

Original Research

Simulation and Prediction of Vegetation Dynamic Change in Three Provinces of Northeast China from 2025 to 2099 Based on Climate Scenarios

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Abstract

As a critical ecological **barrier**, the three northeastern provinces of China have profound ecological significance. The distinctive distribution patterns of vegetation, shaped by specific geographical endowments and climatic regimes, have a unique position among global environmental change research. This study aims to characterize future climate change and vegetation dynamics in response to global warming development, and to reveal the mechanistic responses of future vegetation change to extreme climate changes. In this study, we employed a multiple linear regression model to quantify the spatiotemporal correlations between NDVI and climatic variables (temperature/precipitation), based on high-resolution meteorological datasets and Normalized Difference Vegetation Index (NDVI) time-series (2001-2020). Then we used a univariate linear regression model combined with the Theil-Sen estimator and Mann-Kendall (M-K) test to study vegetation changes under different Shared Socioeconomic Pathways (SSPs245 and SSPs585). The results show as follows: (1) Under the SSP245 and SSP585 climate scenarios, an overall fluctuating upward trend in temperature and precipitation was observed in the three northeastern provinces of China. (2) Under the SSP245 and SSP585 scenarios, NDVI shows a fluctuating decrease and a fluctuating increase, respectively. Spatial heterogeneity was evident in the vegetation distribution pattern. (3) Temperature and precipitation influence vegetation distribution, and NDVI also responds to climatic variation. These findings provide a scientific basis for evidence-based climate adaptation strategies and sustainable ecosystem management in Northeast China.

Keywords: climate scenario, vegetation, NDVI, shared socio-economic pathways (SSPs), the three northeastern provinces of China

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Introduction

According to the sixth assessment report of IPCC, the global average temperature has increased by 0.84-1.10°C [1] compared with 1850-1900. It indicates that global warming has become a fact. The interplay between climatic variations and land-based ecosystems has consistently been regarded as a pivotal concern in the investigation of global transformation [2], and the complex relationship between them has also become the frontier and difficulty of global change research. Climate change will inevitably affect terrestrial ecosystems. Vegetation alterations, being a crucial aspect of terrestrial ecosystems, will either directly or indirectly influence the climate through response mechanisms. Vegetation can reduce water and soil loss and maintain the ecological environment [3], affecting the global carbon cycle [4]. It plays a positive role in the urban microclimate [5], alleviating the urban heat island effect and improving the urban environment [6]. In addition, studies have shown that vegetation resources are positively correlated with economic development [7], and the state of economic development is directly affected by the dynamic changes in vegetation [8]. However, due to global climate anomalies caused by climate change [9] and extreme climatic events [10], research and prediction of vegetation dynamic processes remain challenging.

In recent years, vegetation destruction caused by extreme climate and natural disasters [11, 12] and vegetation degradation under the influence of human economic development [13] have increased. Liu et al. [14] said that the decrease in annual precipitation and the increase in temperature will weaken the availability of water resources, which will also affect the growth of vegetation to a certain extent. In order to better predict vegetation and mitigate vegetation deterioration events, systematic and dynamic vegetation monitoring [15] and climate monitoring [16] play a key role. Normalized vegetation index (NDVI) can characterize the coverage and growth of vegetation to some extent [17].

As we all know, predicting the possible climate scenarios in the future and formulating effective countermeasures are the key to the construction and management of vegetation [18]. Many scholars have studied the future climate development trend [19-21], the future vegetation evolution characteristics [22-24], and the response of vegetation to climate [25-27] at different spatial scales. Some scholars have used projected climate models to simulate and predict climate change [28, 29]. Meanwhile, most current studies on vegetation trend forecasting rely on historical NDVI data to estimate vegetation evolution based on the Hurst index [30-32], grey prediction [27], CA-Markov model [33, 34], and similar methods. These approaches primarily project vegetation patterns from historical change trends, while temperature, precipitation, and other specific factors influencing vegetation growth were not considered.

As a critical ecological barrier, the three northeastern provinces of China have profound ecological significance. The distinctive distribution patterns of vegetation, shaped by specific geographical endowments and climatic regimes, have a unique position among global environmental change research. This study aims to characterize future climate change and vegetation dynamics in response to global warming development, and to reveal the mechanistic responses of future vegetation change to extreme climate changes. In this study, we employed a multiple linear regression model to quantify the spatiotemporal correlations between NDVI and climatic variables (temperature/precipitation), based on high-resolution meteorological datasets and Normalized Difference Vegetation Index (NDVI) time-series (2001-2020). Then we use a univariate linear regression model combined with the Theil-Sen estimator and Mann-Kendall (M-K) test to study vegetation changes under different Shared Socioeconomic Pathways (SSPs245 and SSPs585). The findings offer critical scientific foundations for evidence-based climate adaptation strategies and sustainable ecosystem management in Northeast China.

Materials and Methods

Study Area

The three northeastern provinces are located in northeast China, between 48°N-55°N and 118°E-135°E. From north to south, it includes Heilongjiang, Jilin, and Liaoning provinces. The climate belongs to the temperate monsoon climate zone, with long winters and short summers. The area is dominated by plains and mountains, including the Changbai Mountains, Xing'an Mountains, Sanjiang Plain, Songnen Plain, and Liaohe Plain. The types of vegetation are deciduous coniferous forests, mixed forests of conifers, broad-leaved trees, temperate forest grasslands, meadow grasslands, and arid grasslands (Fig. 1).

Data Sources

The MOD13A2 dataset (2001-2020) was downloaded from the official website (<https://lpdaac.usgs.gov/>). It has a spatial resolution of 1 km and a temporal resolution of 16 days. Data preprocessing included image mosaicking, projection conversion, and the Maximum Value Compositing (MVC) method. The meteorological dataset consists of two parts. One is based on data from 88 meteorological stations in the three northeastern provinces from 2001 to 2020, obtained from the China Meteorological Data Sharing website. The Kriging interpolation method was used to obtain annual precipitation and mean annual temperature data. The other is future climate data obtained from the CMIP6 of the Coupled Model Intercomparison Project, downloaded from <https://pcmdi.llnl.gov/CMIP6/>. In this

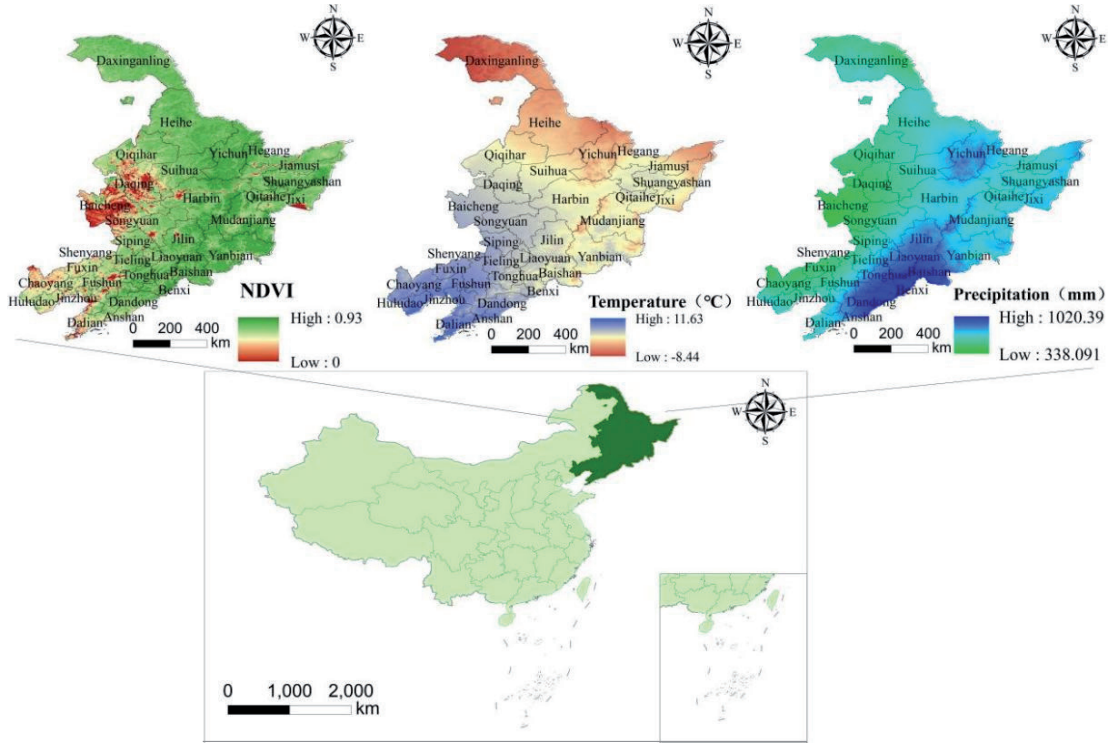


Fig. 1. The distribution map of vegetation, average temperature, and annual precipitation.

study, the SSP245 and SSP585 scenarios were selected to predict temperature and precipitation from 2025 to 2099, and to simulate vegetation growth changes over the same period.

Methods

Multiple Linear Regression Model

In this study, the relationship between climatic conditions and NDVI is fitted and predicted by using a multiple linear regression model. The multiple linear regression model is expressed as [35]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

Where the Y represents NDVI; ($i = 1, 2, \dots, K$) is the regression coefficient; X_1 is precipitation, X_2 is temperature.

Univariate Linear Regression

Univariate linear regression, also known as the linear regression method of the least squares method, can be utilized for analyzing the linear correlation and trend of variation between the dependent and independent variables. The calculation formula is expressed as [36]:

$$S_{slope} = \frac{n \sum_{i=1}^n i * M_{MET_i} - \sum_{i=1}^n i \sum_{i=1}^n M_{MET_i}}{n \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2}$$

Where S_{slope} represents the slope of the trend line; n represents the total number of years in the period from 2025 to 2099, i represents the i -th year in the time period, and M_{MET_i} represents the mean value of temperature or precipitation in the i -th year. $S_{slope} > 0$ means that the temperature and precipitation show an upward trend during the study period. $S_{slope} < 0$ means that the temperature and precipitation show a downward trend during the study period.

Theil-Sen Median Trend Analysis and Mann-Kendall Nonparametric Test

Theil-Sen median trend analysis, combined with the Mann-Kendall test, has found application in the examination of extended vegetation time series [37]. Its calculation formula is:

$$\beta = \text{mean}\left(\frac{X_j - X_i}{j - i}\right), \forall j > i$$

Where, X_j and X_i represent time series data. $\beta > 0$ signifies an upward trend, and $\beta < 0$ indicates a downward trend.

Mann-Kendall is highly regarded as an excellent nonparametric statistical test method due to its ability to function effectively even when samples do not adhere to a normal distribution and are minimally affected by outliers. The detailed procedure for this statistical test is described in the reference [38].

The Theil-Sen median trend analysis is used to study the dynamic change of the NDVI. The Mann-Kendall

method is used to determine whether the vegetation change in the study area is significant or not.

Results

Climate and Vegetation Characteristics in the Three Northeastern Provinces

The temperature, precipitation variations, and the NDVI tendency of the three northeastern provinces of China, as seen from Figs 2 and 3, have an upward trend and are characterized by spatial heterogeneity. The highest temperature value appears in the northeast of Heilongjiang Province, and the improvement area significantly exceeds the extent of degradation.

Spatial and Temporal Characteristics of Future Climate Change in the Three Northeastern Provinces

As shown in Fig. 4, future temperature shows an upward trend, while precipitation exhibits a fluctuating upward trend. The increases in temperature and precipitation under the SSP585 scenario are two to four times higher than those under the SSP245 scenario, respectively. As shown in Fig. 5, the rate of temperature increase is $0-0.026^{\circ}\text{C/a}$. Temperature increase shows spatial heterogeneity under the SSP245 scenario. The rate of temperature increase is $0-0.045^{\circ}\text{C/a}$, and its spatial distribution decreases from south to north under the SSP585 scenario. As shown in Fig. 6, the temperature increase under the SSP585 scenario is significantly higher than under the SSP245 scenario, as is the precipitation.

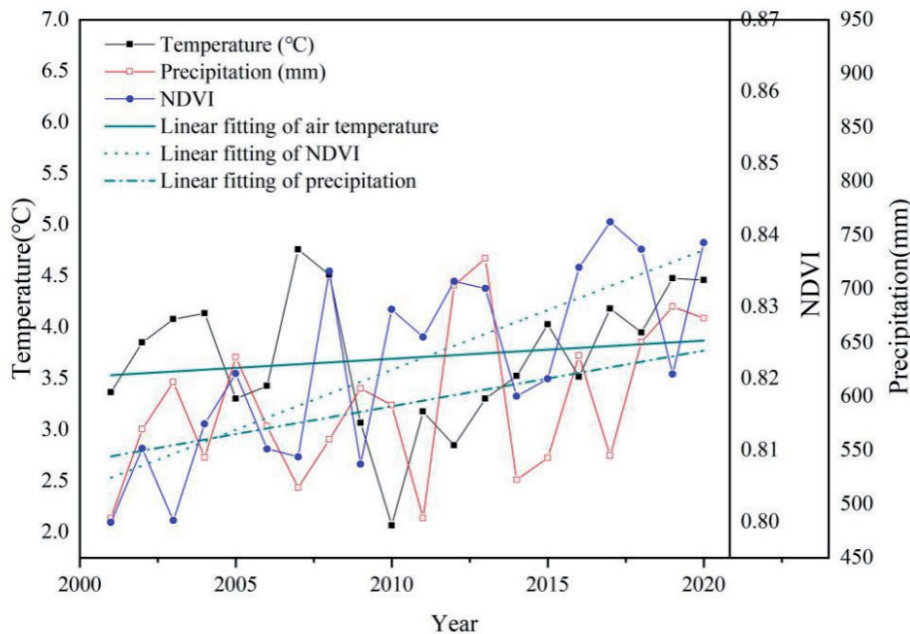


Fig. 2. Temporal variation of temperature, precipitation, and NDVI in three northeastern provinces from 2001 to 2020.

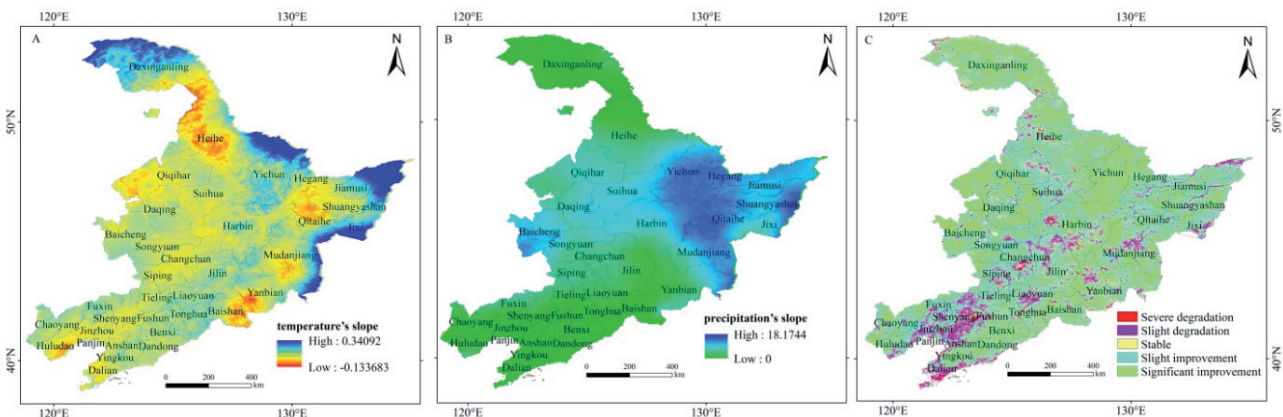


Fig. 3. Spatial variation characteristics of NDVI in three northeastern provinces under future climate scenarios.

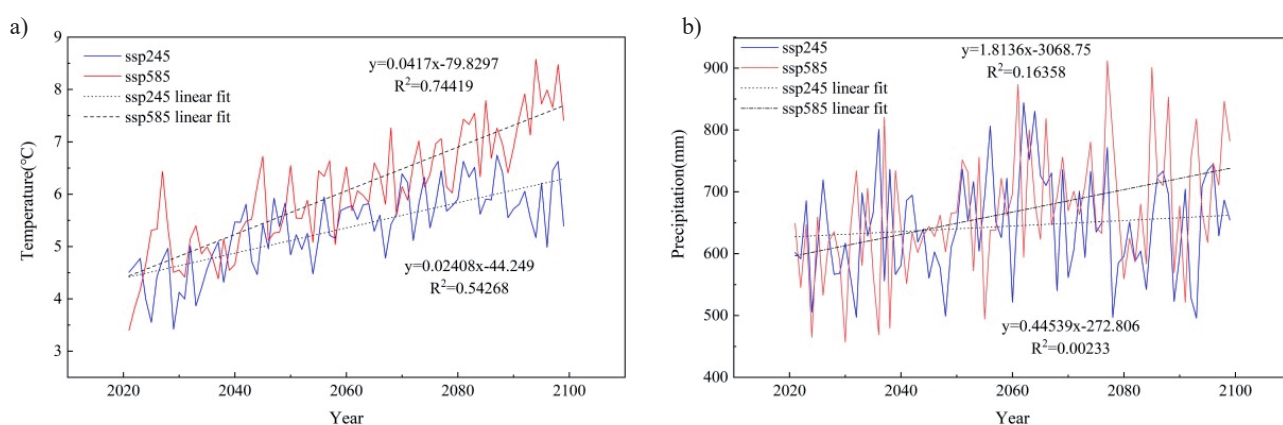


Fig. 4. Interannual variation of a) temperature and b) precipitation in the three northeastern provinces from 2025 to 2099 under the future scenario.

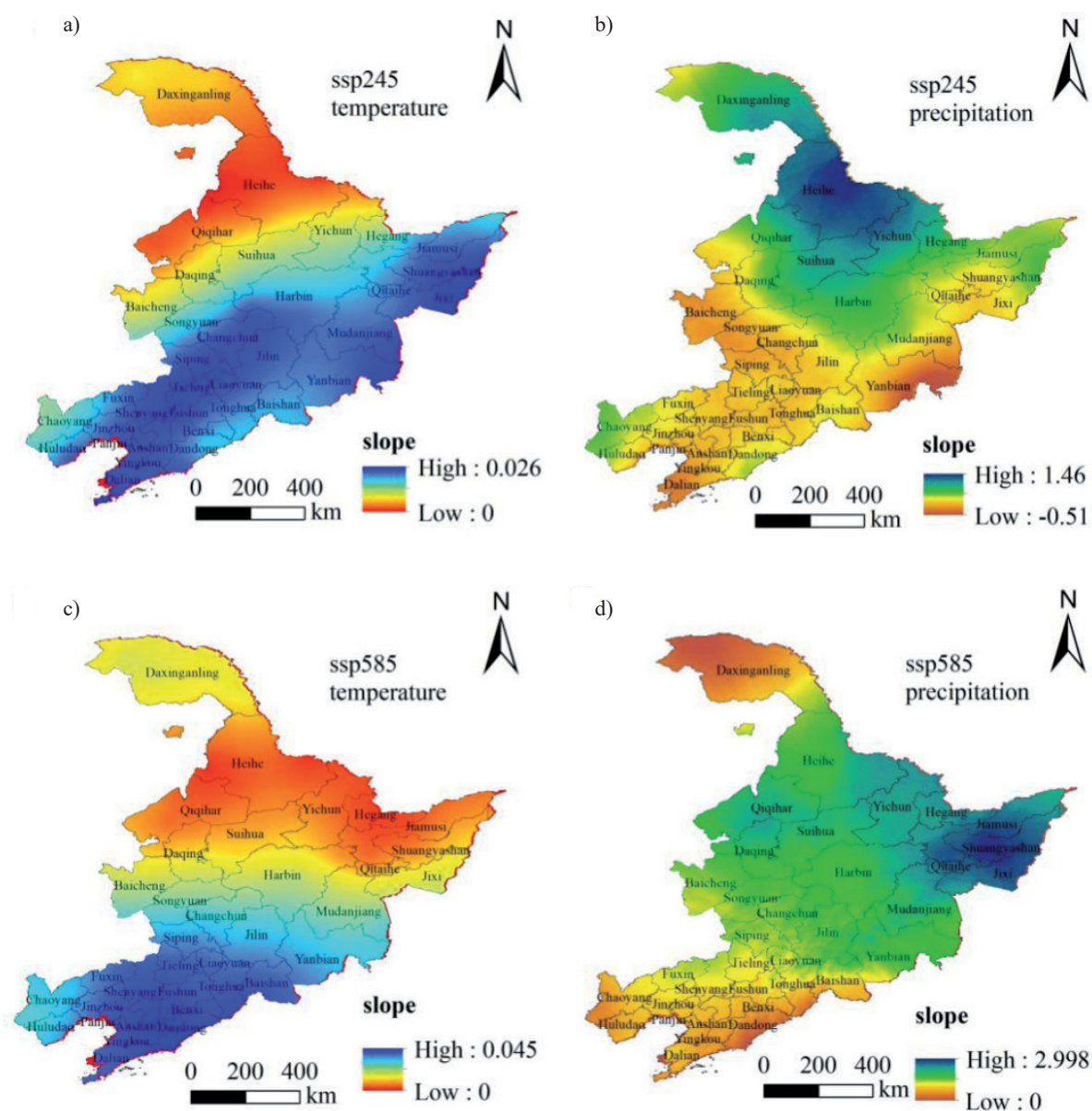


Fig. 5. Variation trend of temperature (a, c) and precipitation (b, d) under ssp585 and ssp245 scenarios in the three northeastern provinces from 2025 to 2099.

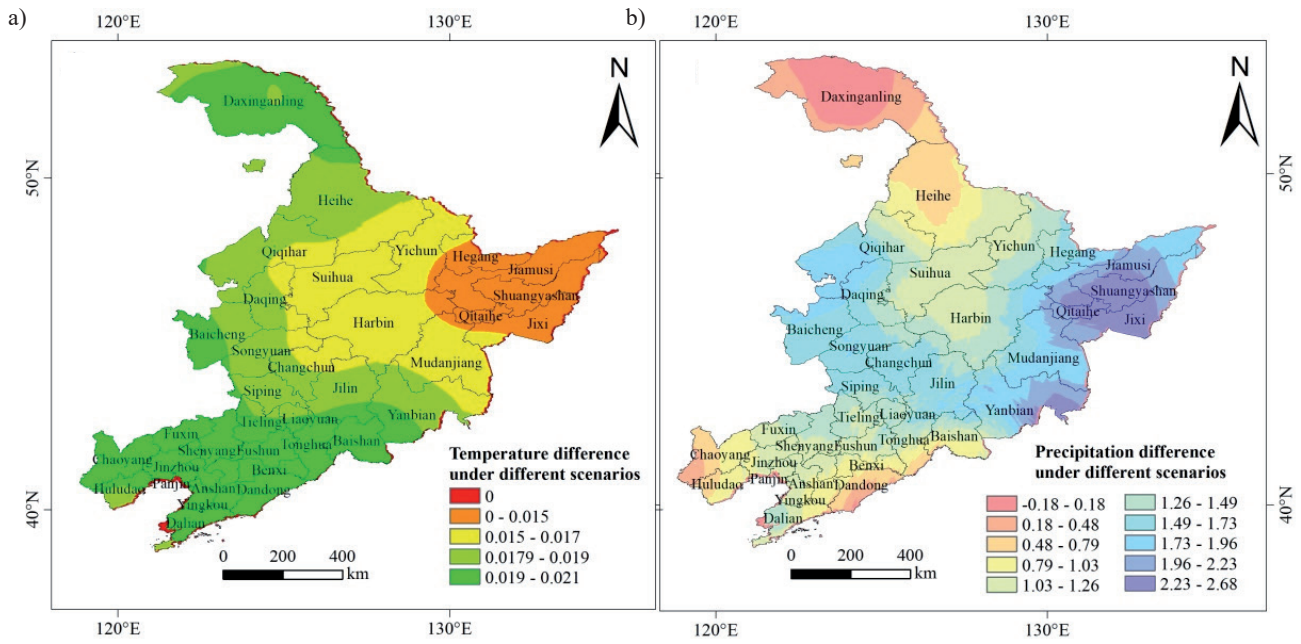


Fig. 6. Difference between a) temperature and b) precipitation under different scenarios in three northeastern provinces from 2025 to 2099.

Spatial and Temporal Variation Characteristics of Future NDVI in Three Northeastern Provinces

In this study, we use a multivariate linear regression model constructed using historical temperature and precipitation data to predict future NDVI under different climate scenarios. To evaluate NDVI prediction accuracy, the random point function available in ArcGIS software was used, and 3000 verification points within the study area were randomly selected to compare

the actual and predicted NDVI values. As shown in Fig. 7, the fitting coefficient (R^2) reached about 0.825, indicating that the multiple linear regression model can better predict future NDVI in the three northeastern provinces under different climate scenarios.

As shown in Fig. 8, the annual mean NDVI value of the three northeastern provinces fluctuates between 0.816 and 0.84 under the SSP245 and SSP585 scenarios. The average NDVI shows a slight downward trend, with fluctuations expected around 2060. In contrast,

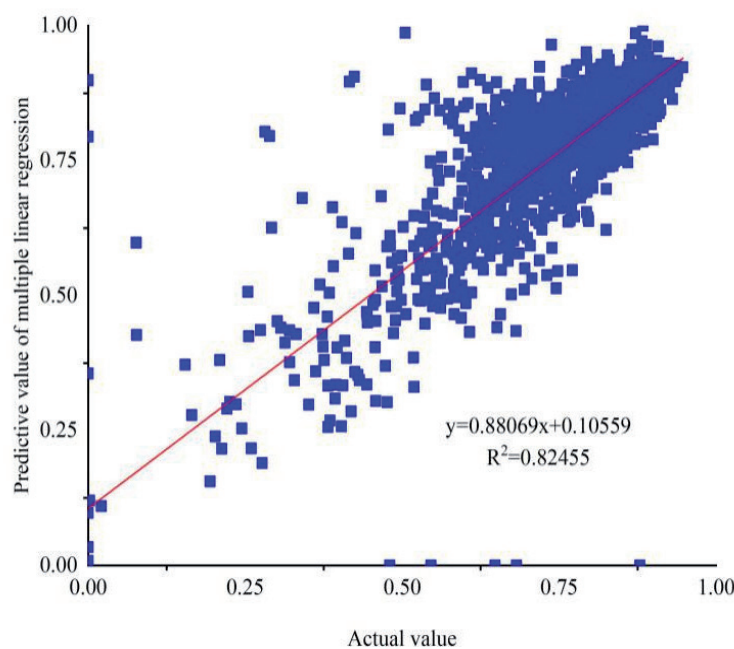


Fig. 7. Verification of NDVI prediction accuracy.

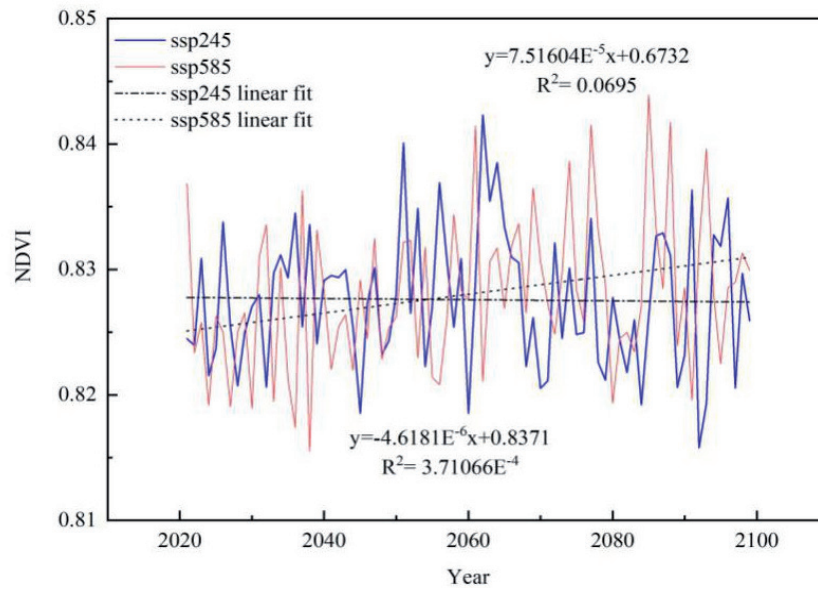


Fig. 8. Interannual variation of NDVI in three northeastern provinces from 2025 to 2099.

the average NDVI shows a slight upward trend under the SSP585 scenario.

In this study, we use the Theil-Sen median trend analysis to reclassify NDVI as stability, degradation, and improvement, and use the Mann-Kendall test method to reclassify NDVI as significant and insignificant (Table 1).

As shown in Table 1 and Fig. 9, it clearly demonstrates that the NDVI exhibits significant spatial heterogeneity in the three northeastern provinces under both the SSP245 and SSP585 scenarios. Under the SSP245 scenario, the NDVI remains stable in most areas of the three northeastern provinces. In general, compared to SSP245, the stable area in the SSP585

Table 1. Classification area of NDVI change trend in three northeastern provinces under different climate scenarios.

Climatic scenario	Severe degradation	Slight degradation	Stable	Slight improvement	Significant improvement
SSP245	5.77%	0.16%	88.43%	0.48%	5.16%
SSP585	13.91%	0.06%	68.90%	0.19%	16.93%

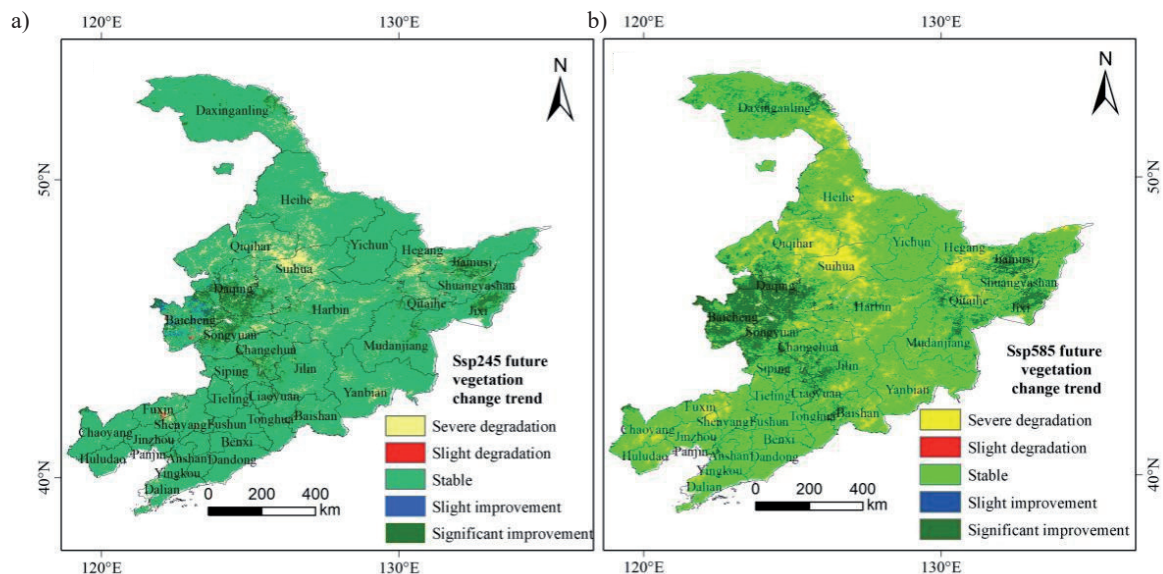


Fig. 9. Spatial variation characteristics of NDVI in three northeastern provinces under future climate scenarios.

scenario is reduced, the area of serious degradation and obvious improvement is increased, and the NDVI of vegetation changes greatly. However, the severely degraded area in the SSP585 scenario is twice as large as that in the SSP245 scenario. The significantly improved area in the SSP585 scenario is more than three times that in the SSP245 scenario.

Response of Vegetation to Climate Change

According to the trend of temperature and precipitation (Fig. 5), the areas with a slow temperature increase rate have more degraded areas of NDVI, and the areas with a fast temperature increase rate show different degrees of improvement in NDVI under the SSP245 scenario. In contrast, there is noticeable consistency in the spatial distribution patterns observed in the increase of precipitation and the NDVI variations. Areas with a large increase in precipitation show obvious degradation of vegetation, while areas with low growth in precipitation show significant improvement in vegetation. Under the SSP585 scenario, the NDVI tends to degrade in areas with a slow temperature rise trend. The NDVI in areas with a rapid temperature rise trend accounts for a large proportion.

In general, whether under the SSP245 or SSP585 scenarios, the spatial distribution of temperature variations and the spatial pattern of NDVI exhibit a discernible positive correlation. The rate of temperature increase in the northern region is gradual, and most of the area experiences vegetation degradation. Combined with the changing trend of precipitation, vegetation in areas with slow temperature increases and high precipitation increases is mostly degraded. In contrast, vegetation in areas with fast temperature increases and low precipitation increases is mostly improved.

Discussion

The annual average temperature under different climate scenarios shows noticeable latitudinal variations, and the magnitude of temperature has a rising trend. By analyzing the temperature and precipitation trends under future climate scenarios in Northeast China from a spatial perspective, it can be seen that the south has a high warming trend and a low precipitation increase, and the climate tends to be warm and dry. This is due to the low latitude in the south, strong solar radiation, less precipitation, and strong evaporation. The north has a low warming trend, a high precipitation increase, and the climate tends to be cold and wet. In general, under the two forecast scenarios, the three northeastern provinces will show an overall warming and humidifying trend in the future. This is consistent with [39] and [40].

The vegetation coverage in the study area will increase in the future. Compared with SSP245, the

vegetation improvement area under the SSP585 scenario will increase. The trend of vegetation in the three northeastern provinces shows spatial heterogeneity. These findings are consistent with [41] and [42].

In this study, a multiple linear regression model was constructed to explore the relationship between vegetation, temperature, and precipitation. It was found that vegetation has a vertical distribution pattern. Vegetation in areas with a high increase in precipitation and a low increase in temperature grows well in the three northeastern provinces. These findings are consistent with [43-46].

Although we have already obtained significant results, some limitations still exist. For example, altitude factors are not considered in this paper, which makes it impossible to determine the causes of vegetation changes in some specific areas. In the Changbai Mountains and the Xing'an Mountains, due to the influence of mountain terrain, there are certain differences in temperature and precipitation in the vertical pattern. In addition, with social and economic development, considering the intensification of human activities and socioeconomic integration, it becomes evident that the influence of human activities cannot be ignored. Therefore, in our future work, it is imperative to consider the combined effects of natural and human activities.

Conclusions

The main conclusions are as follows:

1) Under the SSP245 and SSP585 climate scenarios, there was a fluctuating overall upward trend in temperature and precipitation in the three northeastern provinces of China. The increases in temperature and precipitation in the SSP585 scenario are two times and four times those in the SSP245 scenario, respectively. The future temperature trend will gradually decrease from south to north, while precipitation will show a reduction from the central northern regions toward both the northern and southern areas.

2) Under the SSP245 and SSP585 scenarios, NDVI will show a fluctuating decrease and a fluctuating increase, respectively. There is spatial heterogeneity in the vegetation distribution pattern. The areas of vegetation improvement and degradation under the SSP585 scenario are larger than those under the SSP245 scenario.

3) Temperature and precipitation affect the distribution of vegetation, and NDVI also responds to climate. In the three northeastern provinces, vegetation shows a trend of degradation in regions with a temperature rise and a significant precipitation increase, whereas vegetation in areas with a declining temperature and minimal precipitation growth exhibits greater improvement.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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