Spatio-temporal variability in remotely sensed LST and its impacts by FVC in the Greater Khingan Mountains

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Abstract. The present study explored both the temporal variation and spatial distribution of fractional vegetation cover (FVC) and land surface temperature (LST) in the Greater Khingan Mountains, a location distinguished by four types of surface cover formations and strong gradients in meteorological conditions. Furthermore, we assessed the relationships between FVC and LST in different time-space dimensions. We measured the spatio-temporal variability in LST through a harmonic analysis of time series (HANTS) for 8 days of LST time series product data from the Moderate Resolution Imaging Spectroradiometer (MODIS). Furthermore, the FVC was extracted through linear spectral mixture analysis (LSMA). The results show that the time series image data reconstructed via HANTS are effective for quantifying the morphological dynamics of the thermal environment and enabling sound calculations of environmental variables, such as vegetation abundance. We found significant differences in within-year and interannual variation among different eco-geographical regions. The within-year maximum value of vegetation coverage was observed in July, whereas the surface temperature was highest in June. This finding suggests that the decrease in warming can be mostly attributed to the increase in evapotranspiration associated with increased vegetation activity. In addition, a strong negative correlation was found between the FVC and LST throughout the study area only from April to September, whereas a triangular relationship was found in other months. This study investigated the time series variations in different eco-geographical regions for 2000–2015 and revealed that the most obvious LST and FVC variations occurred at the region II and junction between regions III and IV. An analysis of the average FVC and LST from April to September indicated that 86.9% of the entire study area showed a negative correlation, such that when the FVC increased by 10%, the LST showed a maximum average decrease of 2.76°C. We conclude that the increase in vegetation activity is the main cause of the reduction in the LST and that surface activities and latitude zonality are the main driving factors of the LST differentiation in the Greater Khingan Mountains. These findings will serve as a foundation for future studies seeking to better understand climate change processes and to estimate ecosystem responses to changing climatic conditions.
Keywords: Eco-geographical regions, FVC, LST, Greater Khingan Mountains, vegetation index-LST space, spatio-temporal variability.

1. Introduction

The land surface temperature (LST) is critical to the energy fluxes and exchanges occurring at the interface between the atmosphere and the surface [1-5]. Approximately half of the solar insolation that reaches the uppermost layer of the atmosphere is absorbed at the Earth's surface [2]. Consequently, the surface releases terrestrial radiation as well as latent and sensible heat fluxes into the atmosphere to compensate for this large amount of surplus energy [3, 4]. Plant photosynthesis can take advantage of the conversion of light energy, thereby weakening the effects of heat radiation from the sun and effectively reducing surface temperatures [5-7]. In this context, it becomes essential to both understand and quantify the spatio-temporal association between LST and vegetation status to make predictions about coupled regional and worldwide feedback effects and temperature trends, especially in this time of varying climatic environments.

Recent studies have addressed the association between vegetation greenness and LST [7-11]. Consequently, researchers have used this association to derive various biophysical parameters [10-15] and for mapping [16] and change analysis [17-22]. However, most studies have concentrated on urban areas and have only discussed the changes in LST with biophysical parameters at a given moment in time [21, 23]. Meanwhile, the surface activities of different regions serve as a critical factor in regulating the thermal balance, but few studies have compared different regions over time. In addition, most studies have used the Normalized Difference Vegetation Index (NDVI) in combination with the LST as the foundation for analysis, and several researchers have already discovered a negative NDVI-LST association [1, 21, 24, 25]. As reflected in these recent studies, the NDVI cannot be used to approximate vegetation quantity. Notably, NDVI measurements originate from the near-infrared and observable reflectances from plant canopies as well as from soil background, the atmosphere, plant species, shadows, and leaf areas. Especially in regions with high forest coverage ratios, the phenomenon of supersaturation can occur; thus, NDVI data from these regions are subject to the effects of observational and other types of errors. Consequently, for quantitative analyses of vegetation, the NDVI cannot possibly be an adequate measure [14]. Therefore, the development of representative quantitative parameters to describe the spatio-temporal relationships between the LST and various environmental factors is crucial.

The fractional vegetation cover (FVC) is a crucial biophysical parameter that can directly reflect the surface vegetation status and is an important quantitative index of vegetation and ecosystem changes [26, 27]. The FVC is defined as the ratio of the vertical projection area, which includes plants' branches, stalks and leaves, to the total vegetation area [28, 29]. As a quantitative parameter, the FVC is an important indicator for studying the atmosphere, pedosphere, hydrosphere and biosphere, as well as their interactions. Compared with conventional spectral indices, The FVC which derives from linear spectral mixture analysis (LSMA) is capable of avoiding the supersaturation phenomenon and reduces the influence of background effects related to soil colour or moisture [30]. Additionally, the fraction images obtained through LSMA are easier to interpret than spectral indices because they have a physical meaning [31]. Weng (2004) showed that for all kinds of land cover across various spatial resolutions, compared with the NDVI, the FVC shows a slightly higher coefficient of correlation with the LST [21].

The LST is sensitive to different eco-geographical regions characterized by differences in surface cover type and albedo as well as the available volume of water for evaporative cooling, which regulates the intensity of latent and sensible heat fluxes [32-34]. The eco-geographic regional system, a key ecosystem in geographic zonality, manifests certain patterns of moisture, soil, temperature, biomass, and their respective environments and resources. It could provide a scientific macro-regional framework for monitoring sustainable regional development, regional climate change, vegetation restoration, and ecosystem creation. The Greater Khingan Mountains form a climatic boundary that spans cold and temperate temperature zones and semi-arid, semi-humid, wet, and humid climatic zones. According to
the eco-geographic regional map of China, from north to south, the Greater Khingan Mountain area is divided into four ecological regions: (1) the Northern Greater Khingan Mountain deciduous coniferous forest region, (2) the hill lands of the northern part of the Western Greater Khingan piedmont forest-steppe region, (3) the Middle Greater Khingan Mountain steppe-forest region, and (4) the Southern Greater Khingan steppe region. The boreal forest (taiga forest) is widely distributed throughout the Northern Greater Khingan Mountains, where there is a unique cold temperature zone in China. The landscape type gradually transitions from forest vegetation to forest-steppe and steppe vegetation with decreasing latitude in the Greater Khingan Mountains.

The aim of the present research was to conduct a comparative analysis of the spatio-temporal variability of vegetation in relation to the thermal environment in the different eco-geographical regions of the Greater Khingan Mountains. In this paper, the FVC and LST are used as the indicators to reflect changes in vegetation and thermal balance conditions. The LST was determined through reconstruction utilizing the harmonic analysis of time series (HANTS) tool, and the FVC was derived via LSMA. Then, we quantitatively analysed the effects of the FVC on the LST in the different eco-geographical regions.

2. Study area and dataset

2.1. Study area
The Greater Khingan Mountains are situated in the eastern part of the Inner Mongolia autonomous region of the northern Heilongjiang upstream region and are adjacent to the Siberian Plateau south of the Silas Wood Aaron River upstream mountain region between 115°5′E and 125°16′E and between 40°59′N and 53°33′N. The mountains span 1,500 km from north to south, have an area of 0.32 million km², and reach altitudes of 1,000 to 1,600 m. Although the mountain ridge is not pronounced, the top of the mountain is slowly rising. The Greater Khingan Mountains form a climatic boundary that spans cold and mid temperate temperature zones and semi-arid, semi-humid and humid climatic zones. Moreover, because of hydrothermal, topographical, and other natural conditions, the area boasts rich vegetation types, clear differences in vegetation habitat between different regions, and zonal distributions from north to south. The northern high-latitude areas include cool coniferous forests, which gradually transition with decreasing latitude to temperate steppe landscapes in the south. In terms of temperatures, precipitation levels, and vegetation landscapes, the Greater Khingan Mountains can be subdivided into four distinct eco-geographical regions from south to north. The characteristics of these regions are summarized in Table 1.

Table 1. Eco-geographical regions of the Greater Khingan Mountains.

|                | I     | II    | III   | IV    |
|----------------|-------|-------|-------|-------|
| Temperature conditions | Cold  | Cold  | Mid-temperate | Mid-temperate |
| Moisture conditions    | Humid | Semi-humid | Semi-humid | Semi-arid |
| Main vegetation types  | Coniferous forest | Forest-steppe | Steppe-forest | Steppe |
2.2. Dataset
The data used in this analysis include MODIS LST and vegetation index product data, identified as MOD11A2 and MOD13A1, respectively.

Terra MODIS LST product data (MOD11A2, Version 005) and NDVI data (MOD13A1, Version 005) from 2000 to 2015 were collected from the MODIS website (https://modis.gsfc.nasa.gov). MOD11A2 is an 8-day composite LST product dataset with 1-km resolution. The first LST product (MOD11L2) was obtained by retrieving the LST over the satellite overpass time, utilizing a split-window algorithm. Then, the daily product (MOD11A1) was generated by mapping the pixels in the MOD11L2 product data for one day to locations on a sinusoidal projection. The 8-day composite LST product dataset (MOD11A2) was calculated by averaging clear-sky LSTs from the MOD11A1 dataset over an 8-day period to reduce the large number of data gaps caused by cloud cover. To assess the surface vegetation conditions, vegetation index data (MOD13A1) (i.e., 16-day, 1-km maximum value NDVI composites) were utilized. The vegetation index information (MOD13A1) was obtained from surface reflectance data from EOS (Earth Observing System) Terra MODIS, which were subjected to a correction process for aerosols, ozone absorption, and molecular scattering. This index, generated worldwide over land at 16-day compositing intervals, enables invariant and regular temporal and spatial comparisons of vegetation conditions.

3. Method
3.1. HANTS
The HANTS algorithm [35-36] was developed to eliminate values contaminated by clouds from NDVI time series data and has been successfully applied to reconstruct datasets of cloud-free remotely sensed vegetation products, such as the leaf area index (LAI) and enhanced vegetation index (EVI) [37-39]. Intra-annual LST variations are mainly governed by periodic seasonal solar radiation; thus, LST data show periodic patterns and can theoretically be fitted with a series of harmonics. Several researchers have studied the spatio-temporal variations of the LST based on its periodic signals [40-41]. Therefore,
the HANTS transform may also be used for the simulation of LST time series and the reconstruction of LST data. In addition, since the samples need not be equidistant over time, specific points can be eliminated from a time series with relatively little effort. With the removal of obvious outliers from the time series, the extracted harmonics become much more reliable than the results of the straightforward fast Fourier transform (FFT) algorithm [36].

By considering the most important frequencies of the time profiles, the HANTS algorithm employs a least-squares curve-fitting procedure that is anchored on harmonic components. The fitted curve in the HANTS transform is the sum of the mean value of the time series and several cosine functions with different frequencies:

\[
y(t) = a_0 + \sum_{i=1}^{N} a_i \cos(\omega_i t - \theta_i)
\]

where \(y(t)\) is the fitted curve value at time \(t\), \(a_0\) is the average value of the time series, \(N\) is the number of harmonics, \(a_i\) is the amplitude of the \(i\)-th harmonic, \(\omega_i\) is the frequency of the \(i\)-th harmonic, and \(\theta_i\) is the phase of the \(i\)-th harmonic.

In this study, the HANTS algorithm was applied using HANTS software created by Netherlands’ National Aerospace Laboratory (NLR) (http://gdsc.nlr.nl/gdsc/en/tools/hants). On a per-pixel basis, the HANTS algorithm was applied to the LST and NDVI datasets for the entire study area.

3.2. Pixel dichotomy model
The FVC, or the proportion of the vertical projected area of vegetation relative to the total ground area, is a significant biophysical parameter of terrestrial ecosystems and is commonly used as a gauge for the monitoring and assessment of vegetation variations [42]. LSMA is frequently applied to infer the FVC, especially for pixel dichotomy models, as follows:

\[
F = \frac{\text{NDVI} - \text{NDVI}_{\text{soil}}}{\text{NDVI}_{\text{veg}} - \text{NDVI}_{\text{soil}}}
\]

Where \(F\) is the pixel FVC, \(\text{NDVI}\) is the pixel NDVI, \(\text{NDVI}_{\text{soil}}\) is the bare soil endmember NDVI, and \(\text{NDVI}_{\text{veg}}\) is the vegetation endmember NDVI.

The spectral characteristics of the two endmembers were identified through field measurements and were either extricated directly from the image or approximated using additional data sources, including land cover maps and soil information sets. In this study, we employed Zeng's method (2000) to compute \(\text{NDVI}_{\text{veg}}\) for each study area [43]. First, we calculated the maximum NDVI values over yearly periods in the study areas. Second, we generated histograms of the maximum NDVI values for every study area. Based on these histograms, \(\text{NDVI}_{\text{veg}}\) was defined as the 90th percentile value. \(\text{NDVI}_{\text{soil}}\) was computed using the method described by Wu (2014), in which the Harmonized World Soil Database (HWSD) and the annual minimum NDVI for 2013 are used to identify the \(\text{NDVI}_{\text{soil}}\) value for each type of soil [44-45]. The \(\text{NDVI}_{\text{soil}}\) value for every group was calculated as the average of the smallest NDVI values per soil group per area. Meanwhile, HWSD Version 1.2.1 was used as a source of data regarding global soil variety with 1-km spatial resolution. The determined \(\text{NDVI}_{\text{veg}}\) and \(\text{NDVI}_{\text{soil}}\) values are given in Table 2.
Fig. 2 The spatial distributions of soil type (a) and land cover (b) in the Greater Khingan Mountains.

Table 2. The endmember values of the NDVI for all years (NDVI_{veg}) and for each soil type (NDVI_{soil}) considered in this study.

| Type            | NDVI_{soil} | Year | NDVI_{veg} |
|-----------------|-------------|------|------------|
| Anthrosols      | 0.16        | 2000 | 0.85       |
| Arenosols       | 0.16        | 2001 | 0.89       |
| Calcisols       | 0.12        | 2002 | 0.89       |
| Cambisols       | 0.16        | 2003 | 0.87       |
| Chernozems      | 0.16        | 2004 | 0.88       |
| Fluvisols       | 0.17        | 2005 | 0.88       |
| Gleysols        | 0.13        | 2006 | 0.88       |
| Histosols       | 0.16        | 2007 | 0.89       |
| Kastanozems     | 0.14        | 2008 | 0.88       |
| Leptosols       | 0.15        | 2009 | 0.85       |
| Luvisols        | 0.15        | 2010 | 0.88       |
| Phaeozems       | 0.10        | 2011 | 0.86       |
| Podzoluvisols   | 0.15        | 2012 | 0.86       |
| Regosols        | 0.17        | 2013 | 0.86       |
| Solonchaks      | 0.15        | 2014 | 0.87       |
| Solonetzes      | 0.15        | 2015 | 0.88       |

3.3. Analysis method
A unary linear regression equation reflects a linear relationship between dependent and independent variables [46]; here, the slope reflects the variational tendency of the time series. The trend test statistic is calculated as follows:
Slope = \frac{n \times \sum_{i=1}^{n} (i \times x_i) - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} x_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \tag{3}

Where \( i \) is an index representing the year, with \( n \) being the number of years (\( n=16 \)). Thus, when the slope > 0, the trend is increasing; otherwise, the trend is decreasing.

The correlation analysis method is a standard statistical approach to measuring the systematic relationship between two variables. The correlation coefficient between two variables \( x \) and \( y \) is calculated as follows:

\[
R_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}
\tag{4}
\]

Where \( n \) is the number of samples, \( x_i \) is the value of \( x \) for the \( i \)-th sample, \( y_i \) is the value of \( y \) for the \( i \)-th sample, \( \bar{x} \) is the mean of all \( x_i \) values, and \( \bar{y} \) is the mean of all \( y_i \) values. Testing for the significance of the correlation coefficient typically involves using the \( t \) distribution.

In this study, correlation and linear regression models were used to examine the LST-FVC relationships and variational trends, respectively.

4. Results and discussion

4.1. HANTS applied to the LST/NDVI series

To perform the HANTS analysis, 5 parameters were set, as shown in Table 3. Roerink (2000) provides a comprehensive description of the HANTS parameters [36]. In this research, the number of frequencies was set to 1 (frequency 1 = annual; frequency 2 = semiannual). The high/low suppression flag was set to a low value because cloud contamination leads to abnormally low LST and NDVI values. The valid data ranges were set to -50°C to 50°C for the LST and -1 to 1 for the NDVI. The fit error tolerances were set to 6°C and 0.2, respectively. The degree of over determinedness was set to half the number of time series data: 23 for the LST and 6 for the NDVI. One of the disadvantages of this algorithm is that there are no objective rules for determining the HANTS control parameters. Instead, these parameters must be chosen based on experience (e.g., from a preceding FFT analysis) and after testing several combinations of control parameters.

The HANTS algorithm was applied to the LST and NDVI datasets on a per-pixel basis for each year from 2000 to 2015 over the entire study area. Two examples (one each for the LST and NDVI) of the HANTS-fitted and original values are given in Fig. 3. In this figure, bars denote the original temporal profiles, and dashed lines denote the HANTS-fitted temporal profiles. Blank bars represent missing values, whereas white bars indicate outliers in the original temporal profile that were rejected according to the fit error tolerance of the iterative HANTS procedure. Fig. 3a presents a temporal LST curve containing 6 data gaps and 4 outliers, and Fig. 3b presents a temporal NDVI curve with no data gaps but 2 outliers. The simulation results show that the HANTS algorithm can appropriately and robustly fit temporal curves, even when there are conspicuous data gaps. Fig. 4 shows the original and HANTS-reconstructed LST and NDVI data for one period in the Greater Khingan Mountains; based on these data, we determined which clouds generated numerous missing and abnormal values that affected the application. To generate the data distributions shown in Figs. 4b and 4d, the HANTS algorithm was applied to the time series data to remove cloud-affected observations and reconstruct the time series datasets.

| Table 3. The LST and NDVI parameter sets used to perform the HANTS analysis. NOF: number of frequencies; SF: suppression flag; FET: fit error tolerance; DOD: degree of over determinedness; IDRT: invalid data rejection threshold |
|-----------------|---|-----------------|-----------------|---|
| LST  | 1  | Low  | 50  | -50  | 6  | 23  |
| NDVI | 1  | Low  | 1   | -1   | 0.2| 6   |
4.2. Spatio-temporal variations in the LST and FVC

4.2.1. Spatial patterns. Temperature and precipitation levels influence the effective accumulated temperature and available water levels and consequently control plant photosynthesis, plant respiration, and soil organic carbon decomposition, among other processes, thereby also controlling plant growth and distribution. Vegetation growth in the Greater Khingan Mountains is sensitive to meteorological factors, and the sensitivity to temperature is higher than that to precipitation. The area exhibits distinct latitudinal trends, as it spans 13 latitudes from north to south.

To gain a thorough understanding of the distributions of vegetation and surface temperature conditions, the mean FVC and LST values for the vegetation growth season (from May to October) from 2000 to 2015 were used to characterize the vegetation abundance and surface temperature in the study area (Fig. 5). The vegetation coverage of the Greater Khingan Mountains was found to be higher in the northern and central areas, with average FVC values of 0.82 and 0.78 (Fig. 5a), respectively. Study regions I, II, and III are humid and semi-humid and thus can satisfy the water demand for vegetation growth; additionally, regions II and III are located in a temperate zone and thus provide good temperature conditions for vegetation growth. In region III, forest plants are found in areas of higher elevation, whereas Leymus chinensis and Stipa baicalensis steppes are found in low-elevation areas.
Region II connects the Greater Khingan Mountains to the Hulunbeier steppe. The elevation of this region is relatively low, and human activities interfere considerably with natural vegetation. Since the 1930s, because of imbalanced animal husbandry development, overgrazing has occurred in the steppes, and grassland degeneration has been very pronounced. Indeed, the average FVC was only 0.69. Although region I is located in the cold temperature zone, it covers the southernmost part of the bright southern coniferous forest in Eastern Siberia, resulting in distinct zonal vegetation features. Vegetation types in this region mainly include Larix gmelinii and Pinus sylvestris forest growth. Region IV is located in a semi-arid area with worse hydrothermal conditions than those of the other areas. The elevation of this area is lower, and human disturbances are more pronounced. The average FVC of this area was only 0.56.

The spatial LST distribution is shown in Fig. 5b. The surface temperature is lower in regions I and III and higher in regions II and IV; regions I, III, and IV are distributed in latitude from north to south, with region II spanning similar latitudes as region III. The surface temperatures are driven by solar radiation, and differentiation occurs because of topographical, surface cover, and growth conditions. A small section of undulating terrain in the Greater Khingan Mountains in general and in the study area in particular spans from northern to southern latitudes; thus, the solar radiation levels are mainly determined by latitude. A decreasing trend from north to south is evident. However, the temperatures in regions II and IV are higher than those in regions I and III, mainly because the surface temperature is affected by surface cover in addition to solar radiation. Region II mainly consists of grassland, whereas other areas at the same latitude mainly consist of forests or forest grasslands. The regulation of grassland surface temperature is less significant compared with that in forested areas, resulting in higher regional surface temperatures in region II.

As shown in Table 4, the standard deviations of the LST and FVC values in region I were found to be 3.6°C and 0.07, respectively, which are lower than those in other regions because the land cover type is relatively uniform, mainly consisting of forest. By contrast, regions III and IV are subject to considerable artificial disturbances. The differences in the thermal properties of different land surface types result in differences in surface temperatures between different land use categories, thereby resulting in more pronounced surface temperature variations.

![Fig. 5 Spatial distributions of the FVC (a) and LST (b).](image)
Table 4. Calculated FVC and LST statistics for the different study regions.

|    | Mean FVC | Std FVC | Mean LST (°C) | Std LST (°C) |
|----|----------|---------|---------------|--------------|
| I  | 0.82     | 0.07    | 24.4          | 3.6          |
| II | 0.69     | 0.10    | 34.2          | 5.8          |
| III| 0.78     | 0.13    | 28.4          | 9.3          |
| IV | 0.56     | 0.18    | 33.6          | 10.1         |

4.2.2. Seasonal cycle. Based on the eco-geographical regions in the study area, the mean FVC and LST values were calculated for 2000 to 2015, and curves representing the annual variation in vegetation coverage for the study area were obtained (Fig. 6). The annual variation curves of the FVC and LST each show a single peak, with enhanced vegetation activity beginning in April and the fastest rates of vegetation coverage growth in May and June. Vegetation coverage reached a peak in July and exhibited the greatest decrease in September. Because of the different climatic factors affecting different eco-geographical regions and the effects of microtopographical features on hydrothermal redistribution, the main vegetation types and growth conditions observed in the different eco-geographical regions varied. In order of the maximum vegetation coverage values for the entire year, the study regions can be ranked as follows: I>III>II>IV.

The FVC values in region I were found to be higher than those in the other regions throughout the year. Additionally, the maximum values for regions I and III were found to be similar, and a crossover was observed between regions II and IV. The FVC in region IV was greater than that in region II from January to March and from October to December. This behaviour was mainly driven by the vegetation types. Region I is a forested area, whereas region III consists of forest and grassland. The main tree species found in this area include larch forests of P. sylvestris var. mongolica; thus, vegetation coverage levels here are high. P. sylvestris var. mongolica is a type of evergreen coniferous forest cover; therefore, the winter FVC in this region is also relatively high. Grassland is the main vegetation type found in region II. By contrast, in region IV, forest land, grassland, arable land, and urban green space all occupy significant proportions of the land area. Therefore, in region II, the vegetation levels are higher during the growth season and lower during the non-growth season.

From Fig. 6, it is evident that the highest surface temperature for the entire year occurred in region IV, followed by regions II, III and I; the highest temperature in region II was similar to that in region IV, and other regions presented differing degrees of intersection with different regions. Region IV presented the highest values for the entire year. Because its elevation is relatively low, local human disturbances are extensive, and vegetation coverage levels are low. The highest temperatures found in region II were similar to those in region IV. The main vegetation type in region II is grassland, and the vegetation coverage levels are lower in region I and III. Furthermore, the changes in surface temperature were most pronounced in region II, and high-temperature periods were short, mainly because the seasonal variations of grassland are pronounced. Region III presented higher temperature values than region I, and the variations in both of these regions were less significant than those in region II, mainly because forest vegetation exerts a regulatory effect.

Comparing the surface temperatures and vegetation coverage levels for each region revealed that region I had the highest vegetation coverage and the lowest surface temperatures. Region IV presented the highest surface temperatures but lower vegetation coverage. By contrast, regions II and IV presented low surface temperatures but high levels of vegetation coverage. Both vegetation coverage and surface temperature reached a single peak throughout the year, which was mainly driven by climatic conditions and thus exhibited a seasonal variation pattern. The maximum FVC was reached in July, but the maximum surface temperature was observed in June. These results likely occurred because of evapotranspiration associated with increased vegetation activity in July and because the regulatory effects on temperature were stronger than those of the temperature itself. Consequently, the surface temperature in July was slightly lower than it was in June.
4.2.3. Dynamic trend analysis. Linear trends exclude the effects of short-term climatic patterns on vegetation growth and surface thermal environments and can reflect the dynamic trends of time series data. Fig. 7 presents the spatial distributions of the linear trends in the FVC and LST for the Greater Khingan Mountains from 2000 to 2015. Overall, the surface vegetation cover in the Great Khingan Mountains has improved, and the area showing a decline in surface temperature has expanded. In 75.5% of the pixels, the FVC value has increased, and 79.4% of the pixels show decreases in LST.

The FVC trends for the different eco-geographical areas were analysed, and the proportions of each eco-geographical region that show variation rates in different ranges are presented in Table 5. Overall, the FVC has been increasing. Increasing trends were most apparent in region II and at the junction between regions III and IV. Downward trends were found in the northern part of region I and the central part of region IV. The main land cover type in region I is forest vegetation that is not much affected by human disturbances but has long suffered from wild fires. By contrast, the effects of human activity on the landscape of region IV have been relatively severe and are mainly related to agricultural reclamation, road construction, deforestation, residential construction, and mining. Meanwhile, vegetation coverage in region II and the adjacent areas of regions III and IV has increased considerably. This change can be mainly attributed to the fact that, in recent years, efforts to turn farmland back into forests and grassland, the Three North Shelterbelt Project, fencing enclosures, and ecological protection work have begun to bear fruit. The LST trends in the different eco-geographical regions are shown in Table 2. Throughout the entire study area, the LST has shown a downward trend. The areas of regions III and IV that have...
shown the most significant decreases are, again, mainly concentrated near the junction between the two regions. Meanwhile, the LST has increased in the western part of region I, but not significantly.

![Fig. 7](image)

**Fig. 7** The spatial variation rates of the average FVC values (a) and LST values (b) during the growth season for the four eco-geographical regions of the Greater Khingan Mountains during 2000-2015.

**Table 5.** Variations in the FVC and LST for the different eco-geographical regions of the Greater Khingan Mountains, reported as the percentage of each region exhibiting variation rates in each range.

| FVC   | I (%) | II (%) | III (%) | IV (%) | LST    | I (%) | II (%) | III (%) | IV (%) |
|-------|-------|--------|---------|--------|--------|-------|--------|---------|--------|
| 0.004 | 12.62%| 11.76% | 12.88%  | 9.08%  | ≤0.002 | 3.22% | 5.54%  | 1.07%   | 1.13%  |
| 0.002-0.004 | 10.29% | 50.34% | 27.22%  | 36.20% | 0.001-0.002 | 6.68% | 8.06%  | 3.09%   | 1.39%  |
| 0.001-0.002 | 15.12% | 11.71% | 15.22%  | 8.78%  | 0-0.001 | 18.12% | 15.70% | 11.04%  | 7.41%  |
| 0-0.001  | 23.72% | 14.91% | 28.77%  | 13.35% | -0.001-0 | 30.11% | 22.75% | 22.75%  | 20.67% |
| -0.001 - 0 | 13.09% | 3.75%  | 7.43%   | 4.89%  | -0.002 -0.001 | 25.51% | 21.88% | 22.97%  | 25.56% |
| -0.001- -0.002 | 14.56% | 3.74%  | 4.22%   | 13.73% | -0.004 -0.002 | 11.38% | 15.11% | 14.89%  | 19.68% |
| ≤-0.002 | 10.60% | 3.78%  | 4.26%   | 13.97% | ≤-0.004 | 4.98%  | 10.96% | 24.19%  | 24.16% |

4.3. The impact of the FVC on the LST

4.3.1. Analysis of month-to-month correlations. Over time, the vegetation index-LST (VI-Ts) space has been extensively used for the estimation of both soil moisture and evapotranspiration levels. However, uncertainties in the observed dry edges, commonly extracted from scatter plots, have restricted the application of this method. In this paper, obvious seasonal variations in the vegetation cover and LST have been demonstrated, in section 4.2. To explore the FVC-LST correlations on a monthly scale, the
monthly mean values of the FVC and LST for each month from 2000 to 2015 were used to create monthly LST vs. FVC scatter plots, as shown in Fig. 8.

From January to March, the vegetation coverage and LST showed increasing trends, but the change was slight. Beginning in April, the vegetation coverage and LST increased more rapidly. From April to June, the FVC and LST were significantly negatively correlated. In July, the vegetation cover reached a maximum, with the LST also remaining near its peak. From August to September, vegetation coverage and surface temperature both began to decline rapidly. The surface temperature and vegetation coverage further decreased from October to December; however, this decline was relatively slow, and the negative correlation gradually disappeared. Thus, the LST and FVC initially increased and then decreased throughout the year, showing a significant seasonal variation, but the correlation between the two became progressively more complex. From January to March and from October to December, the relationship between the FVC and LST in the study area showed a triangular distribution, with the uppermost part of the triangle corresponding to region IV, the lower part corresponding to region II, and the lower right-hand part corresponding to region III. Crops began to grow in April and to die from September to October. Therefore, from January to March and from October to December, the difference between bare surfaces and vegetated surfaces was large. Additionally, surface water differentiation was pronounced. During the growth period, vegetation growth was strong, and a correlation between the FVC and LST gradually developed towards the west, mainly because of pronounced vegetation transpiration. From April to September, the FVC was significantly negatively correlated with the LST. By contrast, from January to March and from October to December, there were no significant negative correlations between the LST and FVC.

**Fig. 8** The correlations between the FVC and LST variations observed in the Greater Khingan Mountains. The red areas represent the most densely populated area, followed by the blue areas.
4.3.2. Annual FVC and LST time series. The Pearson correlation coefficient, which is widely employed in correlation research, was used to determine the relationship between the two datasets. We found that the FVC was significantly negatively correlated with the LST from April to September. Therefore, we averaged the FVC and LST data for these months from 2000 to 2015 and analysed their correlations and spatial distributions. The corresponding results are shown in Fig. 9. Throughout the entire study area, 86.9% of the area showed a negative correlation between the FVC and LST. Additionally, negative correlations were found for 88.61%, 85.97%, 87.16%, and 89.19% of eco-geographical regions I, II, III, and IV, respectively. The instances of non-negative correlations were mainly concentrated at the junction between regions I and II, in region III, and in the southern part of region IV.

![Fig. 9](image_url) Correlation coefficients of the annual average LST and FVC.

We then further analysed the quantitative relationships between the FVC and LST for the different eco-geographical regions. After using land cover data to remove data from water bodies, we randomly generated 1,000 sampling points for each region and obtained the FVC and LST values corresponding to each sampling point, which were then used for linear regression analysis. From Fig. 10, it is evident that the correlations between the FVC and LST values differed by region and that these values generally exhibited a negative linear correlation. When the vegetation coverage increased by 10%, the surface temperature decreased by 1.59°C to 2.76°C. Thus, a significant correlation exists between the level of vegetation coverage and the normalized surface temperature, which suggests that increasing the vegetation coverage should improve the thermal environment of the study area.
5. Conclusion

Our evaluation results show that the HANTS algorithm can yield satisfactory fits of LST time series and can eliminate the effects of cloud cover on remotely sensed LST data, despite being originally developed for NDVI image processing. The seasonal LST and FVC variations in the study area were found to exhibit strong unimodal periodic patterns and regional variability between different eco-geographical regions. The LST and FVC values increased beginning in April to reach a maximum in June and July, respectively; the decline of the LST in July was mainly driven by vegetation transpiration. We analysed the average long-term monthly trends of the LST and FVC during the growing season over the study period and observed an increasing trend in the FVC throughout the majority of the study area and a decreasing trend in the LST. High variation rates were observed in region II and at the junction between regions III and IV. An analysis of the correlations between the LST and FVC revealed significant negative correlations in all four eco-geographical regions. The strongest correlation was found in region III, followed by regions I, II, and IV.

The FVC-LST space that was constructed to examine the temporal variability of both vegetation cover and temperature showed that the observed negative FVC-LST relationship was not static. From January to March and from October to December, the relationship between the FVC and LST in the study area showed a triangular distribution, whereas a negative correlation was found from June to September. These findings indicate that different climatic factors are involved during different seasons, resulting in different vegetation activities. Vegetation conditions directly affect thermal radiation, thermodynamics, and a variety of surface features such as soil moisture, thereby resulting in surface temperature differentiation. To study the effects of the FVC on the LST, we conducted a temporal analysis of the FVC-LST space. We found that the decline in warming rates can be attributed to the enhanced vegetation greening resulting from an increase in evapotranspiration. Moreover, the inverse temperature-vegetation association was amplified by the earlier onset of vegetation growth.

Based on the FVC-LST space variability trends recorded in the boreal forest area, the scope of these results can be broadened to inform climate simulations and future analyses of microclimatic levels. It is possible that the magnitude of regional or global warming (or both) will be seen to be reduced by the
effects of vegetation greening if vegetation greening trends are incorporated into the models used to simulate future climate conditions. In our future research, we will conduct another study to confirm the validity and generalizability of the results presented here through the use of such a combined dynamic model of vegetation and climate.

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