

Spatiotemporal Variation Characteristics of Vegetation NPP and Its Driving Forces in the Taihang Mountains (Postprint)

Authors: Li Xiaorong, High-level Conference, Han Lipu, Liu Jintong

Date: 2017-11-09T00:00:00+00:00

Abstract

Based on MODIS NPP data from 2000–2014, combined with concurrent land use change, temperature, precipitation, and DEM data, and employing methods such as trend analysis, correlation coefficient analysis, and zonal statistics, this study investigated the spatiotemporal variation characteristics of vegetation NPP in the Taihang Mountains region from 2000–2014, analyzed the impacts of climate factors (temperature, precipitation, etc.) and anthropogenic factors on vegetation NPP changes, and provides a reference for vegetation resource management and ecological environment regulation in the Taihang Mountains region. The research results indicate: (1) The multi-year average vegetation NPP in the Taihang Mountains region is $284.0 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, with mean NPP values for cropland, forestland, and grassland being $302.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, $258.1 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, and $286.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, respectively. (2) From 2000–2014, vegetation NPP in the Taihang Mountains region showed an overall increasing trend, but most vegetation NPP changes did not reach a significant level; 16.17% of vegetation NPP increased significantly or extremely significantly, mainly distributed on the western side of the Taihang Mountains region; 0.88% of vegetation NPP decreased significantly or extremely significantly, scattered sporadically throughout the study area. (3) The NPP change rates for different vegetation types follow the order: grassland > cropland > forestland. (4) Based on regional average calculations, vegetation NPP in the Taihang Mountains region is significantly positively correlated with precipitation ($P < 0.05$) and negatively correlated with temperature ($P > 0.05$). Based on pixel-based calculations, the area proportion of regions where vegetation NPP is significantly or extremely significantly positively correlated with precipitation is 23.82%, mainly distributed in the northern section of the Taihang Mountains region, with almost no significantly negatively correlated regions; the area proportion of regions where vegetation NPP is significantly or extremely significantly negatively correlated with temperature is 8.42%, mainly distributed on the western side of the Taihang Mountains region,

while the area proportion of significantly or extremely significantly positively correlated regions is 0.81%, mainly distributed at the northernmost end of the Taihang Mountains region. (5) During the study period, climate factors exhibited an overall promoting effect on the increase of vegetation NPP, whereas anthropogenic factors primarily demonstrated an inhibiting effect. Ecological environmental protection in the Taihang Mountains region should still focus on reducing human disturbance.

Full Text

Preamble

Chinese Journal of Eco-Agriculture, Apr. 2017, 25(4): 498-508

ChinaXiv Cooperative Journal

DOI: 10.13930/j.cnki.cjea.160780

Spatio-temporal variations in vegetation NPP and the driving factors in Taihang Mountain Area*

LI Xiaorong^{1,2}, GAO Hui^{1,2}, HAN Lipu¹, LIU Jintong^{1**}

(1. Center for Agricultural Resources Research, Institute of Genetics and Developmental Biology, Chinese Academy of Sciences, Shijiazhuang 050022, China; 2. University of Chinese Academy of Sciences, Beijing 100049, China)

Abstract: Net primary productivity (NPP) is an important indicator of vegetation condition in a given region. Research on NPP is not only crucial for vegetation resource management but also a key component of global change studies. Technological developments (such as remote sensing, geographic information systems, and global positioning systems) have created the conditions for establishing complex process-based NPP models. On this basis, global NPP products that continuously release data for long periods (e.g., MODIS NPP data) have greatly enhanced regional vegetation NPP research. The objective of this study was to analyze spatio-temporal variations in vegetation NPP in the Taihang Mountain Area from 2000 to 2014 using MODIS NPP data. Simultaneously, we investigated the effects of climatic factors (e.g., temperature and precipitation) and human factors (e.g., farming) on NPP changes in the region. Trend analysis, correlation coefficients, and zonal statistics were applied to various datasets (e.g., LUCC, temperature, precipitation, and DEM). Results showed that the average NPP of the study area was $284.0 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, while those of farmland, forest, and grassland were $302.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, $258.1 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, and $286.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, respectively. Geographical location, topography, development history, and human management influenced the distribution of vegetation NPP in the study area. Poor geographical environment was the main reason for the low NPP of forest vegetation in the region. Vegetation NPP generally showed an upward trend, though this was not significant for most of the study area. Approximately 16.17% of the area exhibited significantly or extremely significantly increased vegetation NPP, mainly in the

western part of the study area. In another 0.88% of the area, NPP significantly or extremely significantly decreased. The order of NPP change rates among different vegetation types was: grassland > farmland > forest. Grassland vegetation was more effective for environmental rehabilitation because it had better adaptability to local conditions. Based on calculated regional averages, vegetation NPP was significantly positively correlated with precipitation ($P < 0.05$) but negatively correlated with temperature ($P > 0.05$). About 23.82% of the study area showed a significantly or extremely significantly positive correlation between vegetation NPP and precipitation, mainly distributed in the northern section of the Taihang Mountains. No significantly negative correlation was observed. Furthermore, about 8.42% of the study area showed a significantly or extremely significantly negative correlation between vegetation NPP and temperature, mainly on the western side of the Taihang Mountains. In another 0.81% of the area, vegetation NPP was significantly or extremely significantly positively correlated with temperature, mainly distributed in the extreme north of the study area. Also, the rate of NPP change and the correlation coefficient between NPP and climatic factors were positively correlated with altitude and slope gradients—both were relatively smaller at low altitude and small slope, where human activity intensity was relatively higher. The area with significantly or extremely significantly reduced vegetation NPP was scattered across the study area, especially around construction lands, which was not a result of climatic factors. It was therefore suggested that while climatic factors generally enhanced vegetation NPP, human factors mainly inhibited vegetation NPP in the study area during the study period.

Keywords: Taihang Mountain; NPP; Land use type; Vegetation change; MODIS; Driving factor

Net primary productivity (NPP) refers to the portion of total organic matter produced by vegetation through photosynthesis per unit time and area after deducting autotrophic respiration [1], and is an important indicator reflecting vegetation growth and change. As a key link in ecosystem material cycling and energy flow, vegetation NPP forms the functional basis of the biosphere [2]. Currently, as climate and environmental issues become increasingly prominent, timely and accurate understanding of regional or global vegetation NPP and analysis of its spatio-temporal variation characteristics, as well as comprehension of its relationships with various influencing factors, are of great significance for global change and sustainable development research, while also providing a scientific basis for rational development and utilization of natural resources at the regional scale.

Since the mid-1980s, scholars have addressed the limitations of empirical statistical NPP models by proposing process-based vegetation NPP models that incorporate plant ecophysiological characteristics. The development of remote sensing (RS), geographic information systems (GIS), and global positioning systems (GPS) has provided an important technical platform for the widespread

application of NPP process models [3]. Since the late 20th century, the introduction of remote sensing data such as NOAA/AVHRR and EOS/MODIS has strongly promoted research on vegetation NPP remote sensing models and the application of related data products in China. Sun et al. [4], Piao et al. [5], Chen et al. [6], and Zhu et al. [7] have successively studied the spatio-temporal variation characteristics of vegetation NPP in China. Moreover, with the accumulation of relevant remote sensing data, long time-series remote sensing products have played an increasingly important role in regional vegetation change research.

The Taihang Mountain Area is an important ecological barrier for the Beijing-Tianjin-Hebei region and also an ecologically sensitive zone where the environment is highly susceptible to various disturbances. Development across successive dynasties has caused severe damage to natural vegetation in the Taihang Mountains, resulting in serious soil erosion, frequent drought and flood disasters, and affecting local sustainable social development [8]. Since the founding of the People's Republic of China, ecological restoration efforts over more than half a century have greened barren mountains and produced significant comprehensive benefits [9]. Under current climate change and market economy conditions, vegetation fluctuations on China's land have increased, affecting the normal functioning of regional ecosystem services. Many studies on vegetation change have involved the Taihang Mountain region, but few have focused on NPP, and those that exist have only covered partial areas of the Taihang Mountains. For example, Liu et al. [10] studied the spatial pattern of vegetation NPP in Hebei mountainous areas and found that NPP showed a zonal distribution in the Taihang Mountains of Hebei; Zhang [11] studied the spatio-temporal variation characteristics of vegetation NPP in Hebei and found that the windward slope of the Taihang Mountains had abundant precipitation during the growing season, forming a high NPP value belt; Wang et al. [12] studied NPP in Henan Province and found that the Henan portion of the Taihang Mountains was a relatively low NPP area. Currently, studies treating the entire Taihang Mountain vegetation as a research object are rarely reported.

The Taihang Mountains are located along the eastern edge of China's second topographic step, forming a transition zone from plains to mountainous plateaus, and simultaneously serving as a transition from the economically developed eastern region to the less developed central-western region. Studying vegetation NPP changes at the overall scale of the Taihang Mountains can enhance understanding of vegetation feedback characteristics in ecologically sensitive regions under global change background, which has important practical significance for rational development and utilization of natural resources and sustainable social development in typical mountainous areas. This study uses 3S technology to investigate vegetation changes in the Taihang Mountain Area, understand vegetation change trends, and analyze the driving forces behind these changes, which can help managers improve existing vegetation resource management strategies and more effectively regulate the ecological environment of the Taihang Mountain Area.

1. Study Area Description

There are many definitions of the Taihang Mountain Area boundaries. This study references Fan [13] and treats the Taihang Mountain Area as a geographical unit equivalent to the Lüliang Mountains to the west and the North China Plain to the east. Simultaneously, referring to the ancient concept of the “Eight Taihang Passages” [14], we determined the northern and southern boundaries of the Taihang Mountains. Thus, the natural region of the Taihang Mountains extends from the Yongding River in the north to the Yellow River in the south, from the Fen River valley in the west to the North China Plain in the east, spanning 115 county-level administrative districts across Beijing, Shanxi, Henan, and Hebei provinces (municipalities). The study area (110°14 E-116°35 E, 34°34 N-40°47 N) specifically includes all county-level administrative districts traversed by the Taihang Mountains, with a total area of approximately 13.7×10^4 km², an average elevation of 861 m, and terrain that is high in the northwest and low in the southeast. The regional climate belongs to the temperate continental monsoon climate, with distinct seasons, an average annual temperature of 11.1 °C, and average annual precipitation of 511.7 mm. More than half of the annual precipitation is concentrated in summer. Vegetation conditions in the study area show significant differences with changes in elevation, longitude, and latitude. Flat areas in valleys and basins are mostly farmland or construction land, while rugged steep slopes are mostly forest or grassland [Figure 1: see original paper].

2.1. Data Sources and Processing

DEM data were obtained from the Geospatial Data Cloud Platform of the Chinese Academy of Sciences Computer Network Information Center (<http://www.gscloud.cn>), using ASTER GDEM V2 data jointly developed by Japan’s METI and NASA, calculated from “Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)” data with a spatial resolution of 30 m.

Vegetation NPP data were MOD17A3 products released by the University of Montana for 2000-2014 (<https://lpdaac.usgs.gov>), with a spatial resolution of 1 km and temporal resolution of 1 year. This product is based on MODIS/TERRA satellite remote sensing data and calculates vegetation NPP by referencing the BIOME-BGC model, which estimates NPP by simulating vegetation physiological processes with relatively high accuracy [15]. MODIS NPP data have been validated in numerous studies [16-17]. We used MRT (MODIS Reprojection Tools) software for image mosaicking, projection conversion, and resampling, and ArcGIS 10.2 software for extracting valid values.

Land use data were generated through visual interpretation based on 2010 TM imagery, 30 m DEM, and high-resolution Google imagery, obtained from the Institute of Mountain Hazards and Environment, Chinese Academy of Sciences.

Meteorological data included annual precipitation and temperature data from

2000-2014 for 58 meteorological stations in Beijing, Shanxi, Henan, and Hebei provinces (municipalities) within and around the Taihang Mountain Area, obtained from the China Meteorological Data Sharing Service Network (<http://cdc.cma.gov.cn>). Meteorological data were spatially interpolated using the inverse distance weighted (IDW) method.

All image data were projected using WGS84/Albers Equal Area and further processed and analyzed using ArcGIS 10.2 software.

2.2.1. Vegetation NPP Change Trend Analysis

We used unary linear regression analysis based on pixels to analyze vegetation NPP changes in the Taihang Mountain Area from 2000-2014. The linear regression trend slope represents the NPP change rate [16,18], calculated as:

$$S = \frac{\sum_{i=1}^N (x_i - \bar{x})(t_i - \bar{t})}{\sum_{i=1}^N (t_i - \bar{t})^2}$$

where S is the NPP change rate, $N = 15$ is the number of years, x is the NPP value in year i , and t is the year. Using ArcGIS raster calculation functions, we obtained the vegetation NPP change trend map for 2000-2014. When $S > 0$, vegetation NPP showed an increasing trend, and vice versa.

We used F-test to examine the significance of NPP change trends. This test result only represents the confidence level of the trend change and is independent of the change rate magnitude [16,19]. The test formula is:

$$F = \frac{\sum_{i=1}^N (\hat{x}_i - \bar{x})^2}{\sum_{i=1}^N (x_i - \hat{x}_i)^2 / (N - 2)}$$

where \hat{x} is the regression value of NPP in year i , \bar{x} is the 15-year average NPP, x is the NPP value in year i , and $N = 15$. By checking the F-distribution critical value table for significance testing and combining with NPP change trends, we classified NPP changes into five levels: extremely significant decrease ($S < 0$, $P < 0.01$), significant decrease ($S < 0$, $0.01 < P < 0.05$), non-significant change ($P > 0.05$), significant increase ($S > 0$, $0.01 < P < 0.05$), and extremely significant increase ($S > 0$, $P < 0.01$).

2.2.2. Correlation Analysis Between Vegetation NPP Change and Climate Factors

We used pixel-based partial correlation coefficient analysis to examine the correlation between NPP and precipitation or temperature [16]. Simple correlation coefficients were calculated first, followed by partial correlation coefficients. The simple correlation coefficient formula is:

$$R_{xy} = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}}$$

where R is the correlation coefficient between variables x and y ; x and y represent the NPP and climate factor values in year i , respectively; \bar{x} and \bar{y} represent the multi-year average NPP and climate factor values, respectively; and $N = 15$ is the number of years.

The partial correlation coefficient formula is:

$$r_{12,3} = \frac{r_{12} - r_{13}r_{23}}{\sqrt{(1 - r_{13}^2)(1 - r_{23}^2)}}$$

where $r_{12,3}$ is the partial correlation coefficient between variables 1 and 2 with variable 3 held constant, and r_{12} , r_{13} , and r_{23} are the simple correlation coefficients between variables 1 and 2, variables 2 and 3, and variables 1 and 3, respectively.

We used t-test to examine the significance of partial correlation coefficients [20], with the formula:

$$t = \frac{r\sqrt{N-2}}{\sqrt{1-r^2}}$$

where r is the partial correlation coefficient and $N = 15$ is the number of years. By querying the t-distribution table, we determined the significance of partial correlation coefficients. Combined with the sign of the partial correlation coefficient, we classified them into five levels: extremely significant negative correlation ($r < 0$, $P < 0.01$), significant negative correlation ($r < 0$, $0.01 < P < 0.05$), non-significant correlation ($P > 0.05$), significant positive correlation ($r > 0$, $0.01 < P < 0.05$), and extremely significant positive correlation ($r > 0$, $P < 0.01$).

2.2.3. Regional Statistical Analysis

The study area was divided into zones based on altitude gradients and slope gradients. Combined with land use data, multi-year average NPP, NPP change analysis results, and correlation analysis results between NPP and precipitation or temperature, we used ArcGIS zonal statistics to study vegetation NPP change characteristics in different regions and analyze the effects of human and climate factors on vegetation NPP changes.

3.1. Spatial Pattern of Vegetation NPP

The Taihang Mountains generally run northeast-southwest, spanning 6 latitudes. The eastern and western sides of the mountain range are affected differently by

monsoons, and local terrain in the Taihang Mountain Area is complex and variable, resulting in significant differences in ecological environmental conditions across the region. The multi-year average vegetation NPP in the Taihang Mountain Area was $284.0 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, with farmland, forest, and grassland averaging $302.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, $258.1 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, and $286.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, respectively. Regionally [Figure 2: see original paper], vegetation NPP showed a spatial distribution pattern of low values in the northern section, high values in the southern section, and alternating high and low values in most of the middle section. This pattern is related to both the overall improvement of hydrothermal conditions from north to south at the regional scale and differences in moisture conditions among different geographic regions. Affected by monsoon climate and topography, windward slopes and mid-high mountain areas in the Taihang Mountain Area generally receive abundant precipitation, while valley basins receive less precipitation. Additionally, terrain affects solar radiation distribution, causing higher evapotranspiration on sunny slopes than on shady slopes, leading to more severe vegetation drought stress. Therefore, local afforestation is mostly conducted on shady slopes. Farmland conditions are relatively better, and vegetation growth is generally better than that of natural vegetation with the same growth form. Some prominent low NPP value areas (shown in red) appear in mid-high mountains. Comparing with the land use map reveals that these low NPP areas are mainly forest land. In contrast, forest NPP values in other studies reach $500 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$ [16] or even higher production levels [21], indicating that forest productivity in the Taihang Mountain Area is relatively poor. Combined with the overall low forest NPP in the Taihang Mountain Area, forest vegetation growth experiences significant environmental stress. This is mainly because the average elevation of forest distribution in the Taihang Mountain Area is 1,127 m, the average slope reaches 21.4° , and the average annual precipitation is 507.7 mm—natural conditions are poorer than those of farmland and grassland. On the other hand, mountain ecosystems are more fragile than plain areas. Historical development-induced soil erosion has made mountain soil layers thin, with soil thickness less than 15 cm in many places [22] and large areas of exposed rock in many locations, suitable only for weed growth, which severely limits vegetation development.

3.2. Interannual Variation Analysis of Vegetation NPP

From 2000–2014, vegetation NPP in the Taihang Mountain Area showed an overall fluctuating upward trend, with interannual fluctuations of different vegetation types basically consistent with the overall regional NPP fluctuation [Figure 3: see original paper]. This indicates that the factors influencing overall vegetation NPP changes in the Taihang Mountain Area are global factors that can affect large-scale regions. In 2001, northern China experienced drought, resulting in low NPP values in the study area. In 2003, abundant precipitation in the study area created high NPP values and improved vegetation growth in the following year. Around 2000, the launch of the “Grain for Green Project,” ecological protection measures such as closing mountains for grazing prohibition,

and the process of rural population transfer to cities have all had positive effects on vegetation improvement.

In the spatial distribution map of vegetation NPP change rates [Figure 4a: see original paper], most NPP change rates ranged between -5 and $5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, with positive value areas far exceeding negative value areas. Areas with faster NPP growth were mainly located on the western side of the Taihang Mountains, while NPP reduction areas were mostly scattered across various locations, except for some contiguous distributions in forest land in the southern section. Different vegetation types showed significant differences in NPP change rates, with grassland, farmland, and forest averaging $2.77 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, $2.19 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, and $0.83 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, respectively. The NPP change significance test results [Figure 4b: see original paper] show that most vegetation NPP changes in the study area were not significant. The proportion of area with significantly or extremely significantly increased NPP was 16.17%, mainly distributed on the western side of the Taihang Mountains. The proportion of area with significantly or extremely significantly decreased NPP was only 0.88%, scattered throughout the study area. Among different vegetation types, the proportion of significantly or extremely significantly increased NPP followed the order: grassland > farmland > forest, while the proportion of significantly or extremely significantly decreased NPP followed: forest > farmland > grassland. This is related not only to the poor forest habitats but also to the ecological characteristics of different vegetation types. Forest ecosystems have complex structures and relatively high stability, with smaller vegetation fluctuations under environmental changes. In contrast, grassland and farmland are dominated by herbaceous plants that are sensitive to environmental changes. Particularly, grassland plants have strong adaptability and are more likely to achieve high NPP change rates after environmental improvement. Significantly decreased forest NPP may be more closely related to human activities.

From the spatial distribution of vegetation NPP change significance test results, areas with significantly or extremely significantly increased NPP coincided with high NPP change rate areas, indicating obvious vegetation improvement in these regions during the study period. The proportion of area with significantly or extremely significantly decreased NPP was minimal and scattered, suggesting that most vegetation in negative NPP change rate areas did not significantly deteriorate. Areas with significantly or extremely significantly increased NPP were mainly grassland and farmland, while those with significantly or extremely significantly decreased NPP were mainly construction land, farmland, and forest. The decrease in construction land vegetation NPP resulted from urbanization occupying original vegetation land. Farmland NPP decrease was mostly distributed around construction land, indicating that human factors were the main cause of vegetation deterioration in farmland areas. Forest NPP decrease was mostly located in the southern section of the Taihang Mountains, mostly overlapping with low NPP value areas and low NPP change rate areas, indicating the presence of long-term negative influencing factors or mechanisms in these forest areas. Climate factors affect large areas, but forest vegetation de-

terioration areas were isolated, indicating that vegetation deterioration in these areas was not caused by climate factors. Combined with the rapid development of tourism in the southern Taihang Mountains in recent years, we speculate this may be the result of human destruction.

3.3. Correlation Analysis Between Vegetation NPP and Climate Factors

Based on spatial averaging, precipitation in the study area from 2000-2014 was significantly positively correlated with NPP, with a correlation coefficient of 0.530; temperature was negatively correlated with NPP, with a correlation coefficient of -0.280. The partial correlation coefficient significance test results [Figure 5: see original paper] show that precipitation and vegetation NPP were mainly positively correlated. The proportion of area with significant or extremely significant correlation between precipitation and NPP was 23.82%, almost all showing positive correlation, mainly distributed in the northern section of the Taihang Mountains. The relationship between temperature and vegetation NPP was mainly negative, with the proportion of significantly or extremely significantly negatively correlated area being 8.42%, mainly distributed on the western side of the Taihang Mountains. The proportion of significantly or extremely significantly positively correlated area between temperature and NPP was only 0.81%, mainly distributed in the extreme north of the Taihang Mountains, comprising farmland and forest limited by heat conditions.

The correlation test results between NPP and annual precipitation or average annual temperature for different vegetation types were generally consistent with the regional average conditions [Figure 6: see original paper]. Comparing with NPP change significance test results reveals considerable overlap between NPP significant change areas and NPP-precipitation or NPP-temperature significant correlation areas, indicating that some significant vegetation NPP changes were strongly associated with climate factors.

In the above analysis, precipitation mainly promoted vegetation NPP increase, while temperature mainly inhibited it. These two opposing effects represent the manifestation of drought stress, indicating that drought is an important factor limiting vegetation NPP growth in the Taihang Mountain Area. Some scholars also believe that drought stress on vegetation in the Taihang Mountain Area is relatively severe [8,22-23]. However, precipitation only significantly affected NPP changes at the regional average level; at the pixel scale, the proportion of significantly affected area was small, and temperature's influence on vegetation NPP was even smaller. This indicates that the causes of vegetation NPP changes in the Taihang Mountain Area are complex, with precipitation and temperature being only two of many influencing factors.

3.4. Vegetation Characteristics Changes Along Geographic Gradients

Based on zonal statistics along altitude and slope gradients, the area percentages, average annual NPP, NPP change rates, NPP-precipitation partial correlation coefficients, and NPP-temperature partial correlation coefficients of different vegetation types in the Taihang Mountain Area all showed changes. Area percentages showed that as elevation and slope increased, farmland area proportion decreased while grassland and forest area proportions increased, with forest occupying larger proportions in mid-high elevation and large slope areas [FIGURE:7a,b], indicating that forest and grassland generally have poorer geographic conditions than farmland. NPP changes showed that as elevation and slope increased, forest and farmland NPP tended to decrease, with forest showing a larger decline, while grassland NPP changed little [FIGURE:7c,d], demonstrating adaptability to different geographic environments. Regarding NPP change rates, both farmland and grassland showed a trend of first increasing then decreasing with increasing elevation and slope, while forest fluctuated and decreased [FIGURE:7e,f], indicating that forest vegetation growth is more affected by terrain. Precipitation-NPP correlation showed that forest fluctuated and decreased along the elevation gradient [FIGURE:7g,h], indicating that precipitation's effect on forest vegetation growth decreases with increasing elevation; grassland fluctuated and decreased along the slope gradient, indicating that precipitation's effect on grassland vegetation growth decreases with increasing slope. However, many irregular changes occurred, indicating that precipitation's effect on vegetation growth along geographic gradients is complex. Temperature-NPP correlation showed that the correlation coefficients between NPP and temperature for different vegetation types all exhibited a trend of first decreasing then increasing along geographic gradients [FIGURE:7i,j], indicating that temperature plays different roles at different geographic gradients, with possible shifts in dominant factors. Except for forest, correlation coefficient curves between climate factors and NPP mostly showed convex patterns in mid-altitude and mid-slope areas, similar to NPP change rate curves. Generally, in low-altitude and small-slope areas with intense human production activities, human factors dominate vegetation changes while climate factors play a relatively weak role. In high-altitude and large-slope areas, vegetation NPP changes may be more influenced by ecosystem internal factors such as soil. This reflects that vegetation grows better where climate factors are relatively strong. In low-altitude and small-slope areas where human factors are strong, human activities reduce the improvement magnitude of farmland and grassland. Although humans emphasize forest vegetation construction in these areas, the proportion of forest is small, and human factors mainly inhibit vegetation improvement.

4. Conclusions and Discussion

Based on MODIS NPP data from 2000-2014, combined with land use, temperature, precipitation, and DEM data, and using trend analysis, correlation

coefficients, and zonal statistics, this study investigated the spatio-temporal variation characteristics of vegetation NPP in the Taihang Mountain Area from 2000–2014 and analyzed factors influencing vegetation NPP changes. The conclusions are as follows:

1. From 2000–2014, the multi-year average vegetation NPP in the Taihang Mountain Area was $284.0 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$. The average NPP values for farmland, forest, and grassland were $302.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, $258.1 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, and $286.5 \text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, respectively.
2. From 2000–2014, vegetation NPP in the Taihang Mountain Area showed an overall increasing trend, though most vegetation NPP changes did not reach significant levels. Vegetation NPP significantly or extremely significantly increased in 16.17% of the area and significantly or extremely significantly decreased in 0.88% of the area. Areas with significantly or extremely significantly increased NPP were mainly distributed on the western side of the Taihang Mountains, while those with significantly or extremely significantly decreased NPP were scattered throughout the study area.
3. The NPP change rates among different vegetation types followed the order: grassland > farmland > forest. Grassland, with relatively strong adaptability, better utilized opportunities from environmental changes. Most forest distribution areas had poor habitats, constraining NPP increase.
4. Based on regional average calculations, vegetation NPP in the Taihang Mountain Area was significantly positively correlated with precipitation ($P < 0.05$) and negatively correlated with temperature ($P > 0.05$). Based on pixel calculations, the proportion of area with significantly or extremely significantly positive correlation between vegetation NPP and precipitation was 23.82%, mainly distributed in the northern section of the Taihang Mountains, with almost no significantly negative correlation area. The proportion of area with significantly or extremely significantly negative correlation between vegetation NPP and temperature was 8.42%, mainly distributed on the western side of the Taihang Mountains, while the proportion of significantly or extremely significantly positive correlation area was 0.81%, mainly distributed in the extreme north of the Taihang Mountains.
5. During the study period, climate factors generally promoted vegetation NPP increase, while human factors mainly inhibited it. Ecological environment protection in the Taihang Mountain Area should still focus on reducing human disturbance.

In this study, geographic location, topography, development history, and human management affected the spatial distribution of vegetation NPP in the Taihang Mountain Area through water, heat, soil, and other factors, but moisture conditions were the main limiting factor for NPP growth. Affected by monsoon climate, the Taihang Mountain Area has concurrent rainfall and heat, but po-

tential evapotranspiration is around 1,600 mm (calculated from multi-year average MODIS evapotranspiration data), far exceeding actual precipitation, easily creating drought stress. Long-term soil erosion has resulted in thin soil layers and reduced water conservation capacity, further deteriorating vegetation water conditions. Farmland vegetation grows well under human care; grassland vegetation NPP is lower than farmland but higher than forest due to its strong adaptability. The low forest NPP in this study is related to poor forest habitats but also to inappropriate afforestation activities. Since the 1980s, the Taihang Mountain Area has implemented several ecological projects such as the “Taihang Mountain Greening Project” and “Grain for Green Project.” However, during large-scale afforestation, besides planting in suitable areas, some planting inevitably occurred in unsuitable locations due to quota issues. This not only increased afforestation costs but also violated the principle of “adapting measures to local conditions,” affecting tree growth and resulting in low-quality, low-benefit stands [24–25]. Zhang [11] found that NPP in Hebei Province from 2001–2010 mostly ranged between $200\text{--}400\text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, with farmland NPP greater than forest and grassland, consistent with this study. Wang et al. [12] found that annual NPP in Henan Province from 2000–2010 ranged from $308\text{--}430\text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, with farmland NPP at $300\text{--}500\text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$ and forest NPP in western and southeastern Henan mostly above $500\text{ g(C)} \cdot \text{m}^2 \cdot \text{a}^{-1}$, indicating better overall vegetation growth than in the Taihang Mountain Area.

This study found that vegetation in the Taihang Mountain Area generally improved, consistent with many domestic scholars’ research results. Du et al. [26] found that vegetation NDVI in Xinjiang showed an extremely significant increasing trend from 1982–2012; Li et al. [27] found that vegetation in the Three-River Headwaters region showed an improving trend from 2000–2014 based on NDVI; Wang et al. [12] also found that vegetation NPP in Henan mainly increased from 2000–2010. However, some studies in other regions found no vegetation improvement or even deterioration. Zhang [11] found that vegetation NPP in most areas of Hebei showed a decreasing trend from 2000–2014. Some scholars have pointed out that vegetation change shows obvious regional differences and strong spatial heterogeneity in relationships with climate factors [20]. Therefore, even under large-scale environmental change backgrounds, vegetation responses in different regions may vary greatly.

For vegetation changes in the Taihang Mountain Area, different scholars have obtained different results. Sun et al. [28] found that vegetation coverage in the Hutuo River Basin in central Taihang Mountains showed an overall increasing trend from 1984–2014, but vegetation degradation occurred in relatively low-altitude areas. Although this study also found vegetation degradation in this region, the proportion of significantly degraded areas was small. Considering that Sun et al. [28] included the Shijiazhuang Plain area (not included in this study’ s scope) and had a longer study period, and this region is experiencing rapid urbanization, such differences are likely to occur. Jia [29] studied vegetation cover changes in Beijing based on two-phase TM satellite imagery from 1987 and 2009, finding that vegetation quality mainly improved and at-

tributing the driving force to human ecological engineering factors. This study also believes that ecological measures such as closing mountains for grazing prohibition are beneficial for vegetation improvement and that human factors dominate vegetation changes in low-altitude areas. However, this study found that human behavior in low-altitude areas mostly showed negative rather than positive effects. This study lacks understanding of actual field conditions and integration with socioeconomic data, and only qualitatively analyzing human behavior greatly reduces its practical application significance, which needs improvement in future research. MODIS data themselves have certain accuracy issues and require comprehensive consideration during localization. Currently, various vegetation productivity models have large differences in accuracy and precision, resulting in poor comparability of model application results. Some studies suggest that ensemble prediction methods based on multiple algorithms can effectively improve simulation accuracy and produce significantly better results than single algorithms [31], which may be a future development direction.

References

- [1] Lieth H, Whittaker R H. Primary Productivity of the Biosphere[M]. Berlin Heidelberg: Springer, 1975
- [2] Zhou G S, Zhang X S. A natural vegetation NPP model[J]. Acta Phytocologica Sinica, 1995, 19(3): 193-200
- [3] Sun L W. Temporal and spatial variation of vegetable net primary productivity and influence of climate change and human activity in Qilian Mountains[D]. Lanzhou: Northwest Normal University, 2013
- [4] Sun R, Zhu Q J. Effect of climate change of terrestrial net primary productivity in China[J]. Journal of Remote Sensing, 2001, 5(1): 58-61
- [5] Piao S L, Fang J Y, Guo Q H. Application of CASA model to the estimation of Chinese terrestrial net primary productivity[J]. Acta Phytocologica Sinica, 2001, 25(5): 603-608
- [6] Chen L J, Liu G H, Li H G. Estimating net primary productivity of terrestrial vegetation in China using remote sensing[J]. Journal of Remote Sensing, 2002, 6(2): 129-135
- [7] Zhu W Q, Pan Y Z, Zhang J S. Estimation of net primary productivity of Chinese terrestrial vegetation based on remote sensing[J]. Journal of Plant Ecology, 2007, 31(3): 413-424
- [8] Liu X, Ge J F, Feng X H. Study on ecological security of land resources in Taihang Mountain Hebei[J]. Journal of Arid Land Resources and Environment, 2007, 21(5): 68-74
- [9] Zeng X Z, Yang Y J, Zhang G H, et al. On the greening project of Taihang mountains[J]. Forestry Economics, 2010, (7): 52-54
- [10] Liu Z, Zhao X Y, Mi L D. Study on estimation and spatial pattern of vegetation net primary productivity in mountainous area of Hebei Province based on 3S[J]. Research of Soil and Water Conservation, 2014, 21(4): 143-147
- [11] Zhang S. Research on spatio-temporal distribution of vegetation net primary productivity in Hebei Province based on long time-series multi-source remote

- sensing data[D]. Shijiazhuang: Hebei Normal University, 2015
- [12] Wang X C, Wang S D, Zhang H B. Spatiotemporal pattern of vegetation net primary productivity in Henan Province of China based on MOD17A3[J]. Chinese Journal of Ecology, 2013, 32(10): 2797-2805
- [13] Fan X. Taihang Mountain –The turning from the plateau to the plain is very magnificent[J]. Chinese National Geography, 2011, (5): 15-25
- [14] Wang S Y. A brief discussion on the eight Taihang passages and their vicissitudes in the history[J]. Geographical Research, 1997, 16(1): 68-76
- [15] Li D K, Fan J Z, Wang J. Variation characteristics of vegetation net primary productivity in Shaanxi Province based on MOD17A3[J]. Chinese Journal of Ecology, 2011, 30(12): 2776-2782
- [16] Mu S J, Li J L, Zhou W, et al. Spatial-temporal distribution of net primary productivity and its relationship with climate factors in Inner Mongolia from 2001 to 2010[J]. Acta Ecologica Sinica, 2013, 33(12): 3752-3764
- [17] Zhu F, Liu Z M, Wang Z M, et al. Temporal-spatial characteristics and factors influencing crop NPP across northeastern China[J]. Resources Science, 2010, 32(11): 540-546
- [18] Wu S S, Yao Z J, Jiang L G, et al. The spatial-temporal variations and hydrological effects of vegetation NPP based on MODIS in the source region of the Yangtze River[J]. Journal of Natural Resources, 2016, 31(1): 39-51
- [19] Anayeti A, Shi Q D, Liu M, et al. The vegetation cover changes of regress analysis on using time-serial images of remote sensing[J]. Journal of Xinjiang University: Natural Science Edition, 2014, 31(3): 341-344
- [20] A D, Zhao W J, Gong Z N, et al. Temporal analysis of climate change and its relationship with vegetation cover on the north china plain from 1981 to 2013[J]. Acta Ecologica Sinica, 2017, 37(2): 576-592
- [21] Chen F J, Shen Y J, Li Q, et al. Spatio-temporal variation analysis of ecological systems NPP in China in past 30 years[J]. Scientia Geographica Sinica, 2011, 31(11): 1409-1414
- [22] Li B G. Theory and Technology of Ecological Economic Ditch Construction –A case of Taihang Mountain[M]. Beijing: Science Press, 2015
- [23] Deng W, Dai E F, Jia Y W, et al. Spatiotemporal coupling characteristics, effects and their regulation of water and soil elements in mountainous area[J]. Mountain Research, 2015, 33(5): 513-520
- [24] Yang H Q. The ecological services and sustainable management of the main shrubs in the hill areas of south Taihang Mountains[D]. Zhengzhou: Henan Agricultural University, 2013: 5
- [25] Luo X H, He C Y, Liu X L, et al. Review of domestic research on low-benefit stand[J]. Journal of Sichuan Forestry Science and Technology, 2004, 25(2): 31-36
- [26] Du J Q, Ahati J, Zhao C X, et al. Dynamic changes in vegetation NDVI from 1982 to 2012 and its responses to climate change and human activities in Xinjiang, China[J]. Chinese Journal of Applied Ecology, 2015, 26(12): 3567-3578
- [27] Li H X, Liu G H, Fu B J. Response of vegetation to climate change and human activity based on NDVI in the Three-River Headwaters region[J]. Acta

Ecologica Sinica, 2011, 31(19): 5495-5504

[28] Sun L G, Zheng Z H. RS-based study on dynamic change of vegetation coverage in Hutuo River Watershed in the past 30 years[J]. Geography and Geo-Information Science, 2014, 30(6): 36-40

[29] Jia B Q. Driving factor analysis on the vegetation changes derived from the Landsat TM images in Beijing[J]. Acta Ecologica Sinica, 2013, 33(5): 1654-1666

[30] Chen F J, Shen Y J, Hu Q L, et al. Responses of NDVI to climate change in the Hai Basin[J]. Journal of Remote Sensing, 2011, 15(2): 401-414

[31] Yuan W P, Cai W W, Liu D, et al. Satellite-based vegetation production models of terrestrial ecosystem: An overview[J]. Advances in Earth Science, 2014, 29(5): 541-550

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

Source: ChinaXiv –Machine translation. Verify with original.