Earth's Future

RESEARCH ARTICLE

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Key Points:

- The spatial pattern and temporal changes of China's vegetation community complexity were examined using over half a million field samples
- Despite China is getting greener, China's vegetation community complexity decreased during the past 30 years
- With proper vegetation conservation efforts, human activities can have a positive effect on maintaining vegetation composition complexity

Supporting Information:

Supporting Information may be found in the online version of this article.

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Human-Climate Coupled Changes in Vegetation Community Complexity of China Since 1980s

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Abstract Vegetation community complexity is a critical factor influencing terrestrial ecosystem stability. China, the country leading the world in vegetation greening resulting from human activities, has experienced dramatic changes in vegetation community composition during the past 30 years. However, how China's vegetation community complexity varies spatially and temporally remains unclear. Here, we examined the spatial pattern of China's vegetation community complexity and its temporal changes from the 1980s to 2015 using two vegetation maps of China as well as more than half a million field samples. Spatially, China's vegetation community complexity distribution is primarily dominated by elevation, although temperature and precipitation can be locally more influential than elevation when they become the factors limiting plant growth. Temporally, China's vegetation community complexity shows a significant decreasing trend during the past 30 years, despite the observed vegetation greening trend. Prevailing climate warming across China exhibits a significant negative correlation with the decrease in vegetation community complexity, but this correlation varies with biogeographical regions. The intensity of human activities have an overall negative influence on vegetation community complexity, but vegetation conservation and restoration efforts can have a positive

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effect on maintaining vegetation composition complexity, informing the critical role of vegetation management policies in achieving the sustainable development goal.

Plain Language Summary China, as a country leading in vegetation greening, has experienced remarkable changes in vegetation community compositions. However, its vegetation community complexity, as an important factor indicating terrestrial ecosystem stability and sustainability, has been rarely studied. This study provides a comprehensive understanding on the spatial and temporal changes in China's vegetation community complexity from the1980s to 2015, and highlights a significant decreasing trend despite observable vegetation greening. Climate warming has an overall significant negative correlation with the decrease in vegetation community complexity, but their correlation varies with biogeographical regions. The intensity of human activities have an overall negative influence on vegetation community complexity, but vegetation conservation and restoration efforts can exhibit a positive effect on maintaining vegetation composition complexity, informing the critical role of vegetation management policies in achieving the sustainable development goal.

1. Introduction

Vegetation community is a basic geographic unit with relatively uniform plant species compositions (Jorgensen & Fath, 2014). The heterogeneity of vegetation community types within a terrestrial ecosystem, that is, vegetation community complexity, can mediate its biological processes (e.g., energy harnessing, water and nutrient uptake and cycling) (Bonan, 2008; Davin & Noblet-Ducoudré, 2010; Duveiller et al., 2018; Goodman, 1975), and therefore influences its stability and sustainability to environmental changes (Fornoff et al., 2019; Geng et al., 2019; Goodman, 1975; Ives & Carpenter, 2007; Pennekamp et al., 2018; Pimm, 1984; Schnabel et al., 2019). Revealing factors contributing to vegetation community complexity changes is key to understanding terrestrial ecosystem processes and formulating vegetation management policies (Bryan et al., 2018).

Human actives and global climate change are believed to be two major factors influencing vegetation community complexity changes (Fang et al., 2018; Komatsu et al., 2019), which can both lead to either losses or gains in vegetation community complexity. For example, vegetation community complexity may increase in areas with vegetation restoration and conservation efforts (Bryan et al., 2018; Y. Li et al., 2018; Piao et al., 2015; Strassburg et al., 2017), while decrease in areas with resource overexploitation (e.g., mining, farming, and grazing activities, which may eliminate vegetation coverage or alter vegetation community type) (Fang et al., 2018; Hou et al., 2019; Tian et al., 2014; Y. Wang et al., 2020). Similarly, global climate change may increase vegetation community complexity in areas with extended growing season length (Fang et al., 2004; Fridley et al., 2016; Jeong et al., 2011), while reduce it in areas with an increasing frequency of extreme climate events (e.g., droughts, floods) (Bronstert, 2003; Fettig et al., 2019; Sankaran, 2019).

China, as a country with the world's sixth-largest vegetated area (Chen et al., 2019), has undergone dramatic changes in vegetation distribution and composition during the past 30 years (Su et al., 2020; Zhu et al., 2016). It is reported that China alone accounts for 25% of global anthropogenic vegetation greening since 2000 (including both cultivated greening and reforestation) (Chen et al., 2019), and over 40% of China's vegetated areas have experienced changes in vegetation type due to intensive human activities and unprecedented climate change (Fang et al., 2004; Gao et al., 2019; Su et al., 2020). These changes may alter the complexity of vegetation communities in China's terrestrial ecosystems, and influence their capability of sequestering atmospheric CO_2 to mitigate global warming (Fang et al., 2018; Huang et al., 2018; X. Tang et al., 2018). However, it is still unclear how China's vegetation community complexity changed over the past three decades under the coupled influence of human activities and global climate change, which needs to be investigated urgently.

Spatially explicit vegetation maps that provide information at the formation/subformation levels are the foundation for quantifying vegetation community complexity and examining spatial and temporal variations through time. Recent advances in remote sensing and crowdsourcing techniques have enabled researchers to map national scale vegetation types with high accuracy and efficiency (Su et al., 2016, 2020). We updated the vegetation map of China for the year 2015 using a strategy of "crowdsourcing-change detection-classification-expert knowledge" (Su et al., 2020). By comparing it with the original vegetation map of China from the 1980s (X. Zhang

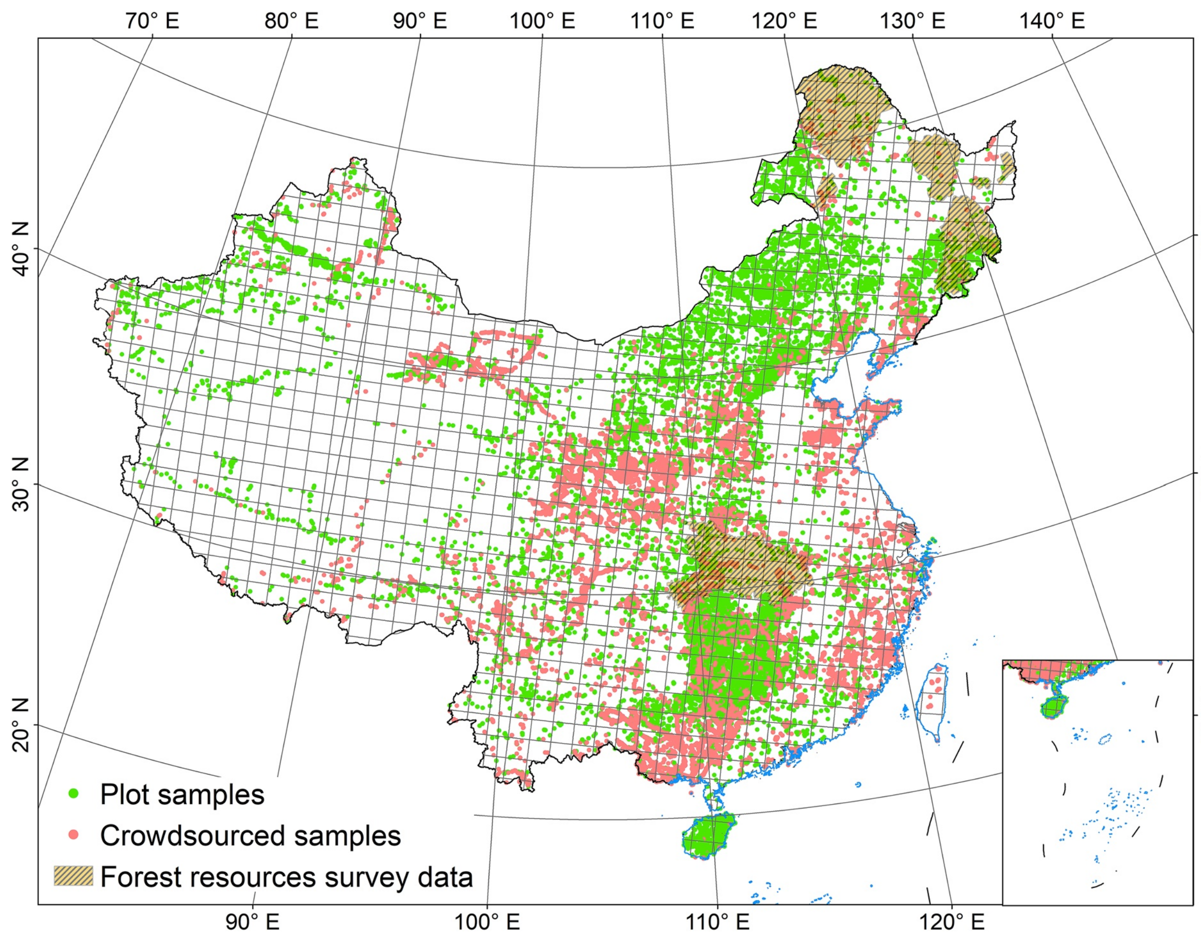

Figure 1. Distribution of field data used in this study. Both point-based field samples (plot and crowdsourced samples) and polygon-based forest resources survey data were collected. Each gray square cell in the background (100 × 100 km in area) represents a unit area used for calculating vegetation community complexity.

et al., 2007), we are able, for the first time, to investigate spatial patterns and temporal changes of China's vegetation community complexity.

Specifically, here we aim to address the following questions. How is vegetation community complexity spatially distributed across China, and what factors influence its spatial distribution? How has China's vegetation community complexity changed from the 1980s to 2015, and how do human activities and changes in climate contribute to changes in vegetation community complexity? A total of 523,398 field samples across China and 547,000 km^2 forest resources survey data were collected to quantify and validate vegetation community complexity along with the two vegetation maps of China. Two terrain variables (terrain elevation and terrain roughness), two climate variables (mean annual temperature [MAT] and mean annual precipitation [MAP]), two anthropogenic variables (gross domestic product [GDP] and human modification index [HMI]), and the annual maximum-value composite (MVC) of normalized difference vegetation index (NDVI) were derived to analyze factors influencing the spatial and temporal variations of China's vegetation community complexity during the past 30 years.

2. Materials and Methods

2.1. Field Data

We collected two types of field data: point-based field samples and polygon-based forest resources survey data to evaluate the accuracy of vegetation community complexity estimates from vegetation maps (Figure 1). A total of 523,398 point-based samples were collected from three sources, including (a) 228,156 crowdsourced samples taken since 2018 using LiVegetation (a self-developed mobile phone application designed to collect

Table 1
A Summary of the Ancillary Datasets Used in This Study, Including Dataset Name, Year, Spatial Resolution, Derived Factors, and Source

Dataset	Year	Resolution	Factors	Source
Biogeographical region map of China	N/A	Vector	N/A	(Z. Wang et al., 2012)
Corrected Shuttle Radar Topography Mission product	2000	30 m	Terrain elevation, terrain roughness	(Zhao et al., 2018)
Monthly average temperature and monthly total precipitation	1985–2015	0.5°	Mean annual temperature, mean annual precipitation	(Legates & Willmott, 1990a; Legates & Willmott, 1990b; Willmott, 2001)
Global Inventory Monitoring and Modeling System	1985–2015	1/12°	Annual maximum-value composite of normalized difference vegetation index	(Pinzon & Tucker, 2014; Tucker et al., 2005)
Gross domestic production	2015	1 km	Gross domestic production	(Han et al., 2011)
Global human modification index	2015	1 km	Human modification index	(Kennedy et al., 2019)

Note. N/A represents the corresponding information is not available.

crowdsourced field samples for producing vegetation maps) (Jin et al., 2021; Su et al., 2020), (b) 170,172 crowdsourced samples from the Chinese Field Herbarium (CFH) platform collected since 2014 (C. Li, 2018), and (c) 125,070 vegetation plot samples taken since 2010. The two crowdsourced samples recorded the location, sampling time, and vegetation formation/subformation type, and vegetation plot samples recorded all abovementioned information as well as field inventory data. Each point-based sample was manually examined based on the following criteria. They should (a) include vegetation formation/subformation information that can be matched to areas on vegetation maps; and (b) contain a latitude and longitude record accurate to at least three decimal places (approximately equivalent to a 100 m georeferencing accuracy). Samples that did not satisfy these criteria were excluded. A total of 230,401 samples were retained for the following analyses. Because only natural vegetation was considered in the calculation of vegetation community complexity, samples with a vegetation group type of cultural vegetation (food and cash crops) were further excluded in the following analyses.

Polygon-based forest resources survey data were distributed in northeast China and Hubei Province across a total area of around 547,000 km^2 (Figure 1). These data, collected since 2015, were a part of the national forest resources survey program and were provided by the National Forestry and Grassland Administration. Each polygon represented a forest stand and provided information about the dominant tree species, which was then matched with the appropriate vegetation formation/subformation type of China's vegetation maps (Su et al., 2020).

2.2. Vegetation Maps of China

In this study, two vegetation maps were used as the foundation to calculate the vegetation community complexity of China and quantify its spatial and temporal changes. The original vegetation map of China (1:1,000,000) (hereafter the original vegetation map) was produced by a team of over 250 scientists and delineated the distribution of 866 vegetation formation/subformation types (which could be grouped into 55 vegetation types/subtypes, and 12 vegetation group types) (X. Zhang et al., 2007). The original vegetation map entirely relied on field surveys, which started in the early 1980s and lasted around 10 years. The updated vegetation map of China (1:1,000,000) (hereafter the updated vegetation map) was produced as an update to the original vegetation map using a strategy called "crowdsourcing-change detection-classification-expert knowledge" (Su et al., 2020). The updated vegetation map used 2015 as the baseline year and utilized the same vegetation formation/subformation classification system as the original vegetation map. Detailed information on the procedure for producing the updated vegetation map can be found in Su et al. (2020). Similar to field samples, cultural vegetation was excluded from both the original and updated vegetation maps since only natural vegetation was considered in the vegetation community complexity calculation.

2.3. Ancillary Datasets

Six ancillary datasets were assembled to explore factors influencing spatial and temporal variations in China's vegetation community complexity, including China's biogeographical region map, two terrain surfaces, climate surfaces, NDVI, GDP, and HMI (Table 1). The biogeographical region map of China was provided by Z. Wang

10.1029/2021EF002553

et al. (2012), which was a revision of the map published by the Editorial Board for Physical Geography of China (Wu, 1985). This map divided China into seven biogeographical regions: southeast China, the eastern Himalayas, the Tibetan Plateau, north China, the Mongolian Plateau, northeast China, and northwest China, represented by Roman numerals from I to VII, respectively.

Two terrain surfaces, including a digital elevation model (DEM) and terrain roughness, were used in this study. The national DEM of China at 30-m resolution was derived from the corrected Shuttle Radar Topography Mission (SRTM) product (Table 1), which corrected the systematic overestimation bias of the original SRTM product in vegetated areas (Zhao et al., 2018). Terrain roughness was derived from the SRTM DEM and calculated as the standard deviation of elevation in a unit area (100 × 100 km in this study).

Two types of climate surfaces, monthly average temperature (Legates & Willmott, 1990a; Willmott, 2001) and monthly total precipitation (Legates & Willmott, 1990b; Willmott, 2001), were collected for the time period of 1985–2015 to examine trends in climate conditions of China (Table 1). These data were interpolated from a large number of weather station records at a spatial resolution of 0.5° latitude × 0.5° longitude (Legates & Willmott, 1990a, 1990b; Willmott, 2001). We further derived MAT (calculated as the mean of monthly average temperatures of each year) and MAP (calculated as the sum of monthly total precipitations of each year) from the monthly temperature and precipitation data, which were used in the following analyses (Table 1).

NDVI is a remotely sensed parameter that can represent vegetation greenness and physiological status (Gan et al., 2021; Ju & Masek, 2016; Piao et al., 2003). Here, we used the most recent time-series NDVI product (NDVI3g) from the Global Inventory Monitoring and Modeling System (GIMMS) project to evaluate vegetation greenness dynamics during last three decades (Table 1) (Pinzon & Tucker, 2014; Tucker et al., 2005). The GIMMS NDVI product was produced from Advanced Very-High-Resolution Radiometer data at a spatial resolution of 1/12° latitude × 1/12° longitude and a temporal frequency of a half month (Pinzon & Tucker, 2014). In this study, we collected GIMMS NDVI data from 1985 to 2015, and calculated a MVC of NDVI for each year to reduce the influence of cloud contamination and atmospheric attenuation (Table 1) (Su et al., 2017; van Leeuwen et al., 1999).

In addition, the national GDP and HMI were collected to reflect the intensity of human activities and evaluate the influence of human activities on vegetation community complexity changes. Here, a gridded national GDP distribution product from Han et al. (2011) was used (Table 1), which was interpolated from 2015 county-level GDP data created by the National Bureau of Statistics of China using land cover type, nighttime light remote-sensing data, and population density as covariables. HMI is a cumulative measure of human modifications on terrestrial areas by examining 13 anthropogenic stressors covering human settlement, agriculture, transportation, mining and energy production, and electrical infrastructure. In this study, we used the HMI product of the year 2015 from Kennedy et al. (2019), which was provided at 1-km resolution with values ranging from 0 to 1, with 1 representing the largest proportion of a landscape being modified by human activities (Table 1). Because the influence of human activities on vegetation community complexity might be a cumulative effect, especially vegetation conservation and restoration activities, here we used the 2015 GDP and HMI instead of its magnitude of changes during the past 30 years.

As can be seen in Table 1, one of the major limitations of the collected datasets was that they were in different spatial resolutions (except the biogeographical map of China) (Table 1). To be consistent with the calculation procedure of vegetation community complexity, all these datasets were resampled to a spatial resolution of 100 km. Considering the fact that the spatial resolutions of these datasets were all finer than 100 km, the down-sampling procedure should not have a significant influence on the following analyses.

2.4. Calculation of Vegetation Community Complexity

In this study, vegetation community complexity was quantified by Shannon entropy, a commonly used index for indicating the complexity of an ecosystem or landscape (Nagendra, 2002; Peet, 1975; Peters et al., 2019) by examining the appearance probability of each type of individuals composed of the ecosystem or landscape (Shannon, 1948). Here, we calculated the vegetation community complexity, that is, the Shannon entropy, using the following equation,

$$VCC = -\sum_{i=1}^{S} p_i \ln p_i \tag{1}$$

where VCC is the vegetation community complexity, S is the total number of vegetation formation/subformation types in a unit area (defined as a 100 × 100 km cell in Figure 1), and p_i is the probability of appearance of a vegetation formation/subformation in a unit area.

To calculate vegetation community complexity from vegetation maps, the probability of appearance of a vegetation formation/subformation in a unit area was calculated using the following equation,

$$p_i = \frac{A_i}{A} \tag{2}$$

where A_i is the total area of a vegetation formation/subformation in a unit area and A is the area of the unit. Vegetation community complexity estimates were calculated for both the original and updated vegetation maps. The estimate from the original vegetation map was used to represent the spatial pattern of China's vegetation community complexity since it was less disturbed by recent human activities. The difference between estimates from the updated and original vegetation maps was calculated to represent vegetation community complexity change from the 1980s to 2015. Note that units with an area smaller than 1 km^2 were excluded in the calculation of vegetation community complexity.

Moreover, vegetation community complexity from point-based field samples and polygon-based forest resources survey data were also calculated, which were used to evaluate the accuracy of those derived from the updated vegetation map. For point-based field samples, the probability of appearance of a vegetation formation/subformation in a unit area was calculated using the following equation,

$$p_i = \frac{n_i}{N} \tag{3}$$

where n_i is the total number of field samples belonging to a vegetation formation/subformation in a unit area, and N is the total number of field samples in the unit area. For polygon-based forest resources survey data, the probability of appearance of a vegetation formation/subformation in a unit area was calculated using the same equation as that for vegetation maps. Since the forest resources survey data did not include vegetation types beyond forest, the resulting vegetation community complexity might be underestimated.

2.5. Statistical Analyses

The accuracy of vegetation community complexity estimates from vegetation maps was evaluated against those from point-based field samples and polygon-based forest resources survey data. To ensure the representativeness of the field data estimates, we excluded cells with fewer than 2,000 field samples and cells with less than 60% coverage of forest resources survey data. Statistical accuracy was assessed using both coefficient of determination (R^2) and the p-value of each statistical test.

To analyze the factors contributing to spatial and temporal variations in the vegetation community complexity, correlations between the original vegetation community complexity and geolocation, terrain elevation, terrain roughness, MAT, and MAP were evaluated using linear regression analysis for terrestrial ecosystems of entire China as well as those of each biogeographical region. Since terrain elevation, terrain roughness, MAT, and MAP had strong influences on the spatial distribution of China's vegetation community complexity, and terrain elevation and roughness had significant influences on MAT and MAP, we further applied path analysis to describe the directed dependencies among them (Heise, 1975). All variables were normalized between 0 and 1 before being fed into the path analysis model. The path analysis was conducted using the Amos software, and the significance of each path was evaluated at a significance level of 0.05.

The significance of the change in China's vegetation community complexity was assessed using the paired two-tailed Student t-test under the null hypothesis that there were no significant differences between the vegetation community complexity estimates from the original and updated vegetation maps. Three statistical measures were reported in this study: t-value, degree of freedom (DOF), and p-value. If the p-value was less than 0.05, the

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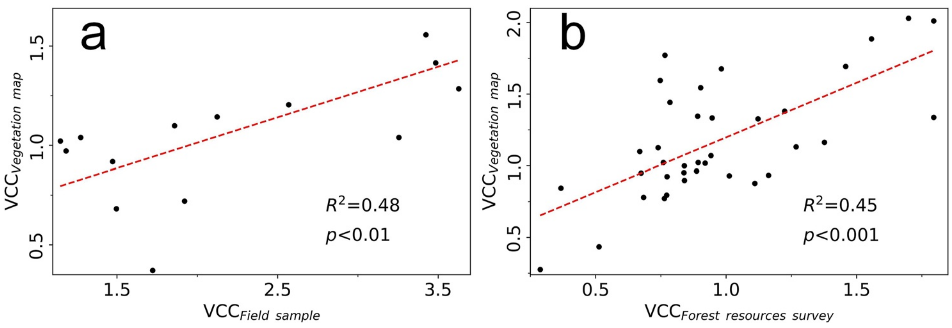

Figure 2. Accuracy assessment of vegetation community complexity (VCC) estimates using vegetation maps. Scatter plots between vegetation community complexity estimates from the updated vegetation map and (a) those from field samples and (b) those from forest resources survey data. Red dashed lines are fitted lines.

null hypothesis was rejected, indicating there was a significant change in China's vegetation community complexity; otherwise, there was no significant change. Temporal trends in MAT, MAP, and NDVI were analyzed using linear regression analysis on each cell. If a cell had a significant linear correlation between a given factor and time (p-value < 0.05), it was recognized as having a significant temporal trend for the corresponding factor. The magnitude of change for the corresponding factor in the cell was calculated as the slope of the linear fit multiplied by the length of the time period. The contribution of climate conditions and human activities to the spatial and temporal changes in China's vegetation community complexity were evaluated using linear regression analysis. Three statistical measures, including slope, Pearson's correlation coefficient, and p-value, were reported. These analyses were conducted for terrestrial ecosystems of entire China and those of each biogeographical region.

3. Results

In this study, both in situ vegetation community complexity estimates (i.e., from field samples and from forest resources survey data) showed good agreements with estimates derived from vegetation maps ($R^2 \geq 0.45$) (Figure 2), indicating vegetation maps are reliable sources for evaluating spatial and temporal variations in China's vegetation community complexity. To explore the spatial patterns and driving factors, we used the vegetation community complexity distribution derived from the original vegetation map of China. The resulting vegetation community complexity reveals large geographical variations across China following a normal distribution (Figures 3a and 3b). There is a weak spatial pattern of increasing complexity from north to south and from east to west (Figure 3a and Figure S1 in Supporting Information S1). Specifically, the eastern Himalayas had the highest average vegetation community complexity, followed by northwest China, the Mongolian Plateau, the Tibetan Plateau, northeast China, southeast China, and north China (Figures 3a and 3c). The vegetation community complexity of the eastern Himalayas, northwestern China, and the Mongolian Plateau was about 44% higher than that of the other four biogeographical regions (Figure 3c). Spatial variation in vegetation community complexity was dominated by variations in terrain, which shows a strong hump-shaped relationship with elevation and a strong linear relationship with terrain roughness (Figures 3d and 3e).

The influence of climate conditions on vegetation community complexity varied by biogeographical regions, although there was an overall decrease in vegetation community complexity as both MAT (Pearson's correlation coefficient (r) = −0.25, $p < 0.05$) and MAP ($r = -0.12$, $p < 0.05$) increased (Figure 4 and Table S1 in Supporting Information S1). MAT had a negative correlation with vegetation community complexity in all biogeographical regions, with the exception of the Tibetan Plateau and northeast China (Figure 4a). This negative correlation was the strongest in north China ($r = -0.78$, $p < 0.05$), followed by northwest China ($r = -0.58$, $p < 0.05$), southeast China ($r = -0.46$, $p < 0.001$), the eastern Himalayas ($r = -0.41$, $p < 0.05$), and the Mongolian Plateau ($r = -0.28$, $p < 0.05$) (Table S1 in Supporting Information S1). The Tibetan Plateau was the only biogeographical region to show a positive correlation between vegetation community complexity and MAT ($r = 0.33$, $p < 0.05$), while northeast China was the only biogeographical region to have no significant correlation between vegetation complexity and MAT (Figure 4a and Table S1 in Supporting Information S1). Correlations for MAP were weaker than those for MAT across China. Three of the seven biogeographical regions (southeast China, the Mongolian Plateau, and northeast China) showed no significant correlation between MAP and vegetation community

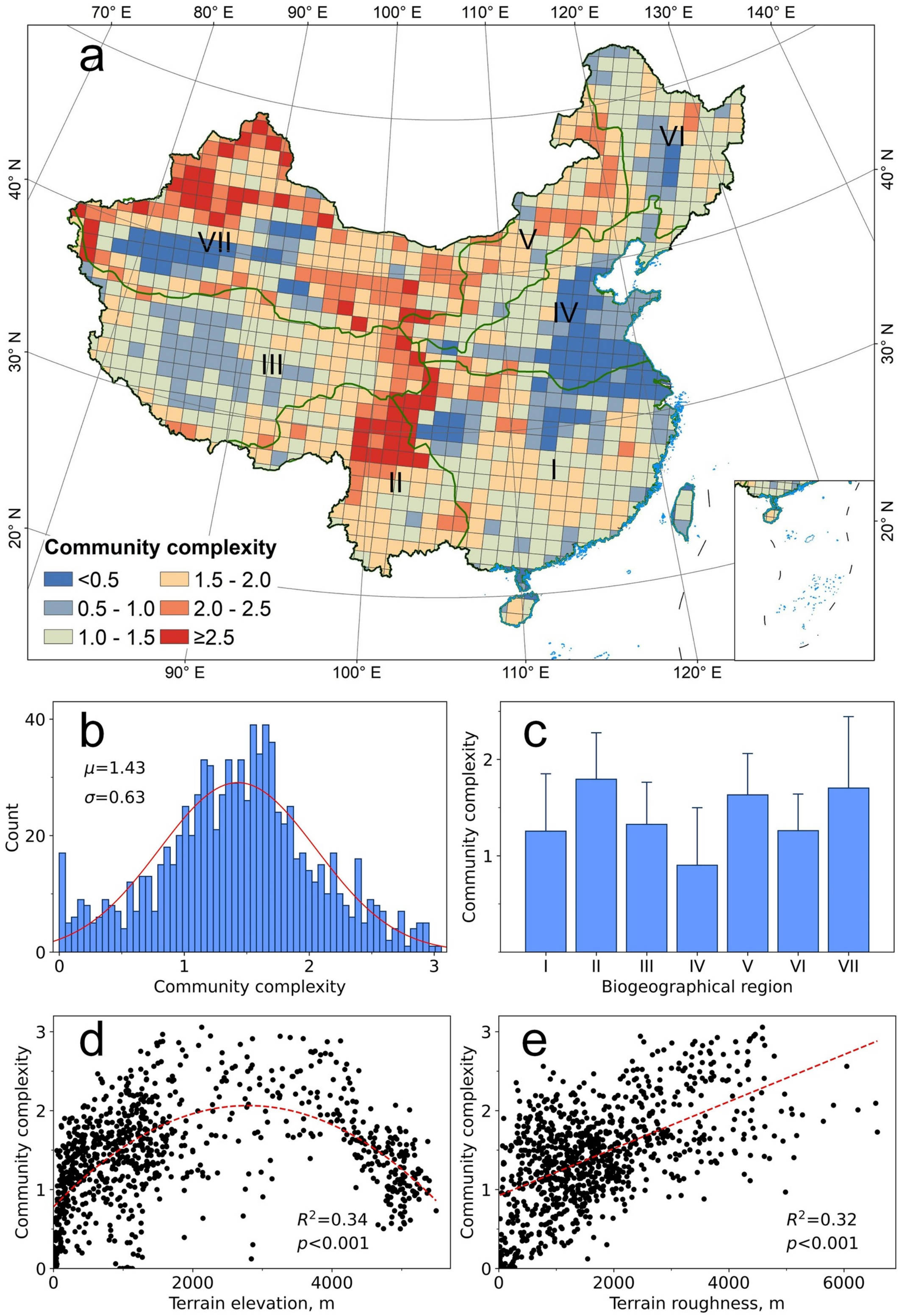
a
b
c
d
e
Community complexity
<0.5
0.5 - 1.0
1.0 - 1.5
1.5 - 2.0
2.0 - 2.5
≥2.5
I
II
III
IV
V
VI
VII
μ=1.43
σ=0.63
Count
Community complexity
Biogeographical region
R²=0.34
p<0.001
Terrain elevation, m
R²=0.32
p<0.001
Terrain roughness, m

Figure 3.

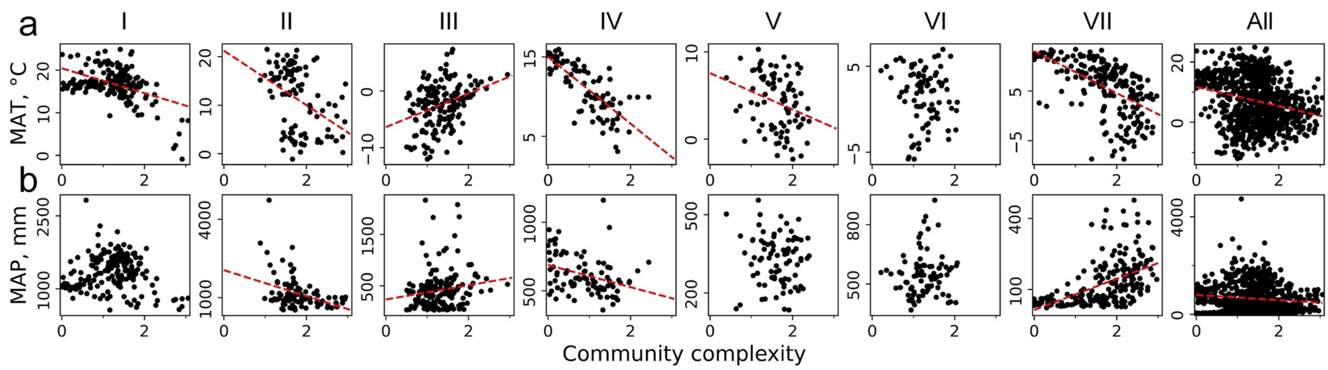

Figure 4. Correlations between vegetation community complexity and climate. Scatter plots between vegetation community complexity and (a) average mean annual temperature (MAT) and (b) average mean annual precipitation (MAP) from 1985 to 2015. All represents data points from all biogeographical regions. Red dashed lines are fitted lines and are presented only if there were significant correlations ($p < 0.05$).

complexity (Figure 4b). As to the remaining four biogeographical regions, vegetation community complexity was negatively correlated with MAP in the eastern Himalayas ($r = -0.38$, $p < 0.05$) and north China ($r = -0.33$, $p < 0.05$), and was positively correlated with MAP in the Tibetan Plateau ($r = 0.16$, $p < 0.05$) and northwest China ($r = 0.50$, $p < 0.05$) (Figure 4b and Table S1 in Supporting Information S1).

Regarding temporal changes, we quantified the change in vegetation community complexity as the difference between estimates from the updated (2015) and original (1980s) vegetation maps. Overall, China's vegetation community complexity decreased slightly (mean = -0.07, $p < 0.05$) during the past 30 years, albeit with large spatial discrepancies (Figures 5a and 5b, and Table S2 in Supporting Information S1). Areas with a negative change in vegetation community complexity were twice as large as those areas demonstrating a positive change, but the absolute change in complexity for 60% of the cells was less than 0.1 (Figure 5a). Nearly 81% of areas having a substantial negative change (<-0.3) occurred in southeast China, the eastern Himalayas, and northwest China. Southeast China alone accounted for half of these changes (Figures 5a and 5c). Northeast China also showed a decreasing trend (Table S2 in Supporting Information S1), but negative changes were largely moderate (>-0.3) (Figures 5a and 5c). Areas connecting the Mongolian Plateau and north China accounted for 34% of the cells with a positive change greater than 0.1 (Figure 5a), although the overall trends for these two biogeographical regions were insignificant (Table S2 in Supporting Information S1). The remaining cells, those with a positive change larger than 0.1, were primarily scattered across southeast China and the Tibetan Plateau (Figure 5a).

Both climatic and anthropogenic factors showed significant correlations with vegetation community complexity change, with the exception of MAP (Figure 6 and Figure S3a in Supporting Information S1). A large proportion of China experienced a significant increase in MAT (Figure S4a in Supporting Information S1), which had a positive effect on vegetation community complexity ($r = 0.15$, $p < 0.001$) (Figure 6a and Table S3 in Supporting Information S1). However, this positive correlation for changes between MAT and vegetation community existed only in southeast China, the Tibetan Plateau, and north China (Figure 6a). In general, human activities had a negative influence on vegetation community complexity, decreasing with both GDP ($r = -0.16$, $p < 0.05$) and HMI ($r = -0.13$, $p < 0.05$) (Figures 6b and 6c and Table S3 in Supporting Information S1). Negative correlations with both GDP and HMI were the strongest in northwest China (GDP: $r = -0.32$, $p < 0.05$; HMI: $r = -0.33$, $p < 0.05$), followed by northeast China (GDP: $r = -0.29$, $p < 0.05$; HMI: $r = -0.32$, $p < 0.05$). Negative correlations with both GDP and HMI were also found in both the eastern Himalayas (GDP: $r = -0.23$, $p < 0.05$; HMI: $r = -0.20$, $p < 0.05$), and north China (GDP: $r = -0.22$, $p < 0.05$; HMI: $r = -0.22$, $p < 0.05$) (Figure 6c and Table S3 in Supporting Information S1). There was no significant correlation with GDP in southeast China, the Mongolian Plateau, or the Tibetan Plateau (Figure 6b and Table S3 in Supporting Information S1). Regarding

Figure 3. Spatial pattern of China's vegetation community complexity. (a) Vegetation community complexity distribution derived from the original 1980s vegetation map of China. Roman numerals I–VII represent the biogeographical regions identified as southeast China, the eastern Himalayas, the Tibetan Plateau, north China, the Mongolian Plateau, northeast China, and northwest China. The Roman numerals representing each biogeographical region will be used in remaining graphs. (b) Histogram of vegetation community complexity, where μ and σ represent mean and standard deviation, respectively. (c) Bar chart of vegetation community complexity (mean + standard deviation) for the seven biogeographical regions. (d) Scatter plot between vegetation community complexity and elevation. (e) Scatter plot between vegetation community complexity and terrain roughness.

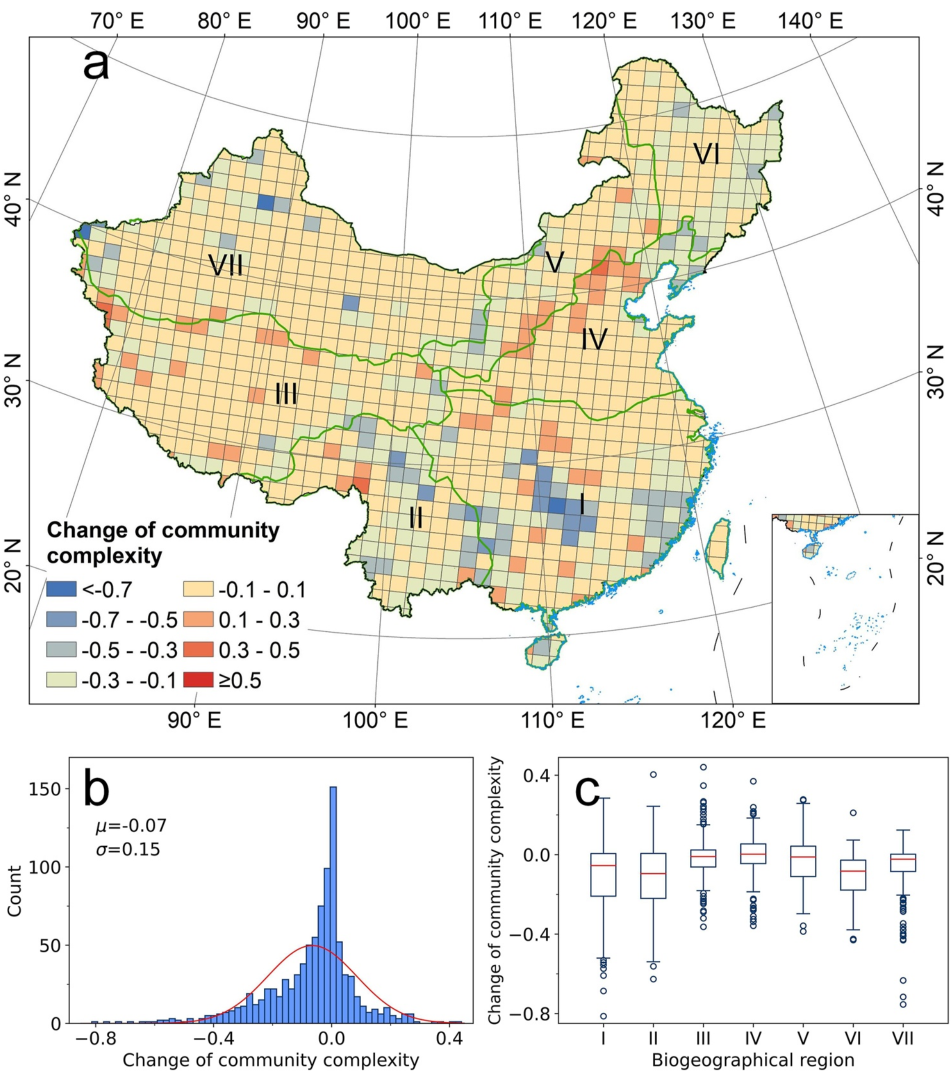

Figure 5. Changes in China's vegetation community complexity from the 1980s to 2015. (a) Map of changes in vegetation community complexity, calculated as the difference between that derived from the updated vegetation map and that derived from the original vegetation map. (b) Histogram of vegetation community complexity change for all regions, where μ and σ represent mean and standard deviation, respectively. (c) Boxplot of vegetation community complexity change for the seven biogeographical regions.

HMI, the Tibetan Plateau showed a negative correlation ($r = -0.17$, $p < 0.05$), while the Mongolian Plateau showed no significant correlation (Figure 6c), and interestingly southeast China showed a positive correlation ($r = 0.19$, $p < 0.05$) (Figure 6c and Table S3 in Supporting Information S1).

4. Discussion

Overall, spatial patterns of China's vegetation community complexity follow the distribution of mountains (Figures 3a and 3e, and Figure S4 in Supporting Information S1). Large variations in local climate brought by steep elevation changes in mountainous areas provide diverse habitats for plant communities (Z. Tang et al., 2006; J.-T. Zhang et al., 2016), where richer vegetation formation/subformation types can develop. The general negative correlations of vegetation community complexity with MAT and MAP may also reflect the controlling effect of elevation since both MAT and MAP have a significant negative correlation with elevation (Figure S4 in Supporting Information S1 and Figure 5). However, climate conditions can outweigh local elevation influences when they become the factors limiting plant growth (Figure 4). For example, the Tibetan Plateau has low MAT and

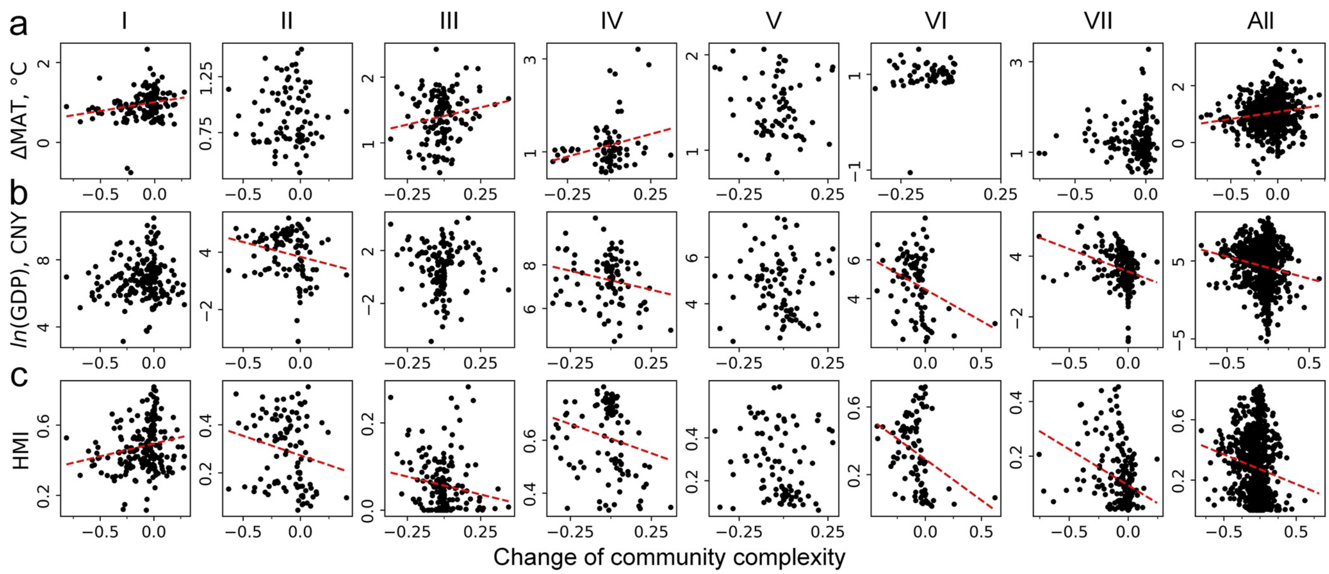

Figure 6. Factors contributing to changes in China's vegetation community complexity. Scatter plots between vegetation community complexity change and (a) MAT change from 1985 to 2015 (ΔMAT), (b) 2015 gross domestic productivity (GDP, natural logarithm transformed), and (c) 2015 human modification index (HMI). All includes data points from all biogeographical regions. Red dashed lines are fitted lines and are presented only if there were significant correlations ($p < 0.05$).

MAP due to its high elevation and the blocking effect of the Hengduan and Himalayan Mountains to the east and south Asian monsoons (Stokstad, 2020; D. Zhang et al., 2000), preventing the formation of complex vegetation communities (Figure 3a). As a result, increases in MAT and MAP in this region may have a more prominent effect on increasing vegetation community complexity (Figure 4). In northwest China, precipitation is the major limiting factor for plant growth (mean MAP = 126 mm) (X. Li et al., 2011). Increases in MAP can support the formation of more complex vegetation communities (Du et al., 2015; Y. Liu et al., 2018), correspondingly raising the vegetation community complexity (Figure 4b). The dominated vegetation types of a region also have influence on the spatial distribution of vegetation community complexity. In northeast China, southeast China, and the eastern Himalayas, high vegetation community complexity cells are mainly contributed by woody plants, while the high vegetation community complexity cells in the Mongolian Plateau, the Tibetan Plateau, and northwest China are mainly contributed by herbaceous plants (Figure S6 in Supporting Information S1). Herbaceous plants have a generally higher vegetation community complexity than woody plants (Lu et al., 2018; Su et al., 2020), which may lead to the relatively high vegetation community complexity in northwest China and the Mongolian Plateau (Figure 3 and Figure S6 in Supporting Information S1).

A vegetation greening trend (increasing NDVI through time) in areas beyond northwest China during the past 30 years was observed in this study (Figure S3c in Supporting Information S1), which is similar to findings in previous studies (Chen et al., 2019; Piao et al., 2015; Zhu et al., 2016). However, vegetation greening does not necessarily correspond to an increase in vegetation community complexity (Figure S2b in Supporting Information S1). Instead, a significant decreasing trend in vegetation community complexity was observed in this study (Figures 5a and 5b and Table S2 in Supporting Information S1). Prevailing climate warming is also an important factor mediating vegetation community complexity (Figure 6a and Figure S3a in Supporting Information S1). In areas with high elevation, temperature is a major factor limiting plant growth (Barber et al., 2000; Körner & Paulsen, 2004), and increasing MAT may provide a more conducive environment for plant growth (e.g., increased vegetation coverage in grasslands and alpine ecosystems in the Tibetan Plateau and northwest China) (Figure S4c in Supporting Information S1), which therefore may increase vegetation community complexity or reduce vegetation community complexity loss (Figure 5a). On the other hand, the contribution of MAP to vegetation community complexity was insignificant and might be caused by the fact that very few cells were observed with significant trends in MAP over the past 30 years (Figure S2a in Supporting Information S1 and Figure 3b). Nevertheless, with the increased frequency of extreme weather events (e.g., drought, flood) being reported (Cai et al., 2014; Coumou & Rahmstorf, 2012), we should not overlook its potential influence on vegetation community complexity.

Human activities can alter vegetation distribution and composition through deforestation, grazing, cultivation, mining, etc. (Figure S7 in Supporting Information S1). With the aim of increasing GDP and improving quality of life, such activities generally have negative influences on vegetation community complexity (Figures 6b and 6c). For example, in the eastern Himalayas, net losses in forest and grassland cover were observed (Figure S7a and c in Supporting Information S1), possibly caused by deforestation and overgrazing; on the Mongolian Plateau, net losses in grasslands were observed (Figure S7c in Supporting Information S1), possibly the result of overgrazing and mining (Tao et al., 2015; Z. Wang et al., 2017); and in northeast China, net losses in forest and shrub were observed (Figure S7a and b in Supporting Information S1), possibly caused by the expansion of cultural lands (Figure S7d in Supporting Information S1). Moreover, in the eastern Himalayas and Mongolian Plateau, widespread shrub encroachments were also observed (Figure S7b in Supporting Information S1), which might be a coupled effect from human activities (losses in grassland and forest) and climate warming (D'Odorico et al., 2010; Thomson et al., 2018). All of these changes tend to simplify vegetation community composition, and therefore reduce vegetation community complexity (Figure S8 and Table S4 in Supporting Information S1).

However, vegetation conservation and restoration efforts with proper polices can maintain or even increase vegetation community complexity. China has made aggressive efforts to rehabilitate vegetation and combat desertification in the Mongolian Plateau, north China, and south China, through projects such as the Three-North Shelter Forest Program and Grain for Green Project (J. Liu et al., 2008). In the Mongolian Plateau and north China, such efforts have significantly decreased the cumulative area associated with cultural vegetation and increased forested areas (Figure S7a and d in Supporting Information S1), leading them to have some of the most clustered areas showing significant increases in vegetation community complexity (Figure 5a). Human activities have a more profound influence on vegetation community complexity in southeast China. Two of China's economic centers (Yangtze Delta and Guangdong Province) have led a rapid expansion of GDP in this region (Hu & Wang, 2006), which comes partially at the cost of overexploitation of vegetation resources, thereby reducing overall vegetation community complexity (Figure 5a and Table S2 in Supporting Information S1) (Du et al., 2019; Seto et al., 2012). Meanwhile, in these economic centers, the importance of vegetation conservation was recognized early on, and vegetation composition has remained relatively stable (Figure S7 in Supporting Information S1). This recognition might explain how HMI significantly reduces potential decreases in vegetation community complexity (Figure 6c). Recently, afforestation efforts have begun in other areas of the region (Figure S7a in Supporting Information S1), but the uniform tree species compositions used have not yet improved vegetation community complexity (Figure S8a and Table S4 in Supporting Information S1) (Cao et al., 2011; Chazdon, 2008; Lautenbach et al., 2017).

5. Conclusions

In summary, this study reveals spatial patterns in China's vegetation composition complexity, and highlights a significant decreasing trend in complexity during the past 30 years despite observable vegetation greening. Both climate warming and human activity intensity can mediate changes to vegetation composition complexity, and our findings suggest that properly designed vegetation conservation and restoration efforts can have a positive effect on maintaining vegetation composition complexity. Nevertheless, there is still debate regarding the complexity–stability relationship (Allesina & Tang, 2012; Goodman, 1975; Grilli et al., 2017; Ives & Carpenter, 2007; Loreau & Mazancourt, 2013; McCann, 2000; Mougi & Kondoh, 2012; Pimm, 1984). How changes in vegetation composition complexity affect the resilience of terrestrial ecosystems to changing climate, and therefore the global carbon cycle, needs further investigations. Moreover, we still lack a complete understanding how plant species composition changes (e.g., native vs. invasive plant species) may influence vegetation community complexity, which needs further investigations as well.

Data Availability Statement

The data used to analyze the spatial pattern and temporal changes of China's vegetation community complexity is accessible here: https://doi.org/10.6084/m9.figshare.14511630.

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