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RESEARCH ARTICLE

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Monitoring the dynamic changes in vegetation cover and driving factors from 2000 to 2020 in the Maoershan Forest Farm region, China, using satellite remote sensing data

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Abstract

Aim of study: Natural climate change is a central driver of global ecosystem and forest change. Climate change and topographical factors have had the greatest impact on different types of forests around the world. We used remote sensing technology to detect and analyze the temporal and spatial changes of forest vegetation to provide reference for regional management.

Area of study: Maoershan Forest Farm, China.

Material and methods: The Landsat images were preprocessed using ArcGIS and ENVI software. The normalized difference vegetation index (NDVI) was calculated to identify vegetation changes from 2000 to 2020. In addition, the vegetation fraction cover (VFC) was calculated using the pixel binary model. The driving factors and their influences on vegetation changes in this region were determined using the random forest algorithm and Pearson correlation analysis method.

Main results: From 2000 to 2020, the NDVI showed an overall increasing trend. The results indicated that compared with the climatic factors, topographic factors were more important to vegetation growth in the study area. Among the topographic factors, elevation was the most important factor affecting vegetation growth and both showed a negative correlation. Among the climatic factors, relative humidity was the primary driving factor affecting vegetation growth and both showed a positive correlation.

Research highlights: Accurate and timely assessment of vegetation change and its relationship to climate and topographical changes can provide very useful information for policy makers, governments and planners in formulating management policies.

Additional key words: forest management; climate change; random forest; NDVI.

Abbreviations used: DEM (Digital Elevation Model); GIMMS (Global Inventory Modelling and Mapping Studies); MODIS (Moderate Resolution Imaging Spectroradiometer); NDVI (Normalized Difference Vegetation Index); VFC (Vegetation Fraction Coverage).

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Introduction

Vegetation cover is an important component of the terrestrial ecosystem. It is not only a linkage between the natural elements such as the atmosphere, soil, and water, but also an important indicator of global climate and ecosystem change (Seidl et al., 2017). In the past few years, with the intensification of global warming and human activities, monitoring and understanding the dynamics of vegetation cover in response to global change has become the core focus of earth system science. Understanding the vegetation cover development and changes contributes to a comprehensive understanding of the regional ecological environment as well as helps in evaluating the quality of the regional ecological environment system, which can provide a guide for formulating sustainable environmental protection strategies (Sun W et al., 2015). Therefore, studies on the long-term dynamic changes in the vegetation cover have become one of the hot spots in the field of ecology.

At present, field-measured and remote sensing inversion are two basic approaches to monitoring changes in the vegetation cover (Ge et al., 2018). The surface measurement method primarily obtains the vegetation growth and cover status through a comprehensive investigation of the vegetation status and digital camera photographs. This method usually involves a detailed survey of the height, density, greenness and distribution of the vegetation. The ground survey method can provide accurate information on the vegetation structure and distribution at a small scale (Talukdar et al., 2020). This method is a way to obtain vegetation structure and distribution information through field survey, visual and manual measurement of vegetation height, greenness and distribution, and record these data. However, as they involve much manpower and material resources and the scope of the survey is small, they could not cover a large area, so it is difficult to effectively estimate the changes in the vegetation cover at a regional scale. With the development of remote sensing technology, the method based on remote sensing provides a unique opportunity for the inversion of vegetation cover in large regions and even the entire country.

The normalized difference vegetation index (NDVI) is very sensitive to the biophysical characteristics of vegetation and is an effective indicator of vegetation growth status. It is the most commonly used remote sensing monitoring index for evaluating the changes in vegetation cover and one of the most effective parameters for evaluating vegetation status (Jiang et al., 2006). The vegetation fraction coverage (VFC) is a comprehensive quantitative index of the terrestrial plant community dynamics, and an important parameter of ecological, climate, and global change. It helps to provide basic and important details about the ecosystems (Amiri et al., 2009). Quantifying VFC is important for assessing the vegetation growth status and its changes at the regional and global scales.

NDVI is the most widely used vegetation index with several studies being carried out to monitor regional long-term vegetation changes based on NDVI data provided by different sensors. The results obtained from these studies have been helpful for qualitative and quantitative evaluation of the growth and vigour of surface vegetation cover (Martínez & Gilabert, 2009; Huang et al., 2021). Studies have also been conducted to monitor the dynamic changes in vegetation based on Satellite Pour l' Observation de la Terre (SPOT) NDVI data or Moderate Resolution Imaging Spectroradiometer (MODIS) data to analyse the changes in vegetation cover and understand the vegetation growth dynamics (Klisch & Atzberger, 2016). Pixel dichotomy assumes that each pixel of information received by the sensor is composed of green vegetation and bare soil. The pixel dichotomy model is developed to estimate the fraction of green vegetation and bare soil in the pixel, based on which the VFC of the pixel can be obtained (Li et al., 2014).

The dynamic characteristics of the changes in vegetation cover are influenced by several external factors (Campbell et al., 2005). Vegetation growth in the natural state is mainly affected by climate change and terrain. In forests, the growth of vegetation is closely related to meteorological factors. All these factors, including temperature, humidity, precipitation, and wind affect the moisture adequacy of vegetation, thereby directly affecting the growth of forest vegetation (Sun W et al., 2015; Wang et al., 2015). For topographic factors, elevation and slope can affect the loss of water from vegetation, while the aspect factor can affect the amount of solar radiation received by the vegetation, which directly affects the degree of vegetation dryness (Tian et al., 2022). Jia et al. (2020) investigated the spatio-temporal variations in characteristics of vegetation cover in the Xijiang River Basin from 2000 to 2013; analysed the correlation between precipitation, slope, and vegetation index; and discussed the influence of climatic and topographic factors on the changes in vegetation cover in Xijiang River Basin. Sun et al. (2022) concluded that the variational trend of vegetation cover and its relationship with climatic factors in the source area of the three rivers in China were mainly affected by altitude and temperature; the vegetation cover of the Gannan Plateau in the upper reaches of the Yellow River had a significant decreasing trend.

With a vast territory and complex natural conditions as well as with the rise in global climate change and human activities in recent years, especially due to global warming, rapid urbanization and large-scale ecological restoration projects since the end of the 20th century, vegetation coverage in China has experienced complex changes. However, there are still some gaps in the study on the long-term dynamic changes in the vegetation cover (Liu et al., 2019). First of all, there are gaps in understanding the fine-scale macro pattern of the changes in the vegetation cover, especially the spatio-temporal variational characteristics at long-time scales. Dynamic monitoring of the changes in the vegetation cover and determining its relationship with

Table 1. Collected Landsat images. Source: Geospatial Data Cloud (www.gscloud.cn/).

Data type	Acquisition date	Spatial resolution	Path/Row
Landsat-5 TM	2000-8-18	30 m	117/028
			117/029
Landsat-7 ETM	2005-8-08	30 m	117/028
			117/029
Landsat-5 TM	2010-9-15	30 m	117/028
			117/029
Landsat-7 ETM	2015-9-05	30 m	117/028
			117/029
Landsat-8 OLI	2020-7-08	30 m	117/028
			117/029

climatic and topographic factors are of great significance for preserving vegetation.

Previous studies have primarily relied on time series analysis of moderate to low spatial resolution remote sensing images such as MODIS and GIMMS products to assess changes in vegetation cover at a large scale. However, for analysing regional changes in vegetation cover, it is crucial to use higher spatial resolution imagery. Therefore, in this study, we utilized Landsat imagery to study vegetation changes detection in Maoershan (Landsat 5 TM, Landsat 7 ETM, Landsat 8 OLI). We used Landsat images from 2000 to 2020 as our data source to calculate NDVI, and the pixel dichotomy method was used to calculate VFC to estimate the multi-period vegetation coverage in the study area (image time was 2000, 2005, 2010, 2015, 2020, five years interval). Furthermore, we analyzed changes in vegetation growth and cover during the aforementioned period, as well as the spatial distribution characteristics of vegetation cover and the correlation between vegetation growth and climatic and topographic factors in Maoershan. The key objective of this study was to monitor vegetation changes in Maoershan from 2000 to 2020 using Landsat images and to investigate the relationship between NDVI and climate and topographical changes.

Material and methods

Study area

The study area is located in Maoershan Experimental Forest Farm (45°14'-29' N, 127°29'-44' E) of Northeast Forestry University in Shangzhi City, Heilongjiang Province, which is the remnant of Xiaoling on the western slope of Zhangguangcai Mountain in Changbai Mountain system, with a total area of 26,496 hectares (Fig. 1). The landform of the experimental forest farm is a low hilly region as a whole. The terrain rises from south to north, with an average elevation of 300 m. The climate in this region is mild and humid, belonging to the continental monsoon climate type. The average annual temperature is about 3°C, and the average annual precipitation is about 723 mm. The major vegetation in this region is typical natural secondary forest, including hard broad-leaved mixed forest dominated by valuable broad-leaved tree species such as *Fraxinus mandshurica*, *Junglus mandshurica*, and *Phellodendron amurense*; soft broad-leaved mixed forest dominated by *Betula platyphalla*, *Populus davidiana*, and *Betula costata*; coniferous forest dominated by *Korean pine*, *Larix gmelina*, and *Pinus sylvestris* var. *mongolica*. The plantation primarily consists of *L. gmelini* and *P. sylvestris* var. *mongolica*, forming a mosaic of natural secondary forests and plantations (Chang et al., 2020).

Data sources

The Landsat images used in this study were downloaded from the Geospatial Data Cloud (https://www.gscloud.cn/) with a spatial resolution of 30 m. In this study, remote sensing images collected by Landsat-5 TM, Landsat-7 ETM and Landsat-8 OLI were used to monitor vegetation status (Table 1). In the first step, radiometric calibration, atmospheric correction and geometric correction are performed using ENVI software based on the Landsat image of the study area. These data pre-processing steps must be done to obtain high-quality results. A total of 10 images were obtained in this study, and the specific data information is shown in Table 1.

Vegetation cover change

The NDVI is an important index for characterizing the vegetation coverage of the land surface, and its value ranges from -1 to 1. In this study, NDVI was used to indicate the vegetation growth status of the current year. VFC, an

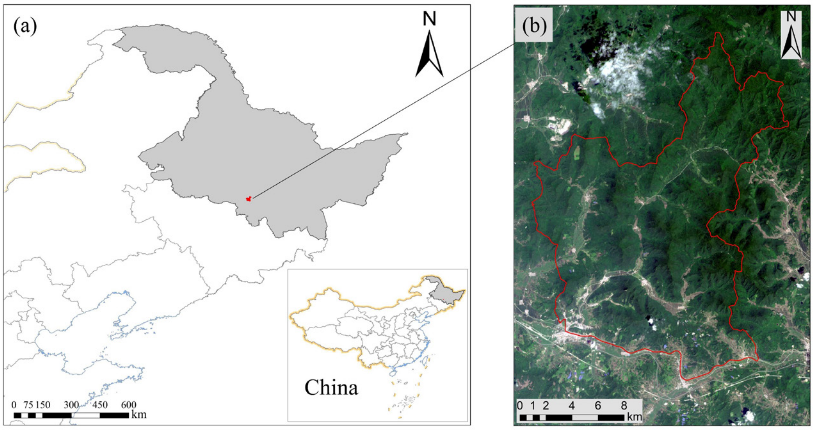

Figure 1. Study area: Maoershan Experimental Forest Farm, Heilongjiang Province, China.

important index reflecting vegetation coverage and ecological environment monitoring, represents the ratio of the vertical projection area of the vegetation in a region to the total area of the region (Gao et al., 2020); it ranges from 0 to 1. VFC is usually calculated using the NDVI-based pixel binary model. In this study, each pixel of NDVI was decomposed into pure vegetation and pure bare soil. VFC was calculated as follows:

$$NDVI = (NIR-R) / (NIR+R) \quad (1)$$

$$VFC = (NDVI - NDVI_{soil}) / (NDVI_{veg} - NDVI_{soil}) \quad (2)$$

where *NIR* represents near infrared band, *R* represents red band, *VFC* denotes vegetation coverage, $NDVI_{soil}$ denotes NDVI value of completely bare soil or non-vegetation covered area, $NDVI_{veg}$ represents NDVI value of pixels completely covered by vegetation, namely, NDVI value of pure vegetation pixels (Li et al., 2021.

Variable importance analysis

Driving factors

Considering the environmental factors affecting vegetation growth, we decided to collect meteorological and topographic factors as influencing factors. Therefore, the data of four factors (daily average temperature, relative humidity, precipitation, and wind speed) were selected as meteorological factors and collected from the China Meteorological Data Network. For topographic factors, the influencing factors were divided into two categories, climate and terrain, including seven variables (Table 2). The altitude, slope, and aspect factors of the study area were extracted from digital elevation model (DEM) data, which were acquired from the geospatial data cloud.

Random forest

The importance of the identified driving factors was ranked by random forest method to determine the key factors affecting the changes in vegetation cover in Maoershan. This method directly measures the influence of each factor on the prediction accuracy of the model. The fundamental idea is to rearrange the eigenvalues and observe the reduction in the accuracy of the model. For unimportant features, this method has little impact on the accuracy of the model, but for important features, it largely reduces the accuracy of the model (Ma et al., 2020). In this study, the "Random Forest" package in R was used for calculating and sorting the importance of each variable. The importance of a certain feature X in the random forest was calculated as follows: (1) for each decision tree in the random forest, the corre-

Table 2. Driving factors affecting vegetation change.

Variable factors	Variable name	Code	Source
Climatic	Daily average temperature	Temp_avg	China Meteorological Data Network (http://data.cma.cn/)
	Daily average relative humidity	Rh_avg	
	Daily average precipitation	Pre_avg	
	Daily average wind speed	Ws_avg	
Terrain	Altitude	ALT	Geospatial Data Cloud (www.gscloud.cn/)
	Slope	Slope	
	Aspect	Aspect	

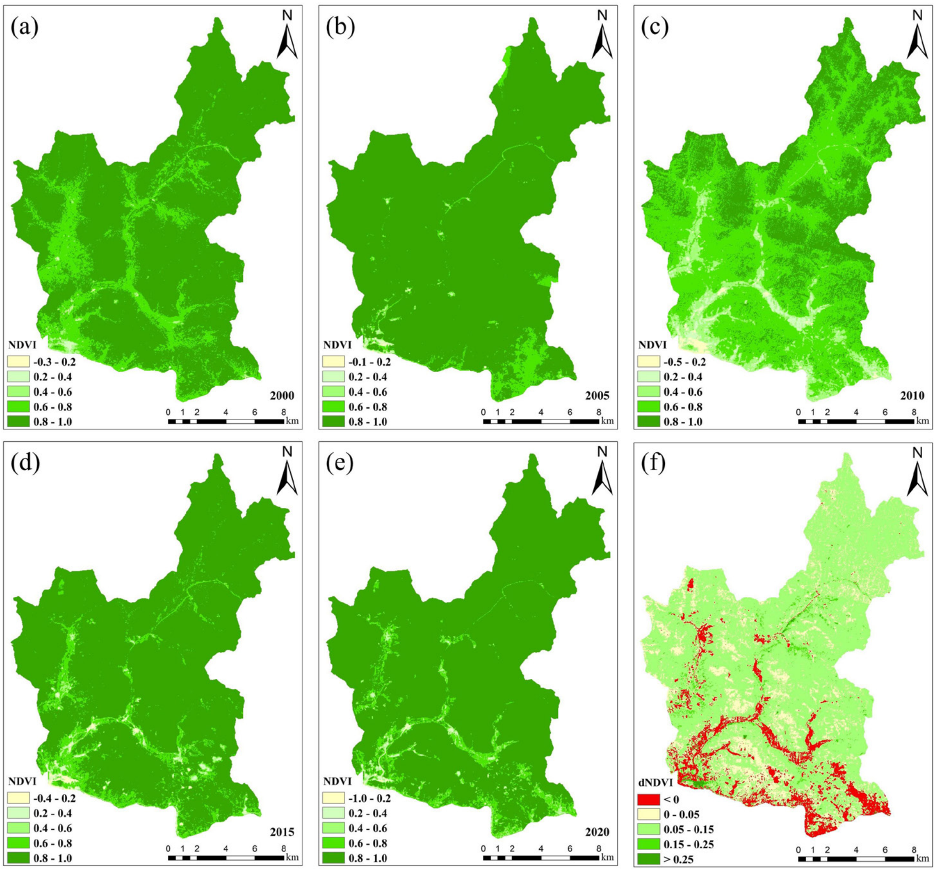

Figure 2. Spatial distribution of normalized difference vegetation index (NDVI) in Maoershan from 2000 to 2020. (a)-(e) represent spatial distribution of NDVI from 2000 to 2020, respectively, and (f) represent changes of NDVI in the past 20 years.

sponding out-of-pocket data (OOB) was used to calculate its out-of-pocket data error, denoted as errOOB1; (2) noise interference was randomly added to feature X of all samples of the data outside the bag (the sample value at feature X can be randomly changed), and the error of its data outside the bag was calculated again, denoted as errOOB2.

If there are N variables in the random forest, then the importance equation of feature X is:

$$Importance = \frac{1}{N}\sum(errOOB2 - errOOB1) \qquad (3)$$

Spearman correlation analysis was also used in this study to analyze the correlation between vegetation change and several factors, test the results of random forest, and further determine the influence of different factors on vegetation change.

Results

Variations in vegetation growth status

From 2000 to 2020, the average NDVI of vegetation in this region was 0.84, the lowest being 0.73 in 2010, and the highest being 0.90 in 2005 (Fig. S1 [suppl]). Further analysis demonstrated an increasing trend of NDVI from 2000 to 2005, a sharp reduction in 2010, and then an accelerating trend until 2020.

The spatial distribution of NDVI (Fig. 2) indicates that the high value was mainly distributed in the northern and central parts of the region. From 2000 to 2020, vegetation NDVI in most areas of Maoershan showed an increasing trend. The areas with a rapid increase rate were mainly located in the north and east of the region; the areas with a slow increase were mainly located in the middle of the region. In addition, vegetation NDVI showed a decreasing trend in the southern and western regions (Fig. 2f).

From 2000 to 2020, VFC in most areas of Maoershan had a decreasing trend with a smaller amplitude (Fig. 3). The spatial distribution of VFC changed greatly over time. Especially in 2010, the part and overall VFC showed a sharp decline (Fig. 3c). A rapid rate of decline was primarily observed in the central part of the region. The areas with a slower rate of decline were mainly located in the northern and eastern parts of the region. In addition, VFC showed an increasing trend in the southwest and other local areas (Fig. 3f). Figs. 2 and 3 show that the period 2005-2010 marked a change due to the loss of vegetation and the poor climatic conditions of 2010, which then drags

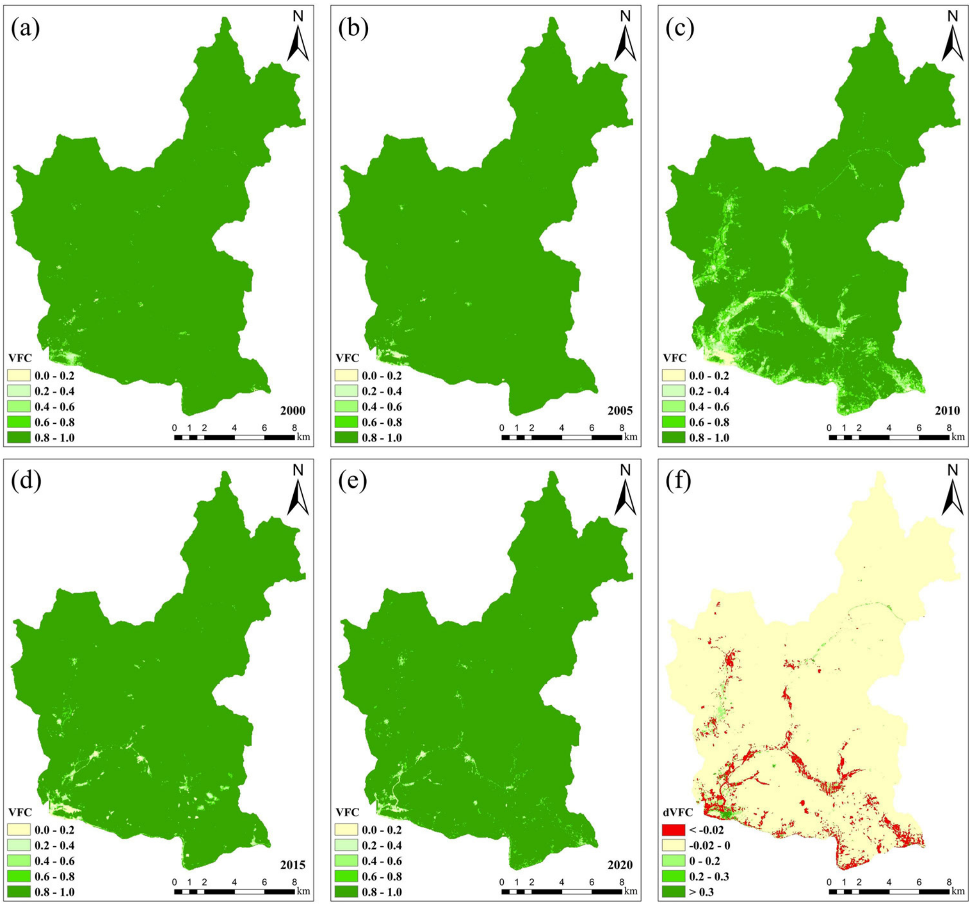

Figure 3. Spatial distribution of vegetation fraction cover (VFC) in Maoershan from 2000 to 2020. (a)-(e) represent the spatial distribution of VFC from 2000 to 2020, respectively, and (f) represent the changes of VFC in the past 20 years.

on the NDVIs and VFCs of the following years, giving negative balances for all those areas that suffered a loss of vegetation.

Analysis of driving factors of vegetation growth

From 2000 to 2020, the average annual temperature in the Maoershan area shows an increasing trend (Fig. S2 [suppl]). The highest average temperature was 5.16℃ in 2005, the lowest average temperature was 1.99℃ in 2010, and the average temperature in the past 20 years was 3.96℃. The annual precipitation also had an increasing trend. The maximum precipitation was 1596 mm in 2020, the lowest was 454 mm in 2000, and the average precipitation was 738 mm (Fig. S2a). Only a slight variation in the annual average relative humidity was observed, with the values initially increasing followed by a decreasing, the average value being 73.3%. The annual mean wind speed was also stable, ranging from 0.02 to 0.49, and the mean value in the 20 years was 2.64 m/s (Fig. S2b).

The topographic conditions (elevation, slope, and aspect) in this region are shown in Fig. S3 [suppl]. The high elevations are located mainly in the north and east of the region, with gradients mostly below 25°.

By utilizing random forest and spearman correlation methods, the importance of climate and terrain factors on NDVI and their specific relationships with NDVI were analyzed. As shown in Fig. 4, terrain factors were found to be more important than climate factors. Among all variables, altitude was the most important driving factor for vegetation growth, followed by relative humidity, temperature, wind speed, slope, precipitation, and aspect.

The Spearman results can accurately determine the influence of changes in each factor on NDVI values. For climate factors, all of them showed a positive correlation with NDVI, including relative humidity, temperature, wind speed, and precipitation (Fig. 4). This indicates that with the increase of relative humidity, temperature, wind speed and precipitation values, NDVI values increased. In other words, the greater the value of these four meteorological factors were related with a greater positive effect on vegetation growth. For the topographic factors, NDVI was positively correlated with slope, and negatively correlated with altitude and aspect (Fig. 4). This indicated that, in the study area, greater slope values were related with higher NDVI values; conversely, the greater the altitude and aspect values (aspect value: northwest > west > southwest > south > southeast > east > northeast > north > flat) were related with lower NDVI values.

Discussion

This study evaluated the changes in NDVI and VFC as well as their distribution in the study area from 2000 to 2020 using Landsat time series image data and analysed the spatio-temporal differences in the vegetation cover in Maoershan. The topographic and climatic factors in this region were identified using the random forest algorithm and the correlation analysis method, and the driving factors and their influences on vegetation change in this region were analysed.

The variations in the NDVI time series in the study area from 2000 to 2020 indicated an initial increase in the NDVI value in Maoershan followed by a decrease, and then again, an increase. However, the entire study area demonstrated an increasing trend of NDVI. The high values were mainly distributed in the northern and central parts of the region. The areas with a faster rate of increase in NDVI were located in the north and east of the region, while the areas with a slower rate of increase were mainly located in the central part of the region. These results were similar to those from previous studies on the changes in the vegetation cover in Northeast China (Mao et al., 2012). In addition, although vegetation NDVI demonstrated an overall increasing trend, it followed a decreasing trend in the southern and western regions. This contrasting phenomenon of regional changes in vegetation may be caused due to the differences in terrain and different vegetation types.

In this study, we used NDVI values acquired every five years to monitor vegetation changes in the study area. The choice of five-year intervals was based on the availability of long-term NDVI data and the need to capture significant changes in vegetation cover and productivity. While using 5-year NDVI values may not capture short-term changes in vegetation, it can provide a broader perspective on long-term trends and changes in vegetation cover. It is also a practical approach, especially in areas with limited data availability or for large-scale assessments. However, we acknowledge that using 5-year intervals may not capture all changes in vegetation, such as those due to natural disturbances or human activities. Therefore, future studies could consider using finer temporal scales or complementary data sources, such as high-resolution imagery or field observations, to improve the accuracy of vegetation monitoring.

In recent years, numerous researchers (e.g., Avetisyan et al., 2022; Yunus & Polat, 2023) have endeavoured to employ alternative vegetation indices in addition to NDVI for the purpose of monitoring and assessing vegetation growth. These vegetation indexes include enhanced vegetation index (EVI), soil adjusted vegetation index (SAVI), normalized difference greenness index (NDGI. They take a more comprehensive approach to considering the various factors that impact vegetation. EVI enhances the stability and sensitivity of vegetation indices by mitigating the impact of atmospheric scattering and shading. SAVI, through modifying the soil reflection, enables a more comprehensive consideration of the interaction between bare soil and vegetation. By contrast, the NDGI not only captures the presence of sparse vegetation well, but also compensates for the effect of dry grass on green-up date extraction. Although these indexes have advantages over NDVI, they also have some limitations. Some studies have suggested that these indices have better applicability for certain types of vegetation (Dai et al., 2023). In addition, differences between these indices can also lead to some difficult to interpret results when comparing vegetation growth in the same area. Therefore, despite its limitations, NDVI remains one of the most widely used vegetation indices due to its high repeatability and broad applicability, providing valuable insights into the study of vegetation growth. Meanwhile, researchers should also prioritize the advancement of novel vegetation indices and select the most appropriate index based on specific analytical requirements.

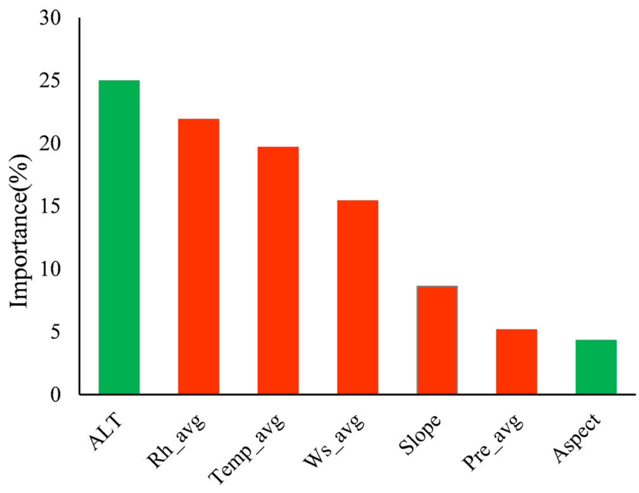

Figure 4. Importance and correlation of the seven variables. The length of the bar indicates the importance: the longer the bar, the higher the importance. The color of the bar indicates correlation: red, positive correlation; green, negative correlation. ALT, altitude; Rh_avg, daily average relative humidity; Temp_avg, daily average temperature; Ws_avg, daily average wind speed; Pre_avg, daily average precipitation.

When using NDVI for vegetation studies, it provides information about the presence of vegetation, but not about the structure of vegetation. This is because NDVI only reflects the chlorophyll content of vegetation, but it cannot distinguish different types of vegetation or different levels of vegetation. Therefore, in order to obtain more comprehensive and accurate structural measurement information, many studies use LiDAR technology, which uses laser scanning, to obtain 3D vegetation structure information (Tang et al., 2022). Compared with NDVI, which can only provide vegetation surface information, LiDAR can obtain vegetation height, coverage, volume, density and other multi-dimensional information. This information cannot only help determine if vegetation is changing, but also provide researchers with more detailed information about the composition, distribution, and changes in vegetation. However, there are some limitations to using the LiDAR technique. First, it requires a lot of data processing and analysis, which requires a high level of technology and computing power. Secondly, the application scope of LiDAR technology is relatively small, mainly limited to some relatively flat terrain and easily accessible vegetation (Dhargay et al., 2022). Overall, combining LiDAR technology can provide more vegetation information, which will help to assess vegetation change more accurately. However, due to the limitation of data collection and study area, the selection of LiDAR technology should be comprehensively considered. Of course, other data and indices can be used to obtain more vegetation information to obtain a more comprehensive assessment of vegetation change.

The driving factors and their influences on vegetation changes in Maoershan were analyzed using a random forest algorithm and correlation analysis. The topographic and climatic factors were the major factors affecting vegetation growth in Maoershan.

In this study, altitude, slope and aspect were selected as three terrain factors affecting vegetation growth. Compared with climate factors, terrain factors had a greater impact on vegetation growth. Among all the variables, altitude was the most important factor affecting vegetation growth, and slope was more important than aspect. Among them, NDVI was negatively correlated with altitude, indicating that the higher altitude values were related with lower NDVI values, which meant that the negative impact on vegetation growth was higher. At very high altitudes, vegetation growth can be inhibited to a certain extent, particularly due to low-pressure and low-oxygen environments in high-altitude areas, and insufficient oxygen can retard the growth of vegetation (Lou et al., 2021). The aspect was less important to vegetation change than elevation. This may be because the aspect variations in the study area led to little differences in the solar radiation received, resulting in a minimal impact of the aspect on vegetation growth (Xiong & Wang, 2022). Previous studies in northern China also reached similar conclusions (Sun Y et al., 2015).

Among the climate factors, the daily average relative humidity was found to be the most important factor affecting the growth of forest vegetation in the study area followed by temperature, and wind speed was a more important factor affecting vegetation than precipitation. Relative humidity can affect the water content of forest vegetation. As high relative humidity increases the water absorbed by vegetation, the growth of vegetation is accelerated (Guang-Lei et al., 2012). Sufficient precipitation can improve soil conditions and increase the water content of vegetation, thereby promoting the growth of vegetation (Wang et al., 2003). The results indicated that temperature had a positive effect on NDVI, indicating that an increase in temperature can promote the growth of vegetation. The major reason for this effect is the direct effect of temperature on the photosynthesis of vegetation. As the increase in temperature accelerates the photosynthesis of vegetation, it contributes to the growth of forest vegetation (Chuai et al., 2013). The variational trend of NDVI from 2000 to 2020 indicated an increase from 2000 to 2005, a sharp decrease in 2010, and then an accelerating trend until 2020 (Fig. S1). NDVI decreases may be due to loss of vegetation or lower local photosynthetic activity. The period 2005-2010 marked a change due to the loss of vegetation and the poor climatic conditions of 2010 (Figs. 2 and 3), which then drags on the NDVIs and VFCs of the following years, giving negative balances for all those areas that have suffered a loss of vegetation. It is worth noting that studies have demonstrated a threshold for the influence of temperature on vegetation growth, and negative effects may occur when the positive effects of temperature on vegetation reach a threshold (Julien et al., 2006). Extremely high temperatures can accelerate the evaporation of vegetation and reduce the water content, which is not conducive to the growth of vegetation. Interestingly, the region demonstrated a sharp increase in relative humidity in 2010, despite a rapid decline in NDVI. The possible reason for this phenomenon is that a rapid decline in temperature might have affected the photosynthesis of vegetation. At this time, the increase in relative humidity factor did not completely improve the growth of vegetation, thereby leading to a sudden decline in NDVI in this region in 2010.

In this study, Landsat images were selected to calculate the time series of NDVI. Compared with previous time series analysis of large-scale which mainly used medium and low-resolution remote sensing images (MODIS, GIMMS products, etc.) to study vegetation change, there was a large improvement in the spatial resolution of the images in this study, with these images more accurately reflecting the changes in the regional vegetation. Moreover, the image selected in this study was easy to obtain and unrestricted, and the time series was long, which increases its use in research and practical value (Ke et al., 2015).

Although topographic and climatic factors are the major factors affecting vegetation growth, and they were analysed in this study, the influence of human activities (including forest management, experimental logging, etc.) should not be ignored, and this is a limitation of this paper. The influence of human activities on vegetation change has both positive and negative aspects. With the increase in population, there is an increase in the negative impact of human activities on the ecological environment, such as coal mining, overgrazing, urban expansion, etc. However, humans can improve the regional ecological environment quality by reducing environmental pollution, returning farmland to forest, improving energy structure, and implementing greening projects. As this research area is located in an experimental forest farm, there is little impact from sudden logging and other management activities. Therefore, the factor 'forest management activities' was not considered a driving factor in this study. However, subsequent studies should take this factor into account. The results of changes in the vegetation cover highlighted in this study are important for the development of a sustainable forest management strategy considering the requirements of all the stakeholders. The results of this study can support long-term monitoring and management of vegetation in the future and contribute to sustainable environmental development.

In summary, by using remote sensing and GIS tools, we analysed the spatiotemporal characteristics and driving factors of vegetation cover on Maoershan from 2000 to 2020. According to our findings, altitude had the greatest impact on vegetation growth, and it was negatively correlated with NDVI. These results suggest that vegetation cover in this region is heavily influenced by environmental factors, which can provide scientific reference for the analysis of vegetation status and evaluation of regional ecological environment. Exploring the impact of driving factors on vegetation, further revealing the reasons for vegetation cover changes, and constructing long-term and high-spatial-temporal resolution vegetation cover change data are the focus of the next step of research.

Authors' contributions

Conceptualization: T. Li.
Data curation: T. Li.
Formal analysis: Y. Gao.
Funding acquisition: T. Li.
Investigation: Y. Gao.
Methodology: T. Li.
Project administration: T. Li.
Resources: T. Li.
Software: Y. Gao.
Supervision: Y. Gao.
Validation: T. Li.
Visualization: Y. Gao.
Writing – original draft: T. Li.
Writing – review & editing: Y. Gao.

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