University, 2024, 57(2): 129-141, 151. Jiang Xiaoxiao, Li Xuemei, Han Hui, et al. Influence of land use transformation on carbon storage change in Gansu Province[J]. Arid Land Geography, 2024, 47(12): 2075-2082. Wang Zhiyuan, Wu Fan, Wan Ding, et al. Multi-scenario simulation of the impact of regional land use change on carbon reserve[J]. China Environmental Science, 2023, 43(11): 6063-6078. Hu Jixi, Le Xianwen, Xu Yong. Esti-



mating terrestrial ecosystem carbon stock changes caused by multi-scenario land use changes based on the FLUS model: A case study of Pingxiang, Jiangxi[J]. Research of Soil and Water Conservation, 2024, 31(2): 299-309. Wang Hong, Yang Dong, Lan Xiaoyu, et al. Prediction of climate productivity of vegetation based on SSPs path: A case study of Shaanxi, Gansu and Ningxia[J]. Plateau Meteorology, 2023, 42(1): 233-243. Yang X, Zhou B, Xu Y, et al. CMIP6 evaluation and projection of temperature and precipitation over China[J]. Advances in Atmospheric Sciences, 2021, 38(5): 817-830.

Han Ziyan, Meng Jijun, Zou Yi, et al. Vegetation dynamics and their response to climate change and ecological protection projects in the Heihe River Basin from 1982 to 2017[J]. Journal of Desert Research, 2023, 43(3): 96-106. Wu Yunli, Zhang Yu, Tian Jiarong. Impacts by climate change and human activities on NDVI in different vegetation types across the Inner Mongolia Plateau[J]. Chinese Journal of Agrometeorology, 2023, 44(12): 1155-1168. Ao Deng, Yang Jiahui, Ding Weiting, et al. Review of 54 vegetation indices[J]. Journal of Anhui Agricultural Sciences, 2023, 51(1): 13-21, 28. Wang Q, Moreno-Martínez Á, Muñoz-Marí J, et al. Estimation of vegetation traits with kernel NDVI[J]. ISPRS

Journal of Photogrammetry and Remote Sensing, 2023, 195: 408-417.

Camps Valls G, Campos Taberner M, Moreno Martínez L, et al. A unified vegetation index for quantifying the terrestrial biosphere [J]. Science Advances, 2021, 7(9): eabc7447, doi: 10.1126/sciadv. abc7447. [40] Pabon Moreno D E, Migliavacca M, Reichstein M, et al. On the po tential of Sentinel-2 for estimating gross primary production[J].

## Spatial Distribution of *Pinus massoniana* and *Pinus tabuliformis* Forests in the Qinba Mountains and the Delimitation of the Subtropical and Warm Temperate Zones

The Qinba Mountains serve as a critical ecological transition zone in China, representing the complex intersection between the subtropical and warm temperate regions. Understanding the spatial distribution of key indicator species, specifically *Pinus massoniana* (Masson' s pine) and *Pinus tabuliformis* (Chinese pine), is essential for accurately delimiting the boundary between these two climatic zones. This study analyzes the geographical patterns of these forest types to provide insights into the environmental factors governing their distribution and the resulting implications for regional bioclimatic classification.

The evolution of light use efficiency (LUE) models has significantly advanced our ability to monitor forest productivity across these diverse landscapes. As noted by Pei et al. [**?**], improvements in these models have addressed various uncertainties, though challenges remain in capturing the nuanced physiological responses of different pine species to varying environmental stressors. These modeling advancements are particularly relevant in the Qinba Mountains, where sharp topographical gradients create distinct microclimates that influence the competitive dynamics between subtropical species like *Pinus massoniana* and temperate species like *Pinus tabuliformis*.

[Figure 1: see original paper]

The spatial distribution of these forests is not merely a reflection of current climatic conditions but also an indicator of broader environmental shifts. By integrating remote sensing data with field observations, this research maps the precise extent of both forest types. The findings suggest that the transition between the subtropical and warm temperate zones in the Qinba Mountains is characterized by a mosaic of vegetation types, where the dominance of *Pinus massoniana* gradually gives way to *Pinus tabuliformis* as elevation and latitude increase.

Furthermore, the delimitation of the subtropical and warm temperate boundary is refined through the analysis of these indicator species. The study employs high-resolution geospatial datasets to correlate forest distribution with thermal and moisture indices. The results indicate that the traditional boundaries may require adjustment to account for the observed shifts in forest composition, which are increasingly influenced by both natural climate variability and anthropogenic factors. This refined boundary provides a more robust framework for ecological conservation and land-use planning in this sensitive mountainous region.

Spatial distribution patterns of Pinus tabulaeformis forest and

Pinus massoniana forest in Qinling - Daba Mountains and the bound

## References

[1] [Author Name Missing]. Boundary of subtropical and warm temperate zones[J]. *Acta Geographica Sinica*, 2020, 75(11): 2298-2306.

[2] Liu Xianfeng, Pan Yaozhong, Zhu Xiufang, et al. Spatiotemporal variation of vegetation coverage in Qinling-Daba Mountains in relation to environmental factors[J]. *Acta Geographica Sinica*, 2015, 70(5): 705-716.

[3] Zhou Yuxia, Liu Hailong, Zhao Zhicong, et al. Spatial system of national parks and protected areas in the Qinba Mountain area[J]. *Strategic Study of CAE*, 2020, 22(1): 86-95.

[4] Chen Chaonan, Wang Liyuan, Zhu Wenbo, et al. Characteristics of extreme climate change in the Qinling-Daba Mountains and its impact on vegetation dynamics[J]. *Journal of Soil and Water Conservation*, 2024, 38(3): 276-287.

[5] Wang Jian, Zhao Mudan, Li Jianbo, et al. Dynamic monitoring and driving forces analysis of eco-environmental quality in the Qinba Mountains based on MODIS time series data[J]. *Mountain Research*, 2021, 39(6): 830-841.

[6] Li Jinke, Yang Yuting, Zhang Huiru, et al. Spatio-temporal evolution of variations of net primary productivity and its natural and human factors analysis in Qinling-Daba Mountains in the past 15 years[J]. *Acta Ecologica Sinica*, 2019, 39(22): 8504-8515.

[7] Wang Yaobin, Zhao Yonghua, Han Lei, et al. Spatio-temporal variation of vegetation net primary productivity and its driving factors from 2000 to 2015 in Qinling-Daba Mountains, China[J]. *Chinese Journal of Applied Ecology*, 2018, 29(7): 2373-2381.

[8] Sun Rui, Chen Shaohui, Su Hongbo. Spatiotemporal variation of NDVI for different land cover types on the Loess Plateau from 2000 to 2016[J]. *Progress in Geography*, 2019, 38(8): 1248-1258.

[9] Wang F, Shao W, Yu H J, et al. Re-evaluation of the power of the···[Incomplete Reference]

Mann - Kendall test for detecting monotonic trends in hydrometeoro

logical time series[J]. Frontiers in Earth Science, Frontiers, 2020, 8: 14, doi: 10.3389/feart.2020.00014.

## Spatiotemporal Path Analysis of Vegetation Coverage and Hydrothermal Factors on the Loess Plateau

Wang Xiong, Zhang Chong, Li Qiang. Path analysis between vegetation coverage and climate factors in the Loess Plateau [J]. Acta Ecologica Sinica, 2023, 43(2): 719-730. Yang Da, Yi Guihua, Zhang Tingbin, et al. Spatiotemporal variation and driving factors of growing season NDVI in the Tibetan Plateau, China [J]. Chinese Journal of Applied Ecology, 2021, 32(4): 1361-1372. Xie Shudi, Mo Xingguo, Hu Shi, et al. Response of vegetation greenness to temperature and precipitation in the Three-North Shelter Forest Program [J]. Geographical Research, 2020, 39(1): 152-165. Fan Yi, Zhao Mudan, Wang Jian. Long-term series changes of vegetation EVI and the influencing factors in the Qinling-Daba Mountains area [J]. Journal of Ecology and Rural Environment, 2022, 38(6): 733-743. Riahi K, van Vuuren D P, Kriegler E, et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview [J]. Global Environmental Change, 2017, 42: 153-168.

Rogelj J, Popp A, Calvin K V, et al. Scenarios towards limiting global mean temperature increase below 1.5 ℃[J]. Nature Climate Change, 2018, 8(4): 325-332.

Zhai Yaqian, Zhang Chong, Zhou Qi, et al. Spatio-temporal variation and interrelationship of vegetation cover and soil moisture in Qinling-Daba Mountains [J]. Journal of Geo-Information Science, 2018, 20(7): 967-977. Xu Haitao. Study on the assessment of ecological status and protection effectiveness in the Qinba Mountains [D].

Chengdu: Chengdu University of Technology, 2021. Wang Zhijie, Su Yuan. Spatiotemporal characteristics of land use change in southern Shaanxi Province in recent 20 years based on RS and GIS [J]. Journal of Natural Disasters, 2017, 26(6): 164-174. Zhang Jingjing, Ba Mingting, Chen Xi. Analysis on the spatiotemporal changes of ecosystem service value in Zhengzhou from 2010 to 2017 [J]. Ecological Science, 2023, 42(3): 177-183.

Simulation of vegetation growth dynamics and climatic driving mechanisms in the Qinling-Daba Mountains under climate scenarios

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## Abstract

The Qinling-Daba Mountains are located at the convergence of the climatic transition zone between northern and southern China and the ecotone between warm-temperate and subtropical regions. As a climate-sen- sitive area, investigating the coupling relationships between vegetation and climate in this area is critical for un- derstanding the evolutionary mechanisms of ecosystems under climate change. This study employs a multiple lin- ear regression model to predict kernel normalized difference vegetation index (kNDVI) values under three Shared Socioeconomic Pathways scenarios from 2024 to 2100, based on MODIS data and climatic factor datasets from 2001 to 2023. The Theil Sen Median estimator and Mann-Kendall test were used to analyze spatiotemporal trends of vegetation changes, and path analysis was applied to dissect the driving mechanisms of key climatic factors.

The results reveal that (1) Temperature is the dominant factor driving vegetation changes, spatially covering 67.27% of the study area, with its positive effects concentrated in the Qinling-Daba Mountain region, whereas the impacts of evapotranspiration and precipitation exhibit significant spatial heterogeneity. (2) The vegetation kND- VI increased by 0.1 from 2001 to 2023, demonstrating a rapid initial growth followed by a gradual slowdown trend, with degradation areas concentrated in low-altitude urbanized zones and high-altitude regions constrained by water-heat limitations. (3) Future scenario simulations reveal that vegetation dynamics stabilize under SSP119, whereas SSP585 demonstrates divergent trends, with the direct inhibitory effects of evapotranspiration coexisting with indirect facilitative effects driven by increased temperatures. (4) The replenishment efficiency of precipita- tion for vegetation diminishes with increasing climate extremes, whereas the direct climatic forcing of temperature significantly intensifies under elevated emission scenarios. (5) Regional vegetation responses indicate signifi- cant spatial heterogeneity, requiring differentiated ecological restoration strategies. These strategies should priori- tize high-altitude vulnerable zones, low-altitude areas disturbed by human activities, and evapotranspiration-sensi- tive regions in the central- eastern sectors. This study reveals the nonlinear response of vegetation to climate change in the Qinling-Daba Mountains, thereby confirming the ecological stability advantages of the low-carbon pathway (SSP119) and providing spatially optimized strategies for vegetation conservation and carbon sequestra- tion enhancement under regional carbon neutrality goals.

## Keywords

kNDVI; SSPs; the Qinling-Daba Mountains; climate factors; multiple linear regression analysis; trend analysis

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

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