

Article

Heterogeneity Analysis of Spatio-Temporal Distribution of Vegetation Cover in Two-Tier Administrative Regions of China

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Abstract: Vegetation cover is a crucial component of regional ecological environments that plays a vital role in maintaining ecosystem balance. This investigation utilized Google Earth Engine and MODIS NDVI products to examine the spatiotemporal heterogeneity of regional vegetation coverage based on the multi-year average NDVI in China. Using the multi-year average NDVI, multi-year change trend slope, coefficient of variation, and Hurst exponent, the spatial and temporal heterogeneity of provincial and prefectural administrative regions were quantified. The results indicated an upward trend in vegetation coverage from 2000 to 2021 at both provincial and prefectural levels, with growth rates of 0.032/10a and 0.03/10a, respectively. Moreover, the multi-year average NDVI significantly correlated with regional precipitation. Notably, vegetation growth was fastest in the Loess Plateau, while degradation was observed in southern Jiangsu and northern Zhejiang. Additionally, the degree of vegetation cover change in Ningxia and Macau was particularly prominent. These findings support the effectiveness of the Loess Plateau greening project and highlight the potential cost of economic and population growth on the ecosystem in eastern and southeastern coastal areas, where local vegetation degradation occurs. This study can serve as a valuable reference for ecosystem restoration and developmental planning at the administrative regional level, with the goal of enhancing vegetation management and conservation efforts in China.



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Keywords: vegetation cover; Google Earth Engine; change trend analysis; spatio-temporal heterogeneity; two-tier administrative regions

1. Introduction

The health of the global ecological environment is under increasing threat from human activities and climate change [1,2]. Vegetation is an important component of the terrestrial ecosystem and provides a comprehensive reflection of the regional ecological environment, as it plays a key role in the global biogeochemical energy cycle, including the cycles of carbon, oxygen, water, and nitrogen [3–5]. The impact of vegetation coverage on the regional ecological balance is closely related to climate change, carbon storage, biodiversity, and soil erosion [6,7]. Therefore, monitoring changes in the dynamics of regional vegetation cover is essential for researchers and decision-makers to formulate policies for vegetation restoration, conservation, and scientific management.

The Normalized Difference Vegetation Index (NDVI) quantifies vegetation growth by computing the discrepancy between near-infrared (NIR) light, which reflects strongly in healthy vegetation, and red light, which vegetation absorbs. This calculation enables the assessment of changes in vegetation coverage, productivity, and overall health [8]. Despite its susceptibility to factors like soil brightness and atmospheric interference, NDVI's extensive historical application, simple computation, and reliance on pre-existing multi-spectral bands give it the ability to quantify vegetation attributes [9,10]. In contrast, the Enhanced Vegetation Index (EVI) and the Soil-Adjusted Vegetation Index (SAVI) exhibit

greater resilience to atmospheric interference and noise. Nevertheless, their enhanced efficacy arises from the incorporation of corrective factors related to both atmosphere and soil properties. This addition introduces more stringent criteria for their application. EVI is well-suited for analyzing areas abundant in chlorophyll, such as tropical rainforests, while SAVI finds applicability in arid regions characterized by sparse vegetation and exposed soil surfaces. However, these enhanced capabilities correspondingly increase the complexity of index acquisition [11]. Consequently, NDVI remains among the most widely employed and suitable spectral vegetation indices for monitoring vegetation growth dynamics, especially in large study areas spanning inter-provincial and regional extents. Ready-made and freely available satellite images offer a cost-effective means of acquiring NDVI data across diverse scales and resolutions. For instance, readily available NDVI data products like MODIS NDVI and AVHRR GIMMS NDVI3G are apt for global, national, and regional scales. Furthermore, medium-resolution vegetation index products can be derived from free satellite images like the Landsat series and Sentinel satellites [12–14].

The land surface layer constitutes a complex localized system [15], while administrative divisions, as a regional categorization system within the overarching framework of national hierarchical management, function as spatial resources. The outcomes of this system inherently reflect the natural geographical diversity to a certain extent [16,17]. Given China's vast expanse and notable disparities between its northern and southern, as well as eastern and western regions, coupled with its diverse climate typologies, the vegetation cover—an inherent natural entity—exhibits substantial regional temporal and spatial variations. This variability in vegetation response is evident through numerous studies highlighting the significant temporal and spatial shifts in the Normalized Difference Vegetation Index (NDVI) across climatic zones and provincial administrative regions [2,14,18]. Although pixel-scale analyses effectively capture nuanced shifts in vegetation cover, the higher granularity often complicates the direct discernment of differences in vegetation changes across administrative regions. In contrast to the prevalent focus on pixel-based examinations of vegetation coverage, this study considers two-level administrative divisions as the minimal spatial unit. It aims to simplify the intricate vegetation coverage challenge by employing regional average NDVI. Anchored in the geographical continuity and integrity of administrative regions, this simplification, while inevitably constrained by the spatial extent and boundaries of administrative divisions, proves notably more representative of the mean level of vegetation coverage within regional purview compared to broader divisions like east, west, north, and south. This approach serves as reference points for both vertical and horizontal comparisons among administrative divisions.

Currently, research pertaining to vegetation cover within administrative regions remains scarce. An exception is Jin's work, which quantifies the NDVI change rate during the growing season for principal provincial administrative regions in the Chinese mainland [19]. Many studies amalgamate alterations in vegetation cover under administrative divisions with nocturnal lighting data and land cover change to explore the intricate connections between vegetation change and multifarious factors. To illustrate, Li [20] establishes a relationship between NDVI shifts and nighttime illumination data using panel data from 31 provincial administrative regions in China. Liu [21], on the other hand, delves into vegetation transformations within urban areas, contextualized by the backdrop of urbanization and the influence of human activities, alongside investigating the phenological changes of urban vegetation.

Furthermore, a plethora of studies concentrate on the divergence in vegetation cover and the extent of disturbance attributable to human activities in localized domains. Examples include the Beijing–Tianjin–Hebei Region [22], the Guangdong–Hong Kong–Macau Greater Bay Area [23], the Qinghai–Tibet Plateau [24], and the Loess Plateau [25]. Despite the extensive body of literature scrutinizing vegetation coverage changes on a national and even regional scale, scant attention has been directed towards conducting relevant research specifically on China's two-level administrative divisions. Given the administrative level's formulation and implementation of numerous ecological policies, quantifying the

spatio-temporal heterogeneity of vegetation coverage across distinct administrative levels assumes paramount importance from a macro perspective. This endeavor contributes to ecological environment safeguarding and vegetation resource management [26]. Furthermore, it furnishes a scientific foundation for appraising regional vegetation coverage, crafting policies for vegetation restoration and management, and facilitating inter-regional comparisons of vegetation coverage and its fluctuations.

Google Earth Engine (GEE), an influential online platform tailored for remote sensing data analysis, furnishes substantial technical underpinning for this research. Covering the spectrum from data pre-processing to result computation, GEE optimizes algorithmic efficiency and precision while ensuring outcome coherence and accuracy. When contrasted with traditional remote sensing image processing techniques mandating radiometric calibration, atmospheric correction, band synthesis, and image cropping, GEE offers a cloud-based high-performance computing environment [27]. This environment not only delivers pre-processed, analyzable geospatial datasets but also provides readily available computing products like NDVI and EVI. Moreover, GEE boasts an accessible code editor interface that empowers users to both upload their datasets and facilitate script sharing with peers. This mechanism actualizes cost-effective, equipment-minimized, multi-temporal data analyses spanning from local to global scopes and obviates the need for local storage, processing, and analysis of vast satellite datasets [28]. Furthermore, specific GEE datasets undergo pre-processing to transform original data into top-of-atmosphere reflectivity and surface reflectivity. This transformation circumvents the necessity for specialized software aimed at radiation calibration and atmospheric correction [29]. As such, GEE presents researchers with an unparalleled avenue to conduct remote sensing research with ease and efficiency.

This paper used the Google Earth Engine to explore the regional vegetation cover status and its spatial and temporal variation patterns in terms of normalized difference vegetation index means. It mainly covers the following aspects:

- (1) What is the overall distribution of multi-year vegetation coverage in China's provincial and prefectural administrative regions?
- (2) What are the interannual variations in vegetation cover within administrative regions, and does vegetation cover exhibit a trend of growth or degradation?
- (3) Where are the extreme areas mainly distributed, and what are the possible reasons for this?

The Google Earth Engine was utilized due to its advantages in processing large-scale geospatial datasets and its accessibility to high-performance computing resources. Through this platform, pre-processed data was readily available for use, eliminating the need for extensive image processing procedures. Additionally, the platform offers NDVI and EVI calculation products, which were used to analyze vegetation cover. This study, focused on NDVI, aims to understand the regional vegetation cover status in China, which has important implications for ecological environment protection and vegetation resource management. The findings of this study would provide valuable scientific reference for regional vegetation cover status evaluation, vegetation restoration and management policy formulation, and inter-regional comparison of vegetation cover status and its changes.

2. Materials and Methods

2.1. Study Area

This paper focused on two administrative levels in China: the provincial-level and the prefectural-level. The provincial administrative regions comprise 34 regions, which include 23 provinces, 5 autonomous regions, 4 municipalities directly under the central government, and 2 special administrative regions. The prefectural administrative regions consist of 369 regions. To facilitate comparisons and complete the results on the map, this study also includes municipalities directly under the central government, counties directly under provincial administration, autonomous counties, and counties directly under provincial administration that are not traditionally considered as part of prefectural-level administrative regions, nevertheless, the cities in Taiwan and Sansha City are excluded

from the study. The vector boundaries of both provincial-level and prefectural-level administrative regions were sourced from the Resource and Environmental Science Data Center (www.resdc.cn, accessed on 20 September 2022).

China is located in East Asia, with an area of about 9.6 million square kilometers, including six geographical regions: Northeast, North, East, South, Southwest, and Northwest. China has a diverse climate, including subtropical, temperate, cold, and tropical climates, which are influenced by natural geographical factors such as continents, oceans, plateaus, and mountains. Precipitation and temperature also show significant regional differences, with abundant rainfall in the southern coastal and southwestern regions, while the northern region is relatively dry. The northern part of the Chinese plain and the northeast region are the coldest areas in China, with extremely low winter temperatures [30].

2.2. Data Sources

2.2.1. NDVI Product

The Medium Resolution Imaging Spectrometer (MODIS) instrument on the Terra platform was launched on 18 September 1999 and became operational in early 2000 [31]. Academia widely uses the publicly available and free MODIS product for diverse applications, including vegetation monitoring and land cover assessment [32,33]. The NDVI dataset provided by MODIS is of high quality and frequently employed for estimating vegetation cover and growth in large-scale areas [34]. To evaluate vegetation dynamics in the study area, the MOD13Q1 V6 product has been available since 2000-02-18T00:00:00, with a spatial resolution of 250 m and a temporal resolution of 16 days. The study spanned 22 years, from 2000 to 2021, and the average NDVI per year within the range of interest was computed on the Google Earth Engine platform. This facilitated trend analysis of long time series and enabled comparisons across different administrative regions.

2.2.2. Average Annual Precipitation

The original data on average annual precipitation for provincial and prefectural administrative regions were sourced from the ERA5-Land dataset, published by organizations including the European Union and the European Centre for Medium-Range Weather Forecasts. ERA5-Land is a reanalysis dataset providing a consistent view of the evolution of land variables over several decades at an enhanced resolution compared to ERA5 [35]. First, 12-month average precipitation grid data were calculated from monthly averages to obtain the annual precipitation grid data. Subsequently, the mean precipitation values were derived for the provincial and prefectural administrative regions in China and were averaged to obtain the annual precipitation averages for the region.

2.3. Methods

The annual average NDVI of each administrative division was exported by the GEE cloud platform through the code editor, and the provincial and prefecture-level administrative regions were imported into the code editor assets in advance. The schematic diagram is shown in Figure 1.

2.3.1. Multi-Year Average NDVI

$$\overline{NDVI}_i = \frac{1}{T} \sum_{t=1}^T NDVI_{i,t}, T = 1, 2, \dots, n \quad (1)$$

In the formula, $\overline{NDVI}_i$ is the regional multi-year average NDVI and $NDVI_{i,t}$ is the regional average NDVI in year i . It can reflect the overall situation of regional vegetation cover in a comprehensive manner. To facilitate comparison between different administrative regions spatially [36,37], the values are graded in conjunction with relevant studies, as shown in Table 1.

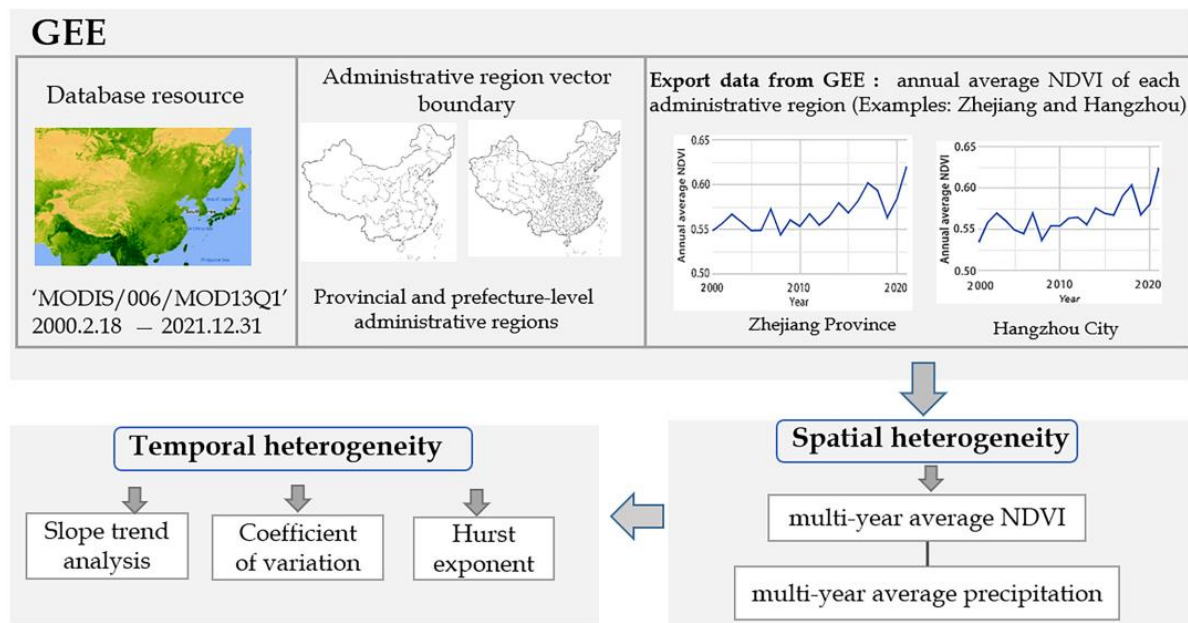


Figure 1. The Research Structural Schematic Diagram.

Table 1. Classification standard of multi-year average NDVI.

Level	Multi-Year Average NDVI
Extremely low coverage	$\overline{NDVI}_i < 0.2$
Low coverage	$0.2 \leq \overline{NDVI}_i < 0.35$
Medium coverage	$0.35 \leq \overline{NDVI}_i < 0.45$
High coverage	$0.45 \leq \overline{NDVI}_i < 0.6$
Extremely high coverage	$\overline{NDVI}_i > 0.6$

2.3.2. Trend Analysis of NDVI Changes

The univariate linear regression method was used to analyze the trends in the annual regional NDVI mean values over a 22-year period, thus reflecting the characteristics of vegetation cover change on an administrative area basis. It was calculated by the formula:

$$Slope = \frac{n \cdot \sum_{i=1}^n i \cdot NDVI_i - \sum_{i=1}^n i \sum_{i=1}^n NDVI_i}{n \cdot \sum_{i=1}^n i^2 - \left(\sum_{i=1}^n i \right)^2} \quad (2)$$

where *Slope* represents the slope of the trend line of the regression equation for the annual mean NDVI. *n* is the number of monitoring years, and the time span of this study is 2000–2021, *n* = 22. *i* is the monitoring year and indicates that the overall trend of regional vegetation cover increases as NDVI increases over time, and vice versa, indicates that regional vegetation cover is degraded. In order to reflect more intuitively the changing status of vegetation cover in Chinese provinces and municipalities, Slope was classified into five classes: slightly degraded, basically unchanged, slightly improved, moderately improved, and significantly improved, based on the information from existing studies [24,38], as shown in Table 2.

Table 2. Classification standard of vegetation cover change trend.

Level	Variation Trend of NDVI Mean Value
Slight degradation	$S < -0.001$
Basically unchanged	$-0.001 \leq S < 0.001$
Slight improvement	$0.001 \leq S < 0.003$
Moderate improvement	$0.003 \leq S < 0.005$
Significantly improvement	$0.005 \leq S < 0.006$
Extremely significant improvement	$S \geq 0.006$

2.3.3. Coefficient of Variation

The coefficient of variation, also known as the ‘coefficient of dispersion’, is an absolute value reflecting the degree of dispersion of the data, the ratio of the standard deviation to the mean, and a normalized measure of the degree of dispersion of the probability distribution, and is used to illustrate the degree of inter-annual variation in vegetation cover in the study area. It is calculated as follows:

$$CV = \frac{SD_{NDVI_i}}{\frac{1}{n} \sum_{i=1}^n NDVI_i} \times 100\% \quad (3)$$

where SD_{NDVI_i} is the standard deviation of the annual mean NDVI over the study period; $\frac{1}{n} \sum_{i=1}^n NDVI_i$ is the mean value of the annual mean NDVI over the study period. A larger coefficient of variation CV indicates greater interannual variability in NDVI and a more discrete annual mean NDVI. The smaller the coefficient of variation, the more concentrated and stable the annual mean NDVI is. Taking into account the actual situation and with reference to existing studies [39], the coefficient of variation of annual mean NDVI values was classified into four levels: low fluctuation, relatively low fluctuation, moderate fluctuation, relatively high fluctuation, and high fluctuation, as shown in Table 3.

Table 3. Classification standard of vegetation cover variation coefficient.

Level	Coefficient of Variation (CV)
Extremely low fluctuation	$CV < 0.04$
Low fluctuation	$0.04 \leq CV < 0.08$
Moderate fluctuation	$0.08 \leq CV < 0.12$
High fluctuation	$CV \geq 0.12$

2.3.4. Hurst Exponent

The Hurst exponent is one of the main methods for quantifying long-term dependence in hydrology, geology, ecology, and meteorology and is a good indicator of the future evolution of regional vegetation cover based on long time series. Its basic principle is based on rescaled polar difference (R/S) analysis, with the following main equation:

For a regional average annual NDVI time series, define the multi-year average NDVI series over the study period as:

$$\overline{NDVI_i} = \frac{1}{T} \sum_{i=1}^T NDVI_i, T = 1, 2, \dots, n \quad (4)$$

The cumulative deviation:

$$X_{(i,T)} = \sum_{i=1}^T \left(NDVI_{(i)} - \overline{NDVI_{(T)}} \right), 1 \leq i \leq T \quad (5)$$

The extreme deviations:

$$R_{(T)} = \max X_{(i,T)} - \min X_{(i,T)}, T = 1, 2, \dots, n \quad (6)$$

The standard deviations:

$$S_{(T)} = \left[\frac{1}{T} \sum_i^T (NDVI_{(i)} - NDVI_{(T)})^2 \right]^{\frac{1}{2}}, T = 1, 2, \dots, n \quad (7)$$

Calculating the Hurst Index:

$$\frac{R_T}{S_T} = c \cdot n^H \quad (8)$$

$$\log(R/S)_n = a + H \cdot \log(n) \quad (9)$$

(8), (9) were used to obtain H values by least squares fitting, c and a are all constant.

The Hurst exponent has a distribution ranging from 0 to 1. If $0.5 < H < 1$, it indicates that future trends are positively correlated with previous trends, and the closer H is to 1, the stronger the persistence. If $H = 0.5$, it indicates that the vegetation cover change trend is a random series within the time series and there is no persistence in its change. If $0 < H < 0.5$, this indicates that the vegetation cover trend has an inverse persistence within the time series, i.e., the future trend is the opposite of the past trend.

3. Results

3.1. Spatial Heterogeneity of Regional Vegetation Cover

3.1.1. Spatial Heterogeneity of Multi-Year Average NDVI in Provincial Administrative Regions

The regional multi-year average NDVI was obtained by calculating the annual average NDVI, which could reflect the overall situation of regional vegetation cover. Figures 2 and 3 presented the multi-year average NDVI value and vegetation cover grade of provincial administrative regions, respectively. As depicted in the maps, Xinjiang and Taiwan had the lowest and highest vegetation cover values among all provincial administrative regions, with values of 0.1 and 0.65, respectively. Furthermore, Xinjiang, Tibet, Qinghai, and Macao exhibited very low coverage levels, whereas Ningxia, Gansu, Inner Mongolia, and Tianjin have low coverage levels. Notably, Taiwan, Hainan, and Fujian were three regions with extremely high coverage levels. The percentage of provinces with very low coverage, low coverage, moderate coverage, high coverage, and extremely high coverage were 8.8%, 14.7%, 29.5%, 38.2%, and 8.8%, respectively. The provinces with high coverage account for the highest proportion and most of them are situated in the subtropical climate region. To summarize, the analysis of provincial vegetation cover revealed a diverse landscape with significant differences across different regions.

3.1.2. Spatial Heterogeneity of Multi-Year Average NDVI in Prefectural Administrative Regions

The spatial distribution of vegetation coverage in prefecture-level administrative regions is illustrated in Figure 4. In contrast to provincial administrative regions, the prefecture-level administrative regions provided a more detailed and comprehensive view of the spatial diversity of vegetation coverage. Overall, vegetation coverage gradually increased from northwest to southeast, with the boundaries of each coverage grade distributed obliquely from northeast to southwest. The proportion of cities with extremely low, low, moderate, high, and extremely high coverage were 10.5%, 14.9%, 23.6%, 43.4%, and 7.6%, respectively. Cities with extremely low vegetation coverage were primarily located in northwest China, central and western Tibet Autonomous Region, and northern Inner Mongolia. The areas with low vegetation cover had the widest longitude range, spanning from southeastern Tibet, some cities in northern Xinjiang to eastern Heilongjiang. Similar

to provincial administrative regions, high-coverage cities constituted the largest proportion of the total and were mainly located in the subtropical climate zone of China. Moreover, it is noteworthy that Suzhou and Wuxi in Jiangsu Province, as well as Zhongshan and Foshan in Guangdong Province, had low vegetation cover. Extremely high vegetation cover was primarily distributed in southern Yunnan, most of Hainan Province, Taiwan Province, and central Fujian, located mainly in the tropical climate region of China.

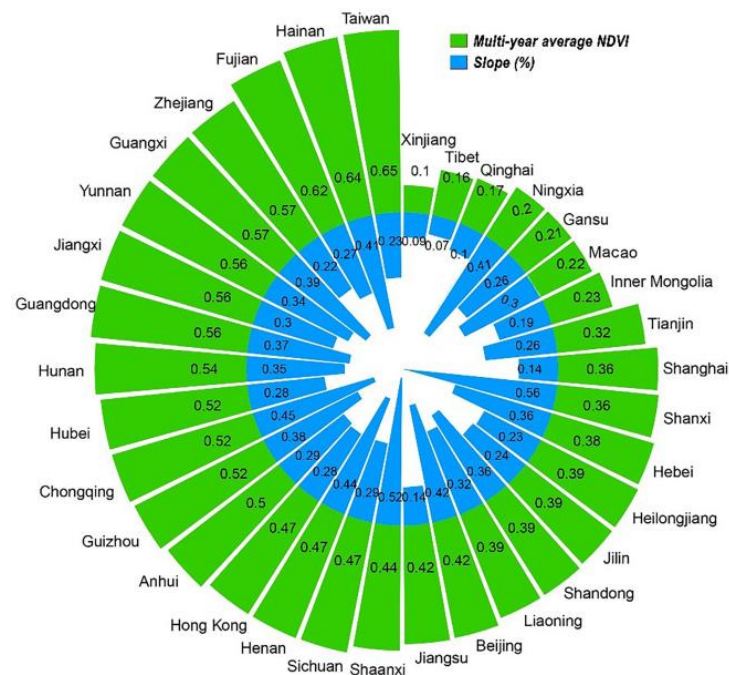


Figure 2. Multi-year and Slope distribution of provincial administrative regions.

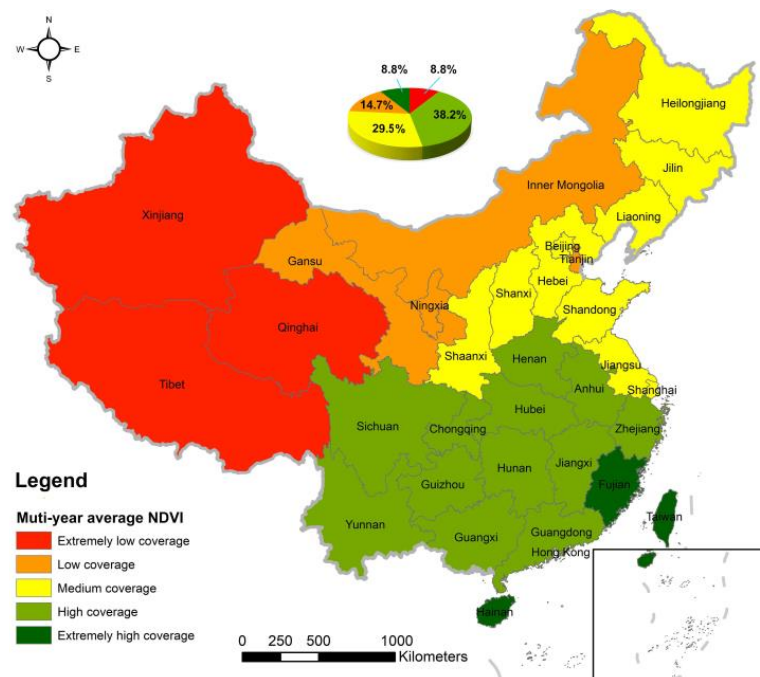


Figure 3. Hierarchical distribution of multi-year average NDVI in provincial administrative regions.

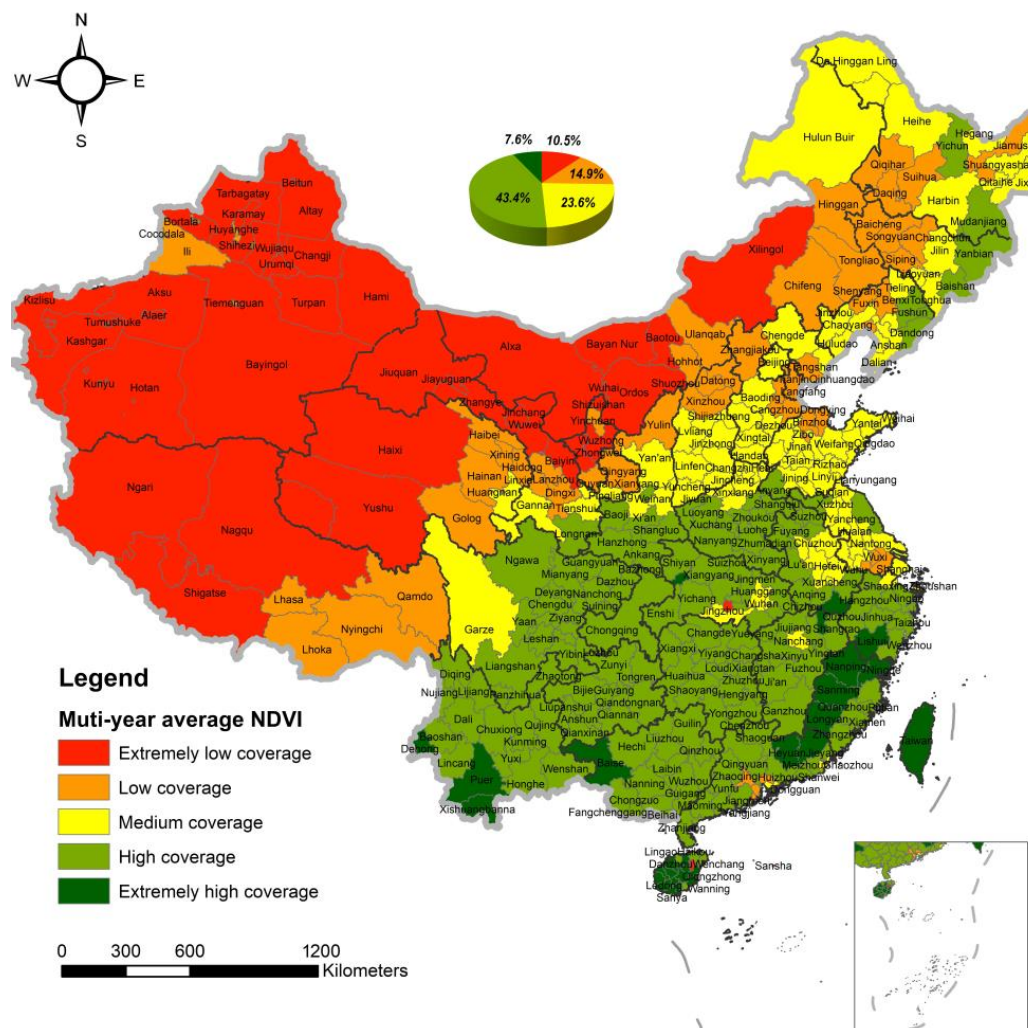


Figure 4. Hierarchical distribution of multi-year average NDVI in prefectural administrative regions.

3.1.3. Linear Correlation between Multi-Year Average Precipitation and Multi-Year Average NDVI

Previous regression analysis studies [40–42] based on pixel scale and the relationship between meteorological stations and NDVI raster pixels showed that precipitation was the main factor affecting the spatial heterogeneity of vegetation coverage distribution. This paper examined the correlation between the multi-year average NDVI and the multi-year average precipitation at the provincial and prefectural administrative levels. As shown in Figure 5, there was a positive correlation between the spatial distribution of the multi-year average NDVI and the multi-year average precipitation. The Pearson correlation coefficients at the provincial and prefectural administrative levels were 0.84 and 0.799, respectively, with a p -value < 0.01, indicating a highly significant correlation.

3.2. Temporal Heterogeneity of Regional Vegetation Coverage

The temporal heterogeneity of regional vegetation coverage mainly reflects the overall vegetation coverage changed over time in a specific area during the study period. The slope of the simple linear regression equation indicated the trend of temporal changes (greening or degradation), while the Hurst exponent indicates the continuity of the changing trend over the past 22 years. The coefficient of variation was used to quantify the interannual variability of the regional average NDVI over the past 22 years.

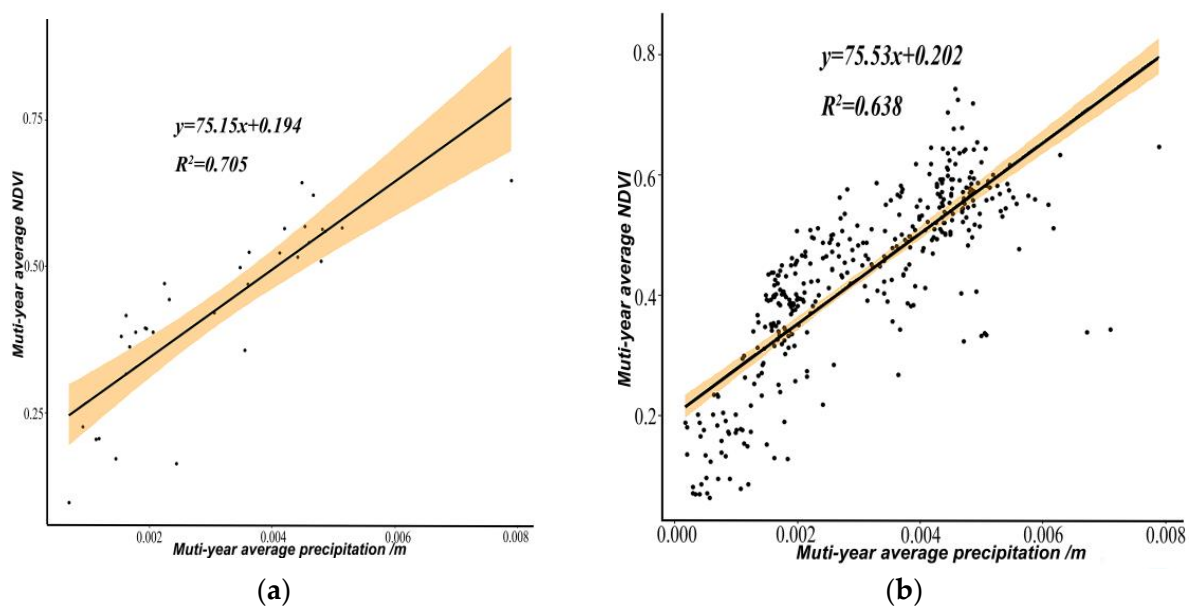


Figure 5. Linear regression of precipitation—annual average NDVI in two-tier administrative regions. (a) Provincial administrative regions. (b) Prefectural administrative regions.

3.2.1. Temporal Heterogeneity of Vegetation Coverage in Provincial Administrative Regions

Figure 6 presents the distribution of the slope change trend and variation coefficient levels of the annual average NDVI in China's provincial administrative regions during the study period. Overall, all 34 provinces, municipalities, and autonomous regions in China have experienced varying degrees of improvement in vegetation coverage since 2000. The most significant improvements were observed in Shanxi and Shaanxi provinces, with moderate growth trends in the eastern, central, and southern regions, while Tibet and Xinjiang showed minimal improvement in vegetation coverage and remained relatively unchanged.

The variation coefficient reflected the degree of deviation of the regional annual average NDVI from the mean. A larger variation coefficient suggested more discrete vegetation coverage between years, indicating greater interference from various conditions. The results show that the Ningxia Hui Autonomous Region exhibited high volatility, followed by Shanxi and Gansu provinces at a moderate level of volatility. Tibet Autonomous Region and the three coastal provinces of eastern China, Jiangsu, Zhejiang, and Fujian, demonstrated extremely low volatility, indicating relative stability.

Figure 7 illustrates the parallel correspondence between vegetation coverage variability and change trends in provincial administrative regions. Most provinces showed slight to moderate improvement in vegetation coverage and extremely low to low volatility, indicating a stable increase in greenness. However, some provinces deviated from this trend, such as Shanxi and Shaanxi, which showed a significant increase in vegetation coverage with a moderate to low volatility coefficient, indicating a sustained and steady improvement. In contrast, Ningxia Hui Autonomous Region and Macao Special Administrative Region had high volatility in vegetation coverage, with relatively insignificant growth trends.

The Hurst exponent for provincial administrative regions ranged from 0.63 to 0.73 during the study period, indicating a positive and sustained trend in the annual average NDVI index within each region. To differentiate the trend variations among the regions, the Hurst exponent was categorized into three levels: $H \geq 0.6$ for strong sustainability, $0.5 \leq H < 0.6$ for weak sustainability, and $H < 0.5$ for reversibility, following the relevant literature [18]. Our results showed that all provinces exhibit strong sustainability, with Gansu, Shaanxi, Shanxi, Ningxia, Sichuan, Xinjiang, and Inner Mongolia having relatively stronger sustainability and Hong Kong, Jiangsu, Tibet, Fujian, and Qinghai having relatively weaker sustainability. This indicates vegetation coverage in most regions.



Figure 6. Hierarchical distribution of Slope and CV in provincial administrative regions.

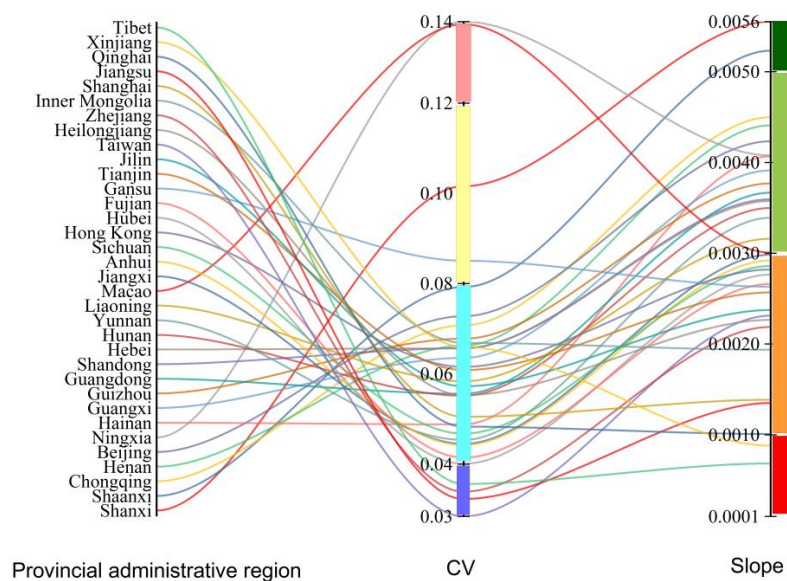


Figure 7. Parallel coordinate plot of CV and Slope in provincial administrative regions.

3.2.2. Temporal Heterogeneity of Vegetation Coverage in Prefectural Administrative Regions

Figure 8 illustrates the spatiotemporal distribution of vegetation cover change trends across prefecture-level administrative regions. At an urban scale, only Taizhou and Jiaxing in Jiangsu Province exhibited slight degradation, while the vegetation cover in other cities remained stable or increased to varying degrees. The proportion of areas exhibiting negligible change was 8.7%, primarily concentrated in the northwest region and the Qinghai–Tibet Plateau. These areas included most regions except for a few cities in northwest Xinjiang, most regions in Tibet and Qinghai, northwest Gansu, and western Inner Mongolia. Additionally, two cities in the eastern part of Heilongjiang, the central and southern parts of Jiangsu, the central and southern parts of Hubei Province, and individual coastal cities in Guangdong and Fujian were also included in this category.

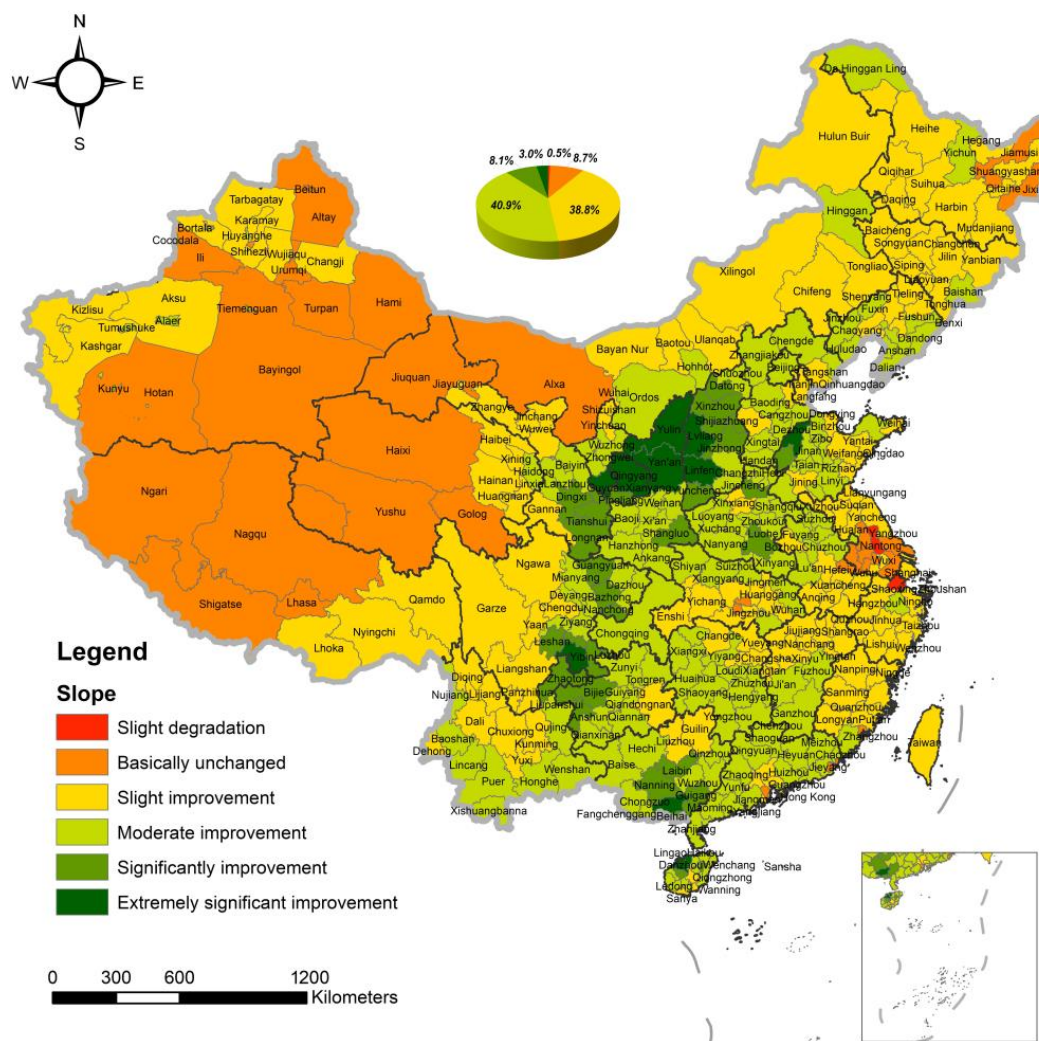


Figure 8. Hierarchical distribution of Slope in prefectural administrative regions.

The majority of cities exhibited slight to moderate growth, with a broad distribution range that accounts for 38.8% and 40.9% of the total area, respectively. The regions exhibiting extremely significant growth are similar to those observed in the provincial-level administrative regions and were primarily concentrated in the Loess Plateau and its surrounding areas, including Guyuan in southern Ningxia, Qingyang in eastern Gansu, Yulin and Yan'an in northern Shaanxi, Taiyuan, Lvliang, and Linfen in western Shanxi. Other areas that demonstrated an extremely significant growth trend include Yibin in Sichuan, Dezhou in Shandong, Qinzhou in Guangxi, and Danzhou in Hainan. The areas of signifi-

cant growth were expanding around the extremely significant greening cities mentioned above, accounting for 8.1% of the total area.

Figure 9 illustrates the distribution of variation coefficient levels for the annual average Normalized Difference Vegetation Index (NDVI) across prefecture-level administrative regions during the study period. A higher variation coefficient indicated a less stable vegetation cover. The proportions of extremely low, low, moderate, and high fluctuation were represented by 11.4%, 67.8%, 16%, and 4.8%, respectively. High fluctuation was predominantly observed in several regions of China, including most parts of the Loess Plateau (e.g., Lanzhou, Baiyin, Guyuan, Qingyang, Yulin, Lvliang, and Datong), central and southern Ningxia (e.g., Wuzhong and Zhongwei), central and southern Inner Mongolia (e.g., Wuhai and Ordos), and some areas in northwestern Xinjiang. Moderate fluctuation was widely distributed in western South Xinjiang, the central and northern regions of Northwest China, North China, Southwest China, and other regions. Extremely low fluctuation was mainly distributed in parts of East China, Central China, Southwest China, southeastern coastal areas, and the southeastern part of the Qinghai–Tibet Plateau.



Figure 9. Hierarchical distribution of CV in prefectural administrative regions.

To further investigate the relationship between the variation coefficient and growth trend and assess the ecological vulnerability of prefectural administrative regions in China, a univariate linear regression analysis was conducted between these two variables, as shown in Figure 10. Points located higher and to the right on the graph indicated a higher variation coefficient and growth trend, respectively, and a positive correlation was observed between the two variables. The proportion of cities located above and

below the regression line was found to be 35% and 65%, respectively. With the exception of Longnan in Gansu, the provinces of Xinjiang, Inner Mongolia, and Ningxia were all located above the regression line, suggesting that their vegetation is more volatile and relatively more vulnerable compared to the greening trend. Conversely, prefecture-level administrative regions in the southeastern and southern areas, including Fujian, Taiwan, Hainan, Guangdong, and Yunnan, exhibited the highest stability, with some cities in Hainan Province showing a high greening trend. Notably, Taizhou, Jiaxing, and Qianjiang cities were located on the left side of the Y-axis and had a relatively high variation coefficient, indicating that their vegetation was deteriorating year by year.

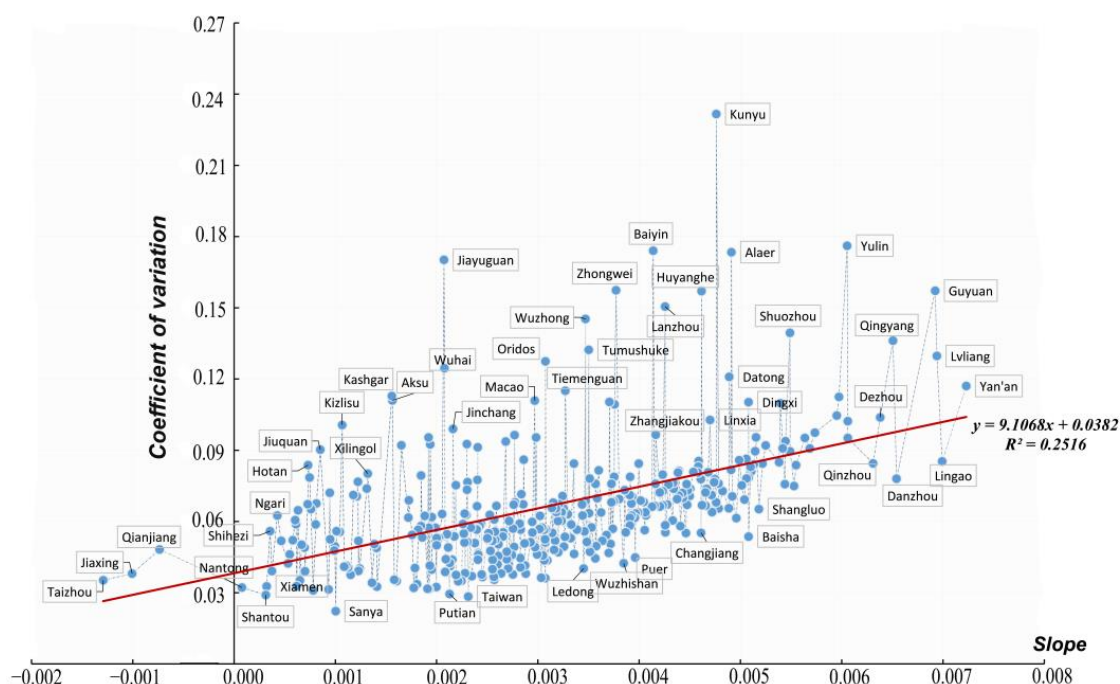


Figure 10. Slope-CV linear regression distribution of prefectural administrative regions.

Regarding the future sustainability of vegetation change trends, Figure 11 illustrates that the majority of cities will continue to exhibit varying degrees of greening in line with past patterns. In general, similar to provincial-level administrative regions, most prefecture-level administrative regions in China will maintain different levels of vegetation coverage to varying degrees in the future. A few cities fall within the random range, while a few cities in southeastern Tibet, southeastern Guizhou, southern Qinghai, and northern Yunnan will demonstrate reverse sustainability, indicating a potential trend of degradation.

3.3. Overall Change Trend of Regional Annual Average NDVI

The previous section analyzed the spatial distribution and temporal variation of vegetation coverage for provincial-level and prefecture-level administrative regions using multi-year average NDVI, annual NDVI trend, variability coefficient, and Hurst index. The annual average NDVI for all regions was obtained, and a linear regression was performed to represent the overall trend of annual NDVI. Figure 11 shows the regression results, with orange and blue lines representing provincial-level and prefecture-level administrative regions, respectively. The vegetation coverage growth rates for these regions are 0.032/10a and 0.03/10a, respectively, with R-squared values of 0.87 for both.

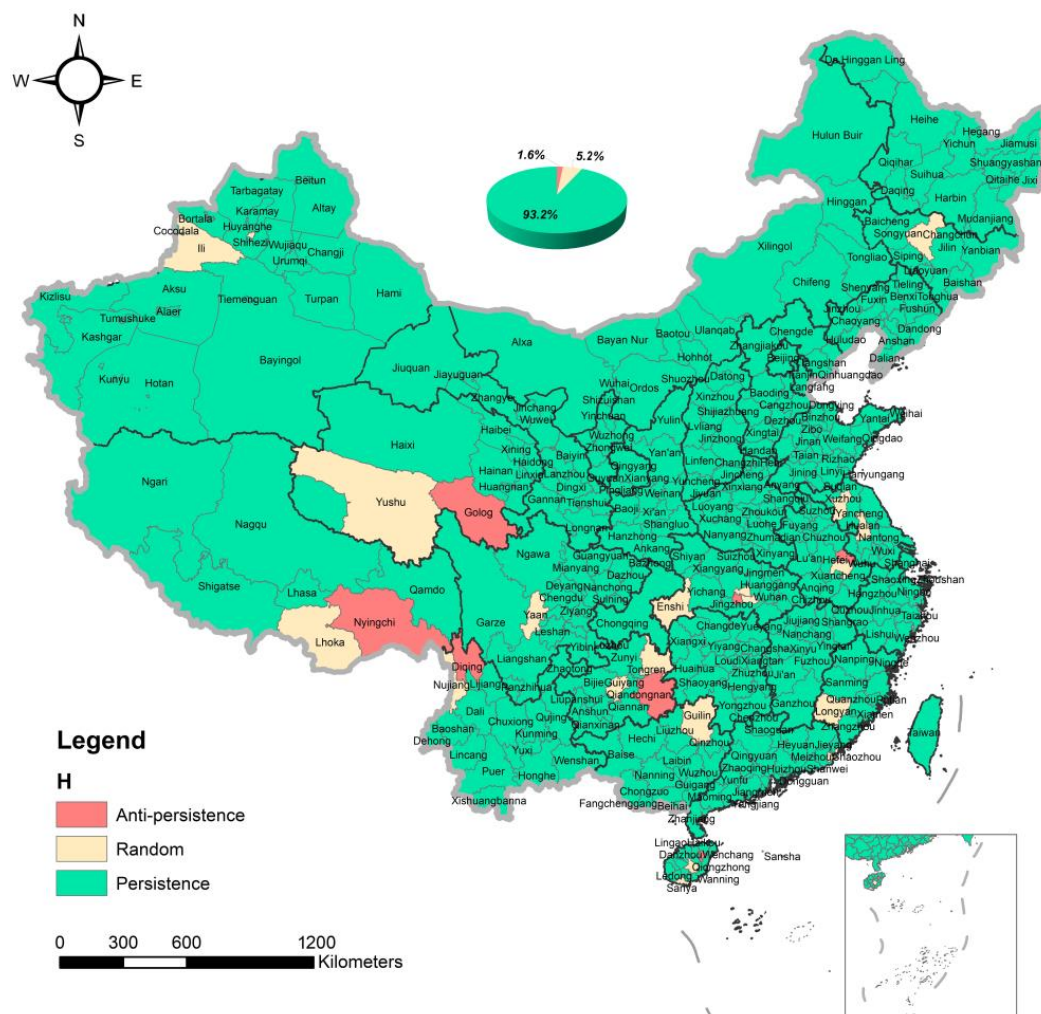


Figure 11. Hierarchical distribution of Hurst exponent in prefectural administrative regions.

4. Discussion

4.1. Provincial Administrative Regions

Between 2000 and 2021, the spatiotemporal heterogeneity of the Normalized Difference Vegetation Index (NDVI) was observed at a two-level regional scale. Specifically, the provincial administrative level showed significant increases in NDVI in Shanxi and Shaanxi Provinces, followed by Chongqing Municipality, which is consistent with another study that analyzed changes in NDVI during the growing season [19]. On the other hand, Tibet and Xinjiang Uygur Autonomous Region exhibited the smallest growth trends. These large-scale and varying degrees of vegetation improvement may be attributed to China's ecological restoration projects, which include the Three-North Shelter Forest Program, Natural Forest Protection Program, and Grain-for-Green Program (GTGP), implemented across 25 provinces and 97% of all counties in China since the late 1970s [43–45]. For instance, the GTGP project facilitated farmland conversion and reforestation in Shaanxi Province, making it the province with the largest number of such activities in recent decades [44,46]. Comprehensive management strategies have enabled significant vegetation restoration in provinces such as Shaanxi, Shanxi, Ningxia, and Gansu, with varying degrees of forest and grassland increase. Remarkably, the vegetation restoration effect covered 88.2% of the Loess Plateau area, concentrated in northern Shaanxi and Shanxi. This change was more prominent at the municipal administrative level. Favorable climatic conditions, such as stable temperatures and increasing precipitation in regions like Shaanxi, Gansu, and Ningxia, have facilitated vegetation restoration [47].

However, compared to the growth rate of vegetation cover, the high volatility of Ningxia Autonomous Region and Macao Special Administrative Region, especially the former located in the Loess Plateau, is particularly noteworthy. Although significant vegetation improvement has been achieved through multiple afforestation policies, vegetation cover remains relatively fragile and sensitive. Research by Sun [48] has shown ecological deterioration in cities like Yinchuan, Shizuishan, and Wuzhong in northern Ningxia from 2001 to 2019. Moreover, although the growth rates in northern Shaanxi and Shanxi are relatively high, the overall vegetation cover remains very low, and the risk of vegetation degradation still exists due to factors such as energy production, chemical infrastructure construction, and mineral resource exploitation [47].

4.2. Prefectural Administrative Regions

The spatial distribution pattern of vegetation coverage at the prefectural administrative level can be summarized as increasing from northwest to southeast. The boundary between extremely low coverage and low coverage, as well as that between low coverage and moderate coverage, roughly coincides with the 400 mm and 800 mm precipitation lines in China, respectively. The 400 mm precipitation line is the natural boundary between semihumid and semiarid regions, while the 800 mm precipitation line is the boundary between semihumid and humid regions [49]. Regions with extremely low vegetation coverage are mainly distributed in the arid and semiarid areas of inland northwest and the cold regions of northern Tibet, while regions with extremely high vegetation coverage are mainly concentrated in the tropical climate zones of southwest and southeast China. These results indicate that the spatial heterogeneity of vegetation coverage is mainly influenced by climate, especially precipitation, which is consistent with the regression results of regional rainfall. Moreover, this also confirms the scientific and rational nature of the method used to calculate the regional average vegetation coverage, which can be used for cross-regional comparisons and provide important references for related research or policy implementation.

The significant growth of prefecture-level administrative regions in China is mainly concentrated from high to low in cities located in the central Loess Plateau, such as Yan'an, Lvliang, Guyuan, Qingyang, and Linfen. Similarly, Yibin in Sichuan, Dezhou in Shandong, and Qinzhou in Guangxi also exhibit significant growth. The vegetation cover in arid and cold regions with precipitation less than 50 mm, like the northwest central and Qinghai-Tibet Plateau, has changed very little, indicating that precipitation has a relatively limited impact on the vegetation in these areas. Notably, Taizhou in Jiangsu, Jiaxing in Zhejiang, and Qianjiang in Hubei show a negative growth trend, with Taizhou having the highest degradation rate of 0.0129/10a. The high variability and low growth or even degradation of vegetation cover in these regions suggest that human activities may have a significant negative impact on the vegetation cover in these areas. A study [50] on the dynamic changes of vegetation in China indicates that the expansion of urban areas at the cost of reducing arable land is the primary cause of the decreasing trend in NDVI in areas like Shanghai, Jiangsu, and Zhejiang, especially in plain areas and around economically developed cities. A recent paper [51] on the relationship between urbanization and vegetation points out that most southern cities still face challenges in coordinating the relationship between urbanization and vegetation. The expansion of cities such as Suzhou and Jiaxing by 50% between 2000 and 2010 suggests that the balance between urban expansion and urban greening is a game between economic development and investment in greening.

In addition, the greening situation in Jixi and Jiamusi in eastern Heilongjiang is also not optimistic, possibly due to extreme events like drought and harsh vegetation growth conditions [30]. At the same time, cities such as Dongguan, Foshan, Zhuhai, Zhongshan, Shantou, Xiamen, and Zhenjiang in the south and southeast coastal areas show unexpectedly poor vegetation conditions, which may be related to the rapid population growth under economic development [52,53]. The high population density significantly affects and changes the land use of the city, although the government and residents increasingly value

urban greening construction. Subsequently, the sparsity of vegetation in newly developed suburban areas of cities shaped by urban expansion and population growth may still persist for a long time.

5. Conclusions

This study is centered on the MODIS MD13Q1 NDVI remote sensing products in China from 2000–2021. The spatial and temporal distribution and changes of regional NDVI over the past 22 years were quantified using the Google Earth Engine cloud platform and provincial and prefectural administrative divisions as analysis scales. Our main conclusions are as follows:

- (1) During the period from 2000 to 2021, China's overall vegetation coverage showed an increasing trend. At the provincial and prefecture levels, the annual growth rates of vegetation coverage were 0.032/10a and 0.03/10a, respectively. At the provincial level, the vegetation coverage in Xinjiang, Tibet, Qinghai, and Ningxia was extremely low, while Taiwan, Hainan, and Fujian showed extremely high coverage levels. During the research period, Shanxi and Shaanxi saw the most significant vegetation improvement, followed by moderate growth trends in the eastern, central, and southern regions, while the vegetation coverage in Tibet and Xinjiang remained unchanged. The vegetation in Ningxia Autonomous Region was at a high level of fluctuation, and its ecological condition remained fragile.
- (2) At the prefecture level, the fastest-growing areas were mainly located in China's Loess Plateau region. In addition, moderate growth occurred on a larger scale. However, cities such as Taizhou in Jiangsu and Jiaxing in Zhejiang have experienced vegetation degradation. Meanwhile, the vegetation growth in the central and western parts of the northwest region, the central and western parts of the Qinghai-Tibet Plateau, the eastern part of Heilongjiang, and the southern parts of Guangdong and Fujian was slow, and they were on the brink of degradation.
- (3) The distribution pattern of vegetation coverage is widely influenced by climate conditions and human activities. At the regional level, the correlation coefficients between rainfall and NDVI mean values of provincial and prefecture-level administrative regions reached 0.84 and 0.8, respectively. Combined with the spatial distribution of vegetation coverage, this indicates that rainfall has a profound influence on the distribution pattern of vegetation. Human activities are also participating in and changing the regional vegetation conditions in an extremely extensive and complex way, both positively and negatively.
- (4) The research results indirectly confirm that the high vegetation growth in the Loess Plateau region demonstrates the effectiveness of a series of ecological greening projects in the area. Conversely, localized vegetation degradation (such as in Taizhou and Jiaxing) in the east and southeast coastal regions of China implies that economic and population growth during specific periods may lead to such degradation.

Vegetation coverage in China has exhibited a general upward trajectory over the 22-year span from 2000. However, it is imperative to focus on local instances of high fluctuations and the degradation of vegetation. In regions characterized by substantial growth rates, the degree of variability surpasses the actual growth rate. This indicates an insufficient stability in vegetation growth, potentially leading to instances of degradation in response to changing environmental conditions. Furthermore, the phenomenon of vegetation degradation occurring in the eastern regions of China, despite the relatively low variability in these areas, suggests that the degradation of vegetation in certain urban areas did not occur or manifest abruptly. Instead, it is a result of prolonged economic development that displaced vegetation over time during the urbanization process. In summary, this study furnishes a comprehensive and scientifically rigorous depiction of the distribution and changes in vegetation cover across China. It introduces an alternative approach to the conventional pixel-based methodology employed in vegetation coverage research, providing invaluable insights into understanding China's vegetation coverage scenario.

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