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Spatiotemporal Distribution of the Impact of Climate Change and Human Activities on NDVI in China

Czasoprzestrzenny rozkład wpływu zmian klimatycznych i działalności człowieka na NDVI w Chinach

Shuyi Dong[1], Wen Zhuang[2], Shuting Zhang[3], Shanshan Xie[4*]

Minnan University of Science and Technology, School of Information Management, No. 1, Longjing Road, 362000, Quanzhou, China
[1]E-Mail: 2480544557@qq.com, ORCID: 0009-0002-0507-1695
[2]E-Mail: 2976047040@qq.com
[3]E-Mail: 2944821173@qq.com
[4]E-Mail (Correspondence Author): 18059722003@163.com*

Abstract

The Normalized Difference Vegetation Index (NDVI) is a vital metric for assessing surface vegetation cover and productivity, and plays a significant role in monitoring environmental changes and ecological health. This study utilizes the Geographically Weighted Temporal Regression (GTWR) model and high-resolution remote sensing data to analyze NDVI fluctuations across mainland China from 2001 to 2020. The objectives are to elucidate the mechanisms by which climate change and human activities influence vegetation dynamics. The main findings are as follows: (1) NDVI fluctuations are significantly correlated with climatic factors such as precipitation, sunlight duration, and average temperature. These correlations reveal how climate conditions affect vegetation dynamics. (2) Human activities, particularly urban expansion, also impact NDVI changes. The study highlights how these activities contribute to variations in vegetation cover and productivity. (3) The analysis identifies distinct regional and seasonal patterns in NDVI changes, demonstrating significant spatiotemporal heterogeneity across mainland China. (4) The results enhance scientific understanding of vegetation change trends in China and provide a basis for developing targeted ecological protection measures and sustainable development policies.

Key words: Normalized Difference Vegetation Index, NDVI, Geographically Weighted Temporal Regression, GTWR, climate change, human activities

Streszczenie

Znormalizowany wskaźnik różnicowy roślinności (NDVI) jest istotnym wskaźnikiem oceny pokrycia powierzchni roślinnością i jej produktywności, a także odgrywa znaczącą rolę w monitorowaniu zmian środowiskowych i zdrowia ekologicznego. W badaniu tym wykorzystano model regresji czasowej ważonej geograficznie (GTWR) oraz dane teledetekcyjne o wysokiej rozdzielczości do analizy wahań NDVI w Chinach kontynentalnych w latach 2001-2020. Celem jest wyjaśnienie mechanizmów, za pomocą których zmiany klimatu i działalność człowieka wpływają na dynamikę roślinności. Główne ustalenia są następujące: (1) Wahania NDVI są istotnie skorelowane z czynnikami klimatycznymi, takimi jak opady, czas trwania nasłonecznienia i średnia temperatura. Te korelacje ujawniają, w jaki sposób warunki klimatyczne wpływają na dynamikę roślinności. (2) Działalność człowieka, w szczególności ekspansja miejska, również wpływa na zmiany NDVI. Badanie podkreśla, w jaki sposób te działania przyczyniają się do zmian pokrycia powierzchni roślinnością i jej produktywności. (3) Analiza identyfikuje odrębne regionalne i sezonowe wzorce zmian NDVI, wykazując znaczną heterogeniczność czasoprzestrzenną w Chinach kontynentalnych. (4) Wyniki te poszerzają wiedzę naukową na temat tendencji zmian roślinności w Chinach i stanowią podstawę do opracowywania ukierunkowanych środków ochrony ekologicznej i polityk zrównoważonego rozwoju.

Słowa kluczowe: Znormalizowany Wskaźnik Zróżnicowania Wegetacji, NDVI, Geograficznie Ważona Regresja Czasowa, GTWR, zmiana klimatu, działalność człowieka

1. Introduction

The Normalized Difference Vegetation Index (NDVI) is a crucial indicator of vegetation cover, extensively used to monitor vegetation growth conditions on both global and regional scales. As one of the most populous and ecologically diverse countries in the world, China's NDVI variations are of significant importance for assessing ecological and environmental quality, predicting climate change trends, and formulating sustainable development policies. In recent years, with the intensification of global climate change and increasingly frequent human activities, the trends in China's NDVI variations have also shown complexity and diversity.

Climate change is one of the key factors influencing NDVI variations. Climatic factors such as precipitation, sunlight, and temperature directly affect vegetation growth and distribution. Increased precipitation can provide sufficient water for vegetation, promoting growth; appropriate sunlight exposure is conducive to photosynthesis, enhancing vegetation productivity. However, extreme climate events such as droughts, floods, and high temperatures can adversely affect vegetation, reducing NDVI values. Therefore, an in-depth exploration of the impact of climate change on NDVI variations in China is significant for understanding its mechanisms, predicting future trends, and formulating response measures. Liu et al. (2021) utilized remote sensing technology to analyze NDVI and Standardized Precipitation-Evapotranspiration Index (SPEI) data from 1998 to 2017 in China. The results indicated a growth rate of NDVI in China of 0.003 year^{-1}, with improved and degraded vegetation regions accounting for 71.02% and 22.97% of the national territory, respectively. The study found that climate change and human activities significantly influenced NDVI variations, with their impact decreasing as elevation and slope increased.

In addition to climate change, human activities are also significant factors affecting NDVI variations. Agricultural development, urbanization, and deforestation can all impact vegetation cover and NDVI values. Agricultural development changes land use types, affecting vegetation cover and growth; urbanization leads to the loss of large areas of natural vegetation, reducing NDVI values; deforestation directly decreases the quantity and coverage of vegetation. The impacts of these human activities may vary by region and over time, necessitating in-depth research using spatial and temporal heterogeneity analysis methods. Chang et al. (2022) studied the spatiotemporal characteristics of NDVI in China from 1998 to 2019, finding a significant positive correlation between NDVI and temperature in the southeastern coastal areas and northern Qinghai-Tibet Plateau. Precipitation was identified as the main factor influencing vegetation dynamics, and ecological engineering projects significantly improved vegetation conditions. Pu et al. (2022) analyzed the NDVI trends in the Giant Panda National Park from 2000 to 2020 and found an overall upward trend with an annual growth rate of 4.7%. Natural factors such as climate and altitude were identified as the primary influencing factors, and the Wenchuan earthquake had a significant impact on NDVI values. Yin et al. (2023) studied vegetation cover changes in the central and southern mountainous and hilly regions of Shandong Province from 1905 to 2020, finding that precipitation was the main factor affecting vegetation cover. However, human activities, especially in recent decades, also played a significant role in the changes in vegetation cover. Li et al. (2024) examined NDVI variations in the Shiyang River Basin from 1990 to 2020, using trend analysis, partial correlation, and residual analysis to determine the impacts of climate change and human activities. The results indicated an upward trend in NDVI, with significant correlations between NDVI and deviations in precipitation and temperature. Changes in land use and groundwater depth also influenced NDVI.

Geographically and Temporally Weighted Regression (GTWR) is an innovative method for spatiotemporal data analysis that effectively considers spatial heterogeneity and temporal non-stationarity. GTWR has shown significant advantages in studying the impacts of climate change and human activities on NDVI. This study applies the GTWR model, combined with multi-year climatic and human activity data, to comprehensively analyze the spatiotemporal distribution of NDVI variations in China and their influencing factors. By constructing the GTWR model, this paper aims to reveal the mechanisms by which climate change and human activities influence NDVI variations in China, providing scientific evidence for the formulation of effective ecological protection and sustainable development policies. The GTWR model has been successfully applied in various fields, such as the analysis of atmospheric CO_2 concentration changes Chen et al.(2024), COVID-19 epidemiological research Sifriyani et al. (2022), and the spatiotemporal analysis of soil Cd pollution Zhao et al. (2023).

2. Literature review

2.1. Scientific significance of NDVI

The Normalized Difference Vegetation Index (NDVI), a widely used vegetation parameter in remote sensing monitoring, has become an essential tool for assessing surface vegetation cover and growth conditions. Through NDVI monitoring, we can effectively understand the growth cycles, spatial distribution, and dynamic changes of vegetation, providing crucial data support for ecosystem assessment, environmental monitoring, agricultural management, and other fields. In ecological research, NDVI is commonly used to analyze the spatial patterns of vegetation, the structure and function of ecosystems, and biodiversity conservation.

Xu et al. (2022) utilized bibliometric methods to analyze NDVI research from 1985 to 2021, revealing exponential growth and diversification trends in NDVI studies, emphasizing its role in the diversification of remote sensing data sources. Fan et al. (2023) studied the spatial patterns and dynamic changes of NDVI on the northern slope of the Tianshan Mountains, verifying its consistency across different spatial scales and demonstrating its applicability over long time scales. Zhang et al. (2023) explored the spatiotemporal evolution of NDVI in Northwest China, highlighting NDVI's importance in assessing ecosystem health and environmental changes. Shrestha et al. (2024) analyzed the spatiotemporal changes of NDVI in Nepal, proving NDVI's broad applicability in diverse terrains and providing important ecological management data. Liu et al. (2021) demonstrated the value of NDVI in large-scale ecological monitoring through the study of spatiotemporal changes in NDVI in China. Zhang et al. (2023) examined NDVI changes in the Ordos and eastern Alxa regions, further proving NDVI's critical role in regional ecological research. Pettorelli (2013) reviewed the extensive applications of NDVI in ecological and environmental research, emphasizing its central role in monitoring vegetation health and predicting environmental disturbances. Jespersen et al. (2021) studied NDVI changes in the moist acidic tundra of Alaska, revealing its significant importance in understanding ecosystem functions and predicting environmental changes.

2.2. Factors influencing NDVI

The fluctuations in the Normalized Difference Vegetation Index (NDVI) result from the combined effects of various factors, with climate change and human activities being the most critical. Climate change significantly impacts vegetation growth and distribution by affecting meteorological factors such as temperature and precipitation. Human activities impact NDVI primarily through land use/cover changes, agricultural activities, and mining activities.

- **Impact of Climate Change on Vegetation**: Liu, Y., et al. (2022) explore the biophysical impacts of vegetation dynamics on NDVI changes in High Mountain Asia, emphasizing the complex relationship between vegetation and environmental factors. Additionally, Xie and Fan (2021) derived drought indices from MODIS NDVI/EVI data and evaluated the effectiveness of various reconstruction methods in the Lancang-Mekong River Basin, emphasizing NDVI's role in accurately reflecting drought severity and distribution.. Moreover, Liu, Q., et al. (2016) investigated NDVI-based vegetation dynamics and their response to recent climate changes in the Tianshan Mountains, showing significant correlations between vegetation activity and climate factors.
- **Impact of Human Activities**: Zhang, Y., et al. (2023) used the geographical detector method to quantitatively analyze the main factors influencing NDVI in the Chengdu-Chongqing region, China, revealing different impacts of climate and human activities on vegetation changes. Furthermore, Zhang, H., et al. (2024) analyzed NDVI dynamics in the Ferghana Basin, showing that both climate change and human activities significantly influenced vegetation cover, with human activities contributing 93.29% to NDVI increases. Guo, L., et al. (2024) used Geographically and Temporally Weighted Regression (GTWR) to analyze the impact of human activities on vegetation restoration in Shangwan Mine, China. The study found that human activities have increasingly contributed to vegetation recovery, surpassing climatic factors since 2010. Liu, Y., et al. (2021) studied the spatiotemporal changes in NDVI in China from 1998 to 2017, finding that climate change and human activities significantly influenced vegetation. Human activities both restored and degraded vegetation, with the impact decreasing at higher elevations.
- Combined Impact of Climate Change and Human Activities: Ren et al. (2023) investigated the changes in vegetation NDVI in Jilin Province from 1998 to 2020, finding that both climate change and human activities jointly influenced the dynamic changes in NDVI, with human activities contributing slightly more than climate change. Yin et al. (2023) analyzed the correlation between tree rings, NDVI, and climate factors in the mountainous and hilly areas of Central South Shandong Province. The results indicated a significant positive correlation between tree-ring width and summer NDVI, suggesting that common climatic factors control both.

3. Research design

3.1. Definition of variables

Socio-economic development and environmental monitoring are both important elements of the United Nations Sustainable Development Goals (SDGs). NDVI, or Normalized Difference Vegetation Index, is a crucial indicator widely used in remote sensing to monitor vegetation cover and growth conditions. The China Ecological Environment Status Bulletin (2022) has pointed out the significance of tracking vegetation dynamics as part of ecological and environmental health assessments. This study uses NDVI as the primary metric to measure vegetation changes, implying that higher NDVI values indicate healthier and denser vegetation cover. Based on the SDGs, key variables include temperature (TEMP), average annual temperature in degrees Celsius, which significantly influences vegetation growth and health. Chang et al. (2022) found a positive correlation between temperature and NDVI in southeast China and the north Qinghai-Tibet Plateau. Precipitation (PREC), the total annual precipitation in millimeters, is another critical variable, with Yuan et al. (2015) found that precipitation intensity significantly affects

NDVI changes in grasslands across northern China, with grassland NDVI being more sensitive to heavy precipitation, especially in arid and semi-arid regions. Land Surface Temperature (LST) also plays a crucial role; higher temperatures negatively affect NDVI, as demonstrated by Hussain et al. (2023) in the Sahiwal region of Pakistan. Land Use/Land Cover (LULC) changes, encompassing urbanization and agricultural activities, are pivotal human activity indicators impacting NDVI. Wu et al. (2023) showed that urbanization significantly influences NDVI trends in the Miaoling Karst Mountain area. Lu et al. (2019) analyzed the vegetation cover in Inner Mongolia's grasslands and found that sunshine duration, along with temperature and precipitation, jointly affects NDVI. These variables collectively provide a comprehensive framework for analyzing the spatiotemporal impacts of climate change and human activities on NDVI in China. The variables are shown in Table 1.

Table 1. NDVI and influencing factor variables, source: own elaboration

Variables	Units	Definition
NDVI	Index	Normalized Difference Vegetation Index
PREC	mm	Amount of precipitation
TEMP	°C	Air temperature
SUN	hours	Duration of sunshine
BUILT	km²	Area of built-up regions

Table 2 shows the sustainable development goals to which the variables correspond. As shown in Table 2, the indicators selected herein capture the content of the United Nations SDGs. For example, PREC corresponds to Clean water and sanitation (Goal 6) and Climate action (Goal 13). Adequate and well-distributed precipitation is crucial for maintaining water resources, which directly impacts human health and agriculture. The United Nations has proposed in SDGs to improve water quality by reducing pollution and to increase water-use efficiency to ensure sustainable water availability by 2030.SUN corresponds to Affordable and clean energy (Goal 7) and Life on land (Goal 15). Solar energy is a renewable resource that can significantly contribute to reducing greenhouse gas emissions and mitigating climate change. Goal 7 calls for substantial increases in the share of renewable energy in the global energy mix. Additionally, adequate sunshine duration supports the health of ecosystems, which is essential for biodiversity and the well-being of terrestrial ecosystems as highlighted in Goal 15.TEMP corresponds to Good health and well-being (Goal 3) and Climate action (Goal 13). Extreme temperatures, both high and low, have significant impacts on human health, agriculture, and biodiversity. Goal 3 aims to reduce the number of deaths and illnesses caused by environmental pollution and climatic extremes by 2030. Goal 13 emphasizes the need for urgent action to combat climate change and its impacts by regulating emissions and promoting climate resilience. BUILT corresponds to Sustainable cities and communities (Goal 11) and Industry, innovation, and infrastructure (Goal 9). The expansion of built-up areas is associated with urbanization and industrial development. Goal 11 aims to make cities inclusive, safe, resilient, and sustainable by improving urban planning and management. Goal 9 focuses on building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation. Properly managed urban expansion can mitigate the adverse effects of rapid urbanization, such as pollution and inadequate infrastructure.

Table 2. Variables and Sustainable Development Goals, source: own elaboration

Variables	Sustainable Development Goals
PREC	Clean water and sanitation (Goal 6)
	Climate action (Goal 13)
TEMP	Good health and well-being (Goal 3)
	Climate action (Goal 13)
SUN	Affordable and clean energy (Goal 7)
	Life on land (Goal 15)
BUILT	Sustainable cities and communities (Goal 11)
	Industry, innovation, and infrastructure (Goal 9)

The descriptive statistics of the variables are shown in Table 3. As can be seen from Table 3, NDVI values range from 0.10 to 0.72, with an average value of 0.46.

Table 3. Descriptive statistics of the initial indicators by provinces, source: own elaboration

Variables	Min	Q1	Median	Mean	Q3	Max
NDVI	0.10	0.38	0.46	0.46	0.60	0.72
PREC	0.58	1.61	2.50	2.88	4.09	6.45
TEMP	2.58	9.70	14.80	13.75	17.38	25.84
SUN	989.90	1704.99	2075.01	2086.60	2514.43	3150.88
BUILT	63.00	666.25	1179.00	1394.96	1713.00	6501.00

3.2. Research methodologies

3.2.1. Trend analysis

In this study, the annual change rates of NDVI and other climatic factors were calculated using the linear trend analysis method. This method is based on a linear regression model that estimates the annual change slope of NDVI and other climatic factors, thereby assessing the rate of change of each variable over time. Taking NDVI as an example, the calculation formula is as follows:

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

In the formula,i represents the year,n is the total number of years during the study period, and $NDVI_i$ is the NDVI value for the $i-th$ year. The calculated slope directly shows the magnitude of change for each climatic factor. A positive slope indicates an increasing trend in NDVI, while a negative slope indicates a decreasing trend. The absolute value of the slope represents the rate of change.

3.2.2. Spatiotemporal heterogeneity analysis

This study employs the Geographically and Temporally Weighted Regression (GTWR) model to explore the spatiotemporal heterogeneity of the impacts of climate change and human activities on NDVI. Existing literature typically utilizes Geographically Weighted Regression (GWR) and Temporally Weighted Regression (TWR) to address spatiotemporal heterogeneity issues. However, these two methods cannot simultaneously analyze spatiotemporal heterogeneity. Huang et al. (2010) proposed the GTWR model, which is an improvement over the GWR and TWR models, utilizing panel data regression. Bai et al. (2016) demonstrated in regression analysis that the GTWR method is superior to GWR. The calculation formula for GTWR is as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p}\beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \quad (2)$$

In the formula,u_i and v_i represent the longitude and latitude coordinates of the observation point, respectively; u_i, v_i, t_i is the space-time coordinates of the $i-th$ sample point; β_0 is the regression constant of sample point i, that is, the constant term of the GTWR; β_k is the $k-th$ regression parameter of point i, and x_{ik} is the value of independent variable x_k at point i, that is, the value of each explanatory variable in the GTWR model.

3.3. Overview of the study area

3.3.1. Selection of the study area and its representativeness

The study area for this research is China's administrative divisions. According to the National Bureau of Statistics, China's 34 provincial-level administrative units can be divided into five regions: the East, Central, West, Northeast, and Hong Kong-Macao-Taiwan. Due to missing data in some regions, the study area is limited to mainland China, excluding Hong Kong, Macao, and Taiwan. Mainland China spans a wide range of latitudes, stretching from Mohe in the north to Hainan Island in the south, and includes temperate, subtropical, and some tropical climate zones. The diverse climatic zones and varied topography (such as vast plains, continuous mountain ranges, and plateaus) provide a unique natural and geographical context for this study on vegetation changes.

Moreover, this area is characterized by complex ecosystems, with densely populated cities coexisting with vast agricultural lands. The rapid economic growth and urbanization process have significantly impacted vegetation cover through human activities such as urban expansion, industrial production, agricultural cultivation, and forestry development. Therefore, mainland China serves as a typical example for studying vegetation dynamics under global environmental changes and is an ideal experimental field for exploring the impacts of climate change and human activities on vegetation change.

3.3.2. Explanation of the study period and its representativeness

Analysis of Remote Sensing Data Availability: With the rapid development of satellite remote sensing technology, the MODIS (Moderate Resolution Imaging Spectroradiometer) satellite has been providing high-quality NDVI data since 2001. The temporal and spatial resolutions of these data meet the requirements of this study.

Key Period for Climate Change: The early 21st century marks a significant phase of accelerated global climate change. During this period, mainland China experienced notable climate fluctuations, including extreme weather events and seasonal climate pattern changes, providing valuable empirical data for studying climate impacts.

Critical Period for Socioeconomic Development: During this time, China's rapid economic growth, urbanization, and industrialization significantly influenced land use and vegetation cover. Additionally, government policies such as the Grain for Green Program and the construction of an ecological civilization effectively promoted vegetation restoration.

Data Consistency and Comparability: By selecting a continuous 20-year period, the study's results become more comparable, facilitating the exploration of long-term trends and cyclical patterns in vegetation changes.

Within this timeframe, a comprehensive analysis of the impacts of climate change and human activities on vegetation NDVI can deepen the understanding of historical dynamics and current conditions of vegetation. This, in turn, aids in predicting future trends and provides a theoretical basis for formulating relevant ecological protection policies.

3.4. Data sources

This study provides a detailed analysis of the changes in the Normalized Difference Vegetation Index (NDVI) in mainland China from 2001 to 2020, examining its interactions with climate change and human activities. Various data sources were used for the analysis, with specific details on their origins and preprocessing methods described below:

- NDVI

Source: The NDVI data were obtained from NASA's Earthdata platform (https://search.earthdata.nasa.gov/search).
Preprocessing: The raw NDVI raster data from the MODIS satellite were processed using raster calculation tools. The average raster values for each province in mainland China were computed to obtain the monthly NDVI values for each province.

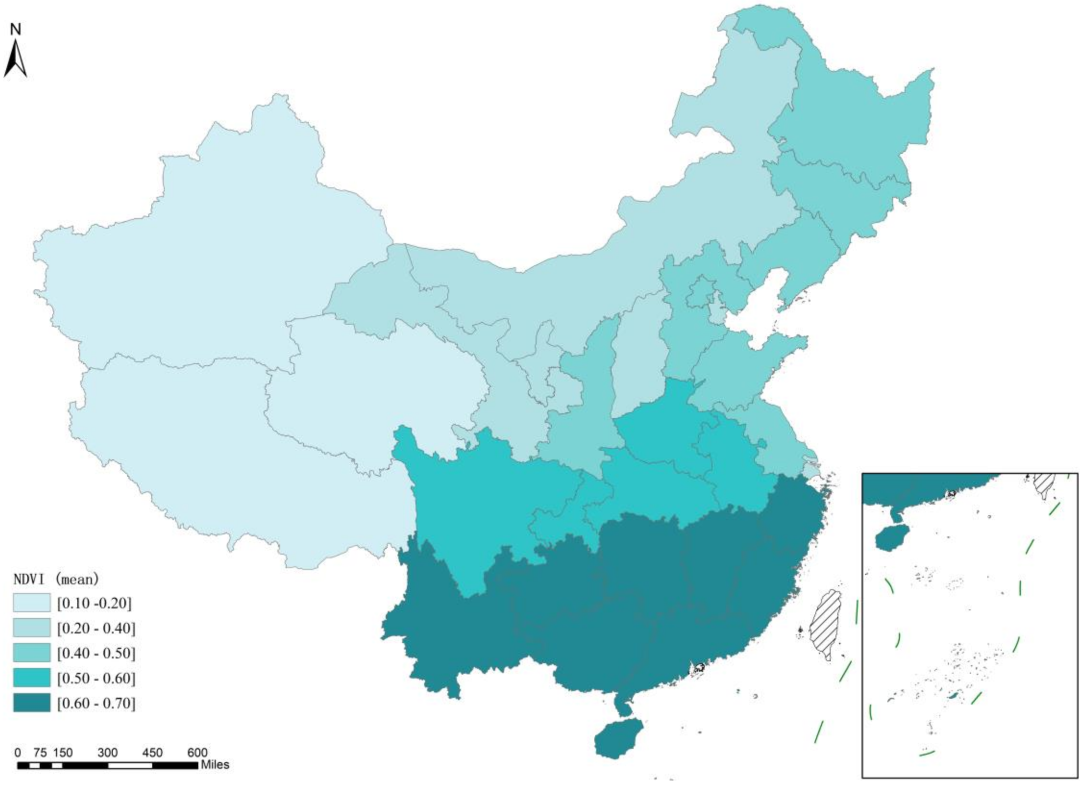


Figure 1. Geographical Location and Multi-Year Average NDVI Spatial Distribution in China, source: own elaboration

- PREC

Source: The precipitation data (PREC) were obtained from the ERA5-Land dataset published by the European Centre for Medium-Range Weather Forecasts (ECMWF) (https://www.ncei.noaa.gov/data/global-summary-of-the-day/archive).
Preprocessing: The raw data consisted of monthly average precipitation raster data. The raster values within each province were averaged using raster calculation tools to obtain the monthly average precipitation data for each province.

- TEMP

Source: The temperature data (TEMP) were obtained from meteorological observation station data published by the National Centers for Environmental Information (NCEI) under NOAA (https://www.ncei.noaa.gov/data/global-summer-of-the-day/archive/).
Preprocessing: The raw data were daily meteorological indicators recorded at observation stations. Using the latitude and longitude of the stations and their average temperature data, an interpolation was performed to create a national average temperature raster map. Based on the administrative boundaries of prefecture-level cities and the temperature raster map, the average temperature data for each province were computed. The daily average temperature values were then used to calculate the monthly average temperatures

- SUN

Source: The sunshine duration data (SUN) were obtained from the China Ground Climate Data Daily Dataset V3.0.

Preprocessing: The raw data were daily station data saved as monthly TXT files. These data were first processed into monthly CSV files, retaining the necessary latitude, longitude, and monthly cumulative sunshine duration values. The monthly CSV files were then interpolated using inverse distance weighting after projecting the data. Finally, the data were divided and stitched together according to administrative divisions to obtain the monthly average sunshine duration for each province.

- BUILT

Source: The built-up area data (BUILT) were obtained from the China Statistical Yearbook published by the National Bureau of Statistics of China.
Preprocessing: Missing data for certain years were handled using mean imputation to ensure continuity in the time series data.

4. Results and discussion

4.1. Trends in the development of NDVI

Table 4. Average NDVI for different regions from 2001 to 2020, source: own elaboration

Year	Eastern	Central	Western	Northeast	Nationwide
2001	0.47	0.48	0.35	0.39	0.42
2002	0.48	0.51	0.37	0.41	0.44
2003	0.48	0.5	0.37	0.42	0.44
2004	0.49	0.51	0.37	0.42	0.44
2005	0.48	0.51	0.37	0.42	0.44
2006	0.49	0.52	0.37	0.42	0.44
2007	0.50	0.53	0.38	0.43	0.45
2008	0.50	0.53	0.38	0.44	0.46
2009	0.50	0.53	0.38	0.41	0.45
2010	0.50	0.53	0.38	0.41	0.45
2011	0.50	0.53	0.38	0.42	0.45
2012	0.51	0.54	0.39	0.44	0.46
2013	0.51	0.54	0.4	0.42	0.46
2014	0.51	0.56	0.4	0.44	0.47
2015	0.53	0.56	0.41	0.45	0.48
2016	0.53	0.56	0.41	0.44	0.48
2017	0.53	0.57	0.41	0.45	0.49
2018	0.53	0.56	0.42	0.45	0.48
2019	0.53	0.56	0.42	0.46	0.48
2020	0.54	0.58	0.42	0.45	0.49

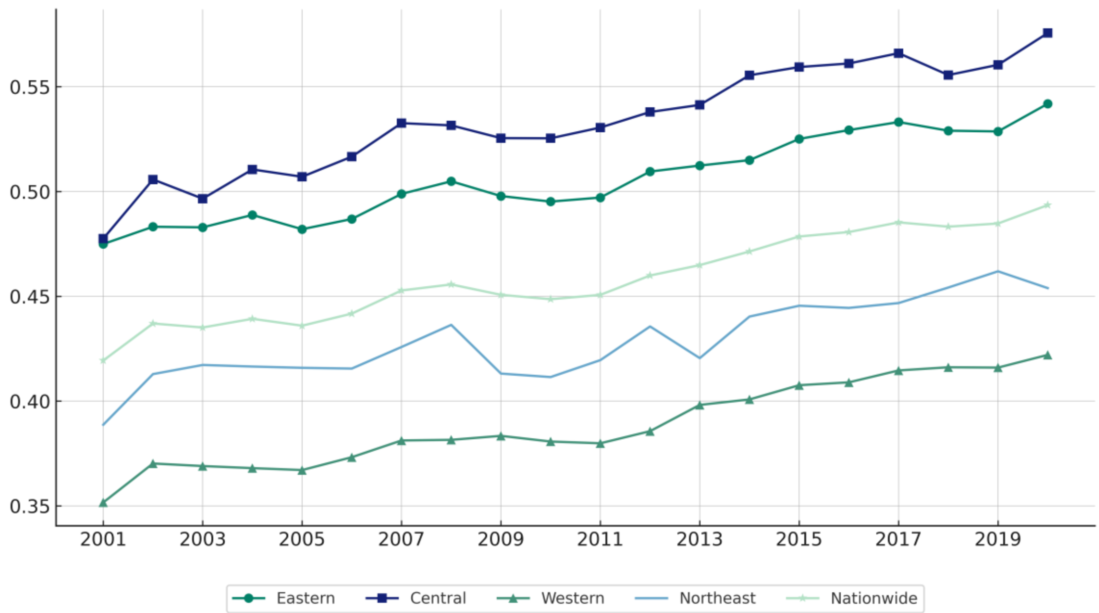


Figure 2. Trends in average NDVI for different regions from 2000 to 2020, source: own elaboration

Figure 2 shows that the temporal evolution of NDVI in different regions is highly consistent. From a national perspective, although NDVI decreased from 2011 to 2016, it rapidly increased in 2019 and reached its highest point during the observation period in 2020. In the eastern region, the NDVI value was 0.4971 in 2011, the highest value during the observation period. From 2005 to 2019, the NDVI in the eastern region consistently exceeded the national average, with the exception of 2020, when it fell below the national average. In the central region, NDVI values were consistently the highest among all regions, except from 2011 to 2015. In the western region, NDVI values were the lowest among all regions each year. In the northeastern region, in contrast to the central region, NDVI values were highest from 2011 to 2015. Additionally, NDVI values in all regions were at their lowest in 2019.

The evolution of NDVI in different regions can be divided into three phases: 2001-2007, 2008-2014, and 2015-2020. The first phase was characterized by a slow increase in NDVI. In the second phase, NDVI showed stable growth from 2008 to 2014. The third phase was marked by continuous growth, with NDVI values in different regions reaching their highest levels during the observation period from 2016 to 2020.

4.1.1. Temporal variation of NDVI

As shown in Figure 3, the overall condition of vegetation cover in China has been continuously improving. The increase in spring NDVI may be related to rising temperatures and increased rainfall, although the growth rate slowed between 2015 and 2020, possibly due to extreme weather events such as early spring droughts. Summer NDVI shows very stable and continuous growth, reflecting the optimal growth conditions for vegetation in summer with ample sunlight and suitable precipitation. Although autumn growth is steady, vegetation gradually enters a dormant state, maintaining overall good health, especially after 2018 when the growth trend became significantly more pronounced. NDVI for the entire growing season (April to October) has shown continuous growth since 2001, despite some annual fluctuations, which may be linked to the implementation of vegetation restoration and environmental protection measures at the national level. The imagery reveals how China has effectively promoted and protected its vegetation environment over the past two decades, ensuring the health and sustainability of its ecosystems.

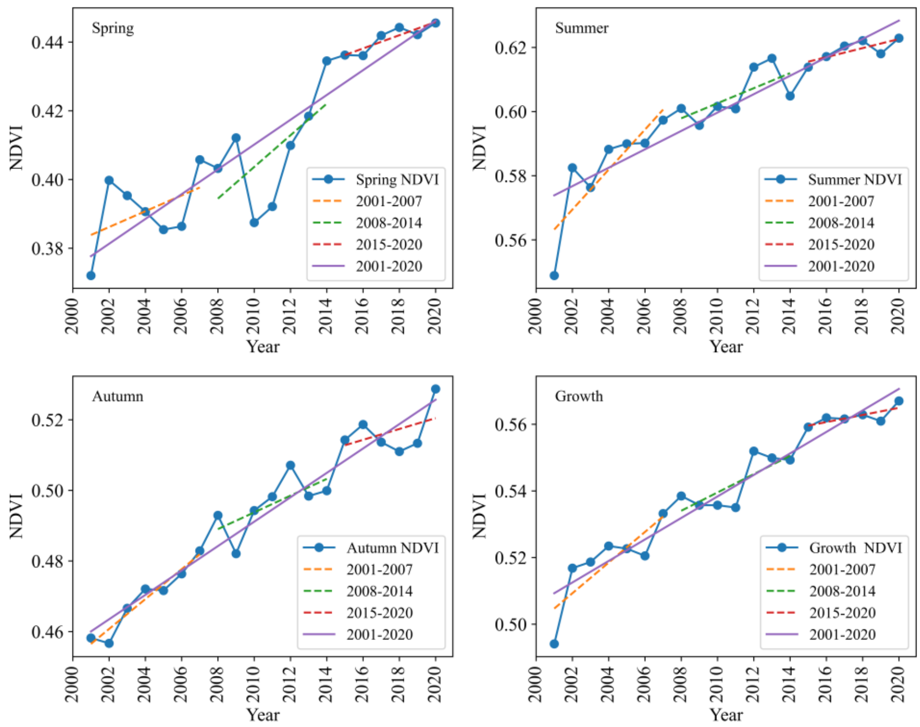
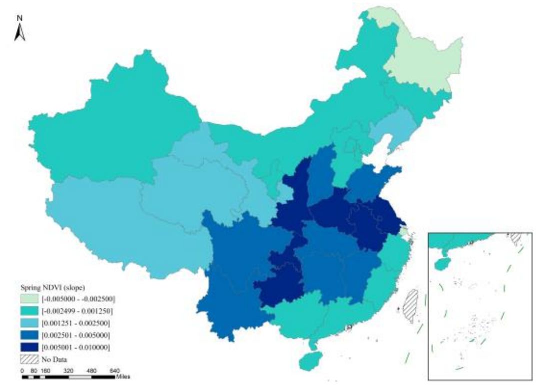


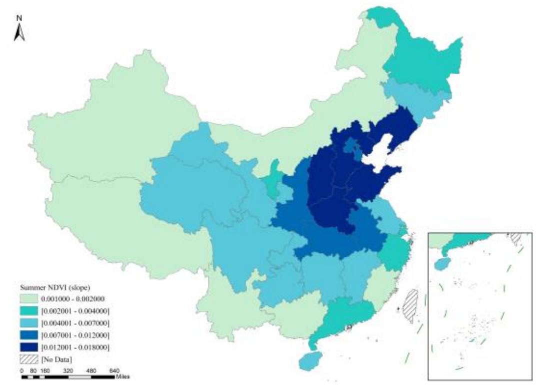
Figure 3. Interannual Variation Trend of Average NDVI in China from 2001 to 2020, source; own elaboration

4.1.2. Spatial variation of NDVI

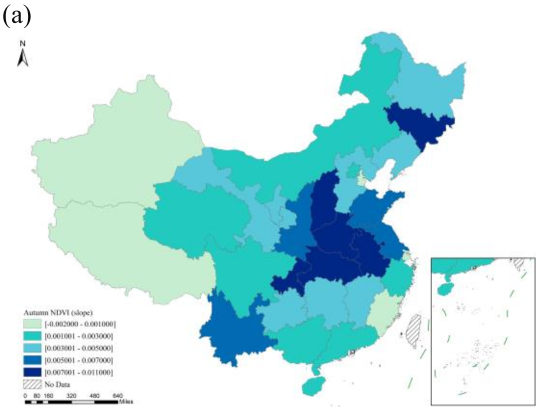
Figure 4 shows the spatial distribution of NDVI change rates in China from 2001 to 2007. The vegetation growth in most parts of China exhibited a positive growth trend. In the spring, vegetation in the southern regions, especially in central and southwestern China, became active earlier and grew faster. In contrast, some northern areas, such as parts of Northeast China, showed negative NDVI growth due to the late arrival of spring and slow temperature rise. In the summer, with the increase in precipitation and suitable temperatures, vegetation growth was particularly vigorous in the southwestern regions, such as around the Sichuan Basin, showing widespread positive growth rates in NDVI. In the autumn, although vegetation growth slowed in the northern regions due to the gradually cooling climate, the southern regions, especially coastal and South China, maintained a rapid growth rate, indicating a longer growing season. Throughout the growing season, most areas from central to southern China showed positive NDVI growth, especially in central and southern China, which is consistent with the favorable climatic conditions and longer growing seasons in these regions.



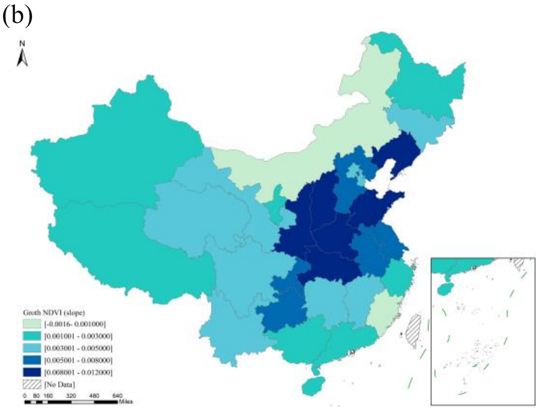
(a)



(b)



(c)



(d)

Figure 4. The spatial distribution of NDVI change trend rates in China from 2001 to 2007: (a) Spring (b) Summer (c) Autumn (d) Growth, source: own elaboration

As shown in Figure 5, the NDVI change rates in China from 2008 to 2014 exhibit significant regional differences, highlighting the complexity of vegetation growth. In the spring, provinces in the northeast and northwest showed negative NDVI growth due to the late arrival of spring and slow temperature rise, while the central and southern regions displayed higher positive NDVI growth due to early spring warmth and sufficient precipitation. In the summer, the eastern and southern coastal provinces, as well as southwestern regions such as Sichuan and Yunnan, experienced particularly vigorous vegetation growth due to abundant rainfall and favorable climate conditions, leading to a significant increase in NDVI values. In the autumn, although the growth rate in the southern regions slowed down, the North China and Northeast regions maintained good NDVI growth due to favorable autumn climate conditions. Throughout the entire growing season, the central and eastern coastal provinces and southern regions such as Guangdong and Fujian continued to show positive NDVI growth, indicating that the climate conditions in these areas are highly conducive to sustained vegetation growth and maintenance.

The spatial distribution of NDVI change rates in China from 2015 to 2020 is shown in Figure 6. Overall, the NDVI growth rates in different regions of China exhibit seasonal differences, but throughout the entire growing season, most areas show sustained positive growth, especially in the central and southern regions. In the spring, these regions benefit from favorable temperatures and sufficient precipitation, leading to active vegetation growth. In contrast, some areas in the northeast show slight negative NDVI growth due to the late arrival of spring and slow temperature rise. In the summer, almost all regions, particularly the eastern and southern coastal areas as well as southwestern regions such as Sichuan and Yunnan, exhibit significant positive growth. This is related to the abundant rainfall and suitable temperatures in these areas during summer. In the autumn, due to mild climate and moderate precipitation, most regions continue to maintain positive growth. Southern regions like Guangdong and Fujian show more significant NDVI growth in autumn due to the longer growing season and favorable late-season precipitation.

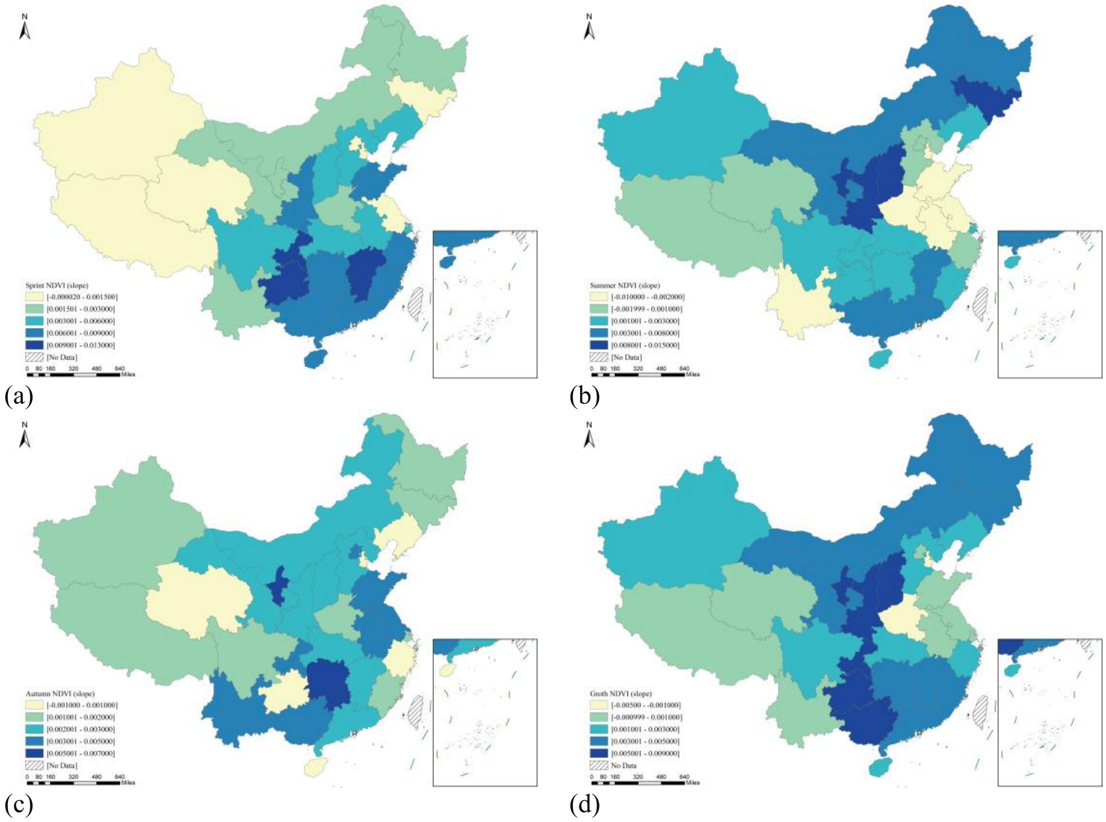


Figure 5. The spatial distribution of NDVI change trend rates in China from 2008 to 2014: (a) Spring (b) Summer (c) Autumn (d) Growth, source: own elaboration

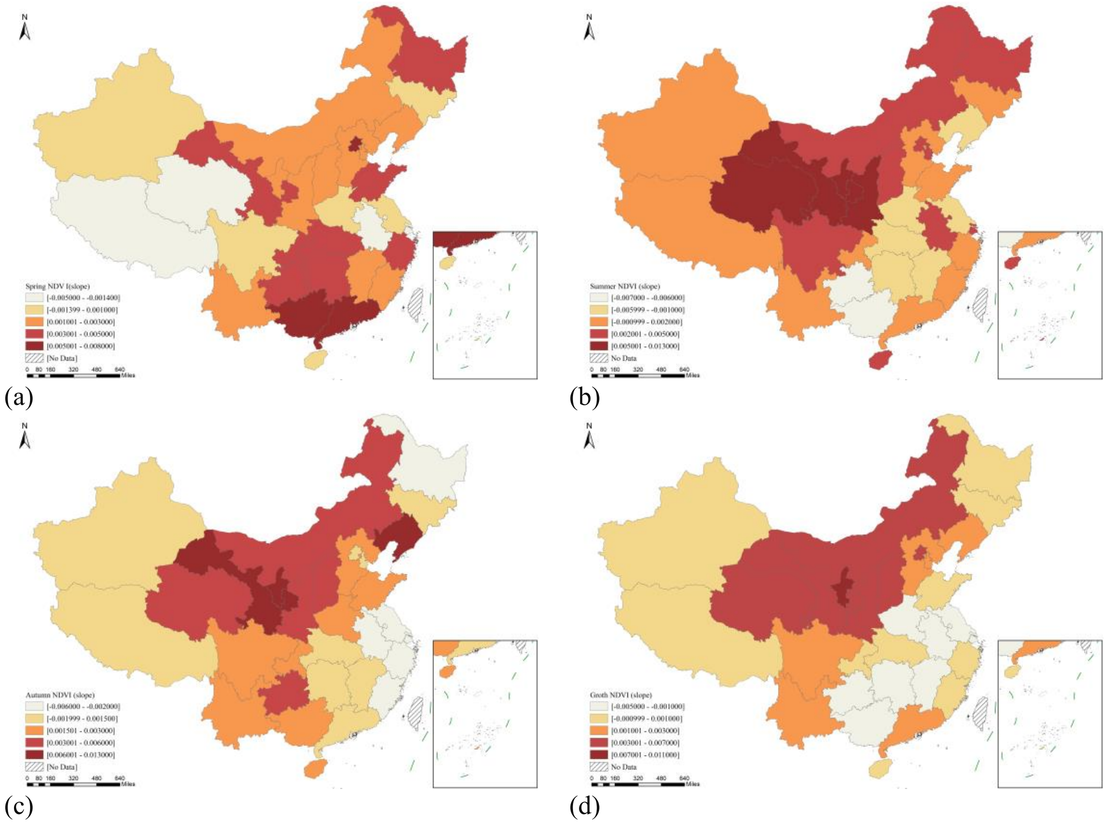


Figure 6. The spatial distribution of NDVI change trend rates in China from 2015 to 2020: (a) Spring (b) Summer (c) Autumn (d) Growth, source: own elaboration

Figure 7 shows the spatial distribution of NDVI change rates in China over the entire study period from 2001 to 2020. Overall, from 2001 to 2020, the vegetation growth status in most parts of China has shown improvement. This may be related to climate change, changes in land use practices, and the implementation of regional vegetation management and protection policies. In areas where vegetation restoration and environmental protection measures are more concentrated, vegetation growth has significantly improved. These findings can further guide environmental management and vegetation restoration strategies in China and its different regions to address potential environmental challenges in the future.

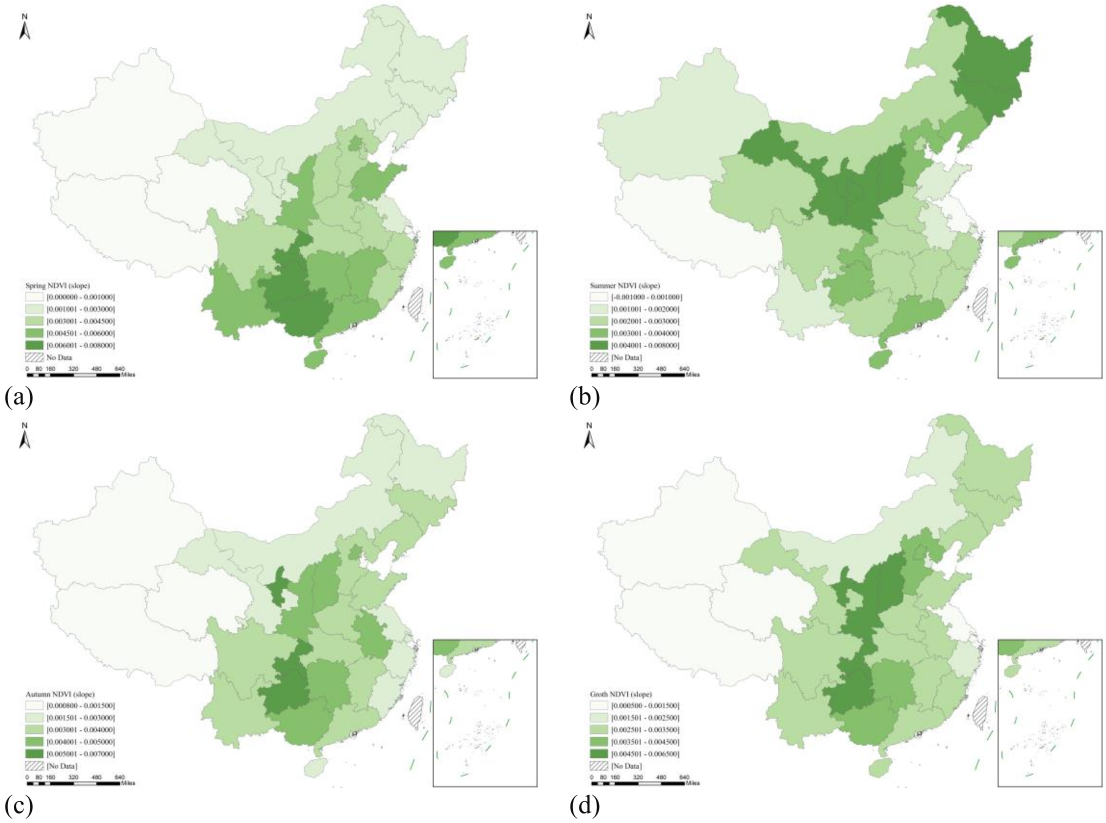


Figure 7. The spatiotemporal distribution of NDVI change trend rates in China from 2001 to 2020: (a) Spring (b) Summer (c) Autumn (d) Growth, source: own elaboration

4.2. The spatiotemporal distribution of factors affecting NDVI

By comparing the fitting performance of OLS, TWR, and GWR, it is demonstrated that the GTWR model exhibits higher accuracy and applicability in studying the influencing factors of NDVI in China. Specifically, the adjusted R-squared values for OLS, TWR, and GWR are 0.79, 0.80, and 0.95, respectively, while the GTWR model achieves an adjusted R-squared value of 0.96. In summary, TWR, which accounts for temporal non-stationarity, performs better than OLS, and GWR, which accounts for spatial non-stationarity, also outperforms OLS. Moreover, all criteria for assessing model fitting usefulness indicate that the GTWR model, which considers both temporal and spatial non-stationarity, provides the best accuracy and applicability compared to the other models. Table 5 lists the descriptive statistics of the regression coefficient estimation results calculated by GTWR. For example, on average, PREC and TEMP have a positive impact on the NDVI index, indicating that an increase in precipitation and temperature helps to improve the vegetation index. However, the average value of SUN is negative, suggesting that an increase in sunshine duration may have a negative impact on the vegetation index. Additionally, the average value of BUILT is also positive, implying that an increase in built-up area has a positive impact on the vegetation index.

Figure 8 shows the temporal evolution of the impact of climate and human factors on NDVI. Overall, the influence of different variables fluctuates. First, the impact of PREC on NDVI is generally positive and shows an upward trend from 2001 to 2020, with a significant increase particularly after 2014. This indicates that as precipitation increases, vegetation growth conditions improve, leading to higher NDVI values. Secondly, the impact of SUN on NDVI is generally negative, although it shows a trend towards positive influence. There are some fluctuations between 2010 and 2012, but the overall impact remains negative. TEMP's impact on NDVI is generally positive and remains relatively stable over time, although there are slight negative fluctuations around 2005 and 2017, reflecting the impact of local climate anomalies on NDVI. Finally, the negative impact of BUILT on NDVI gradually weakens and stabilizes after 2010, indicating that urbanization processes lead to reduced vegetation cover, negatively affecting NDVI. Overall, PREC has a significant positive impact, TEMP has a relatively stable positive impact, SUN has a negative impact but is gradually trending towards a positive influence, and the negative impact of BUILT is gradually weakening but still present. By combining regional differences and historical climate data, the specific impacts of these variables in different regions and time periods can be further analyzed, providing scientific basis for environmental protection and urban planning.

Table 5. Description statistics of GTWR results, source: own elaboration

Variables	Min	Q1	Median	Mean	Q3	Max
Intercept	-0.73	0.13	0.29	0.23	0.39	0.77
PREC	-0.05	0.03	0.12	0.18	0.28	0.86
TEMP	-0.57	0.05	0.27	0.29	0.52	1.59
SUN	-0.34	-0.11	-0.02	-0.03	0.04	0.31
BUILT	-0.26	-0.03	0.10	0.10	0.17	0.89

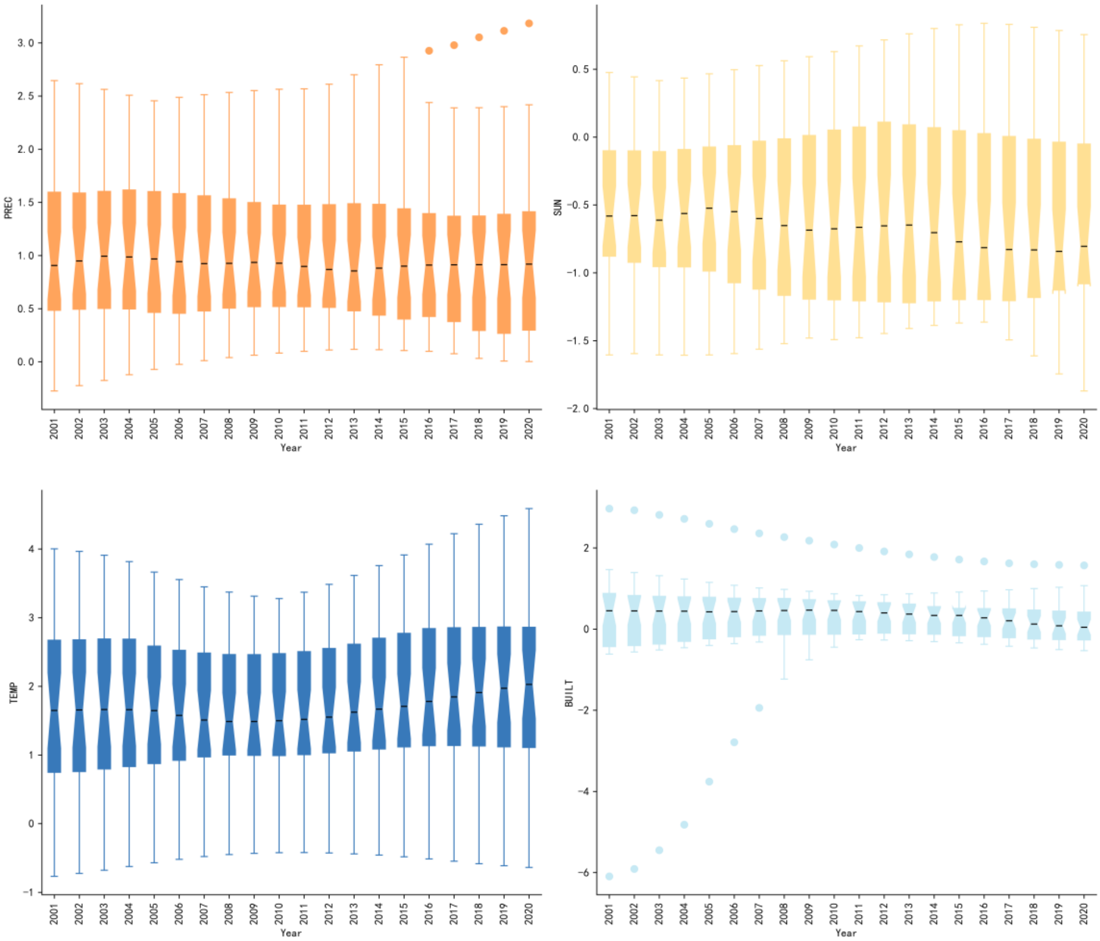


Figure 8. Temporal Evolution of Regression Coefficients for Influencing Factors in GTWR, source: own elaboration

4.2.1. The influence of PREC on NDVI

As shown in Figure 9(a), the impact of PREC on NDVI remains consistent across regions, all showing a positive influence. Particularly in the western regions, the positive impact of PREC on NDVI has been continuously strengthening, indicating the critical importance of water resource management and protection in these areas. To improve vegetation cover and environmental quality, the eastern, northeastern, and central regions also need to emphasize the rational use and management of water resources. Therefore, to effectively enhance vegetation cover and ecological environment quality, the following measures should be adopted in various regions: increase water resource management efforts, improve irrigation efficiency, and strengthen ecological protection.

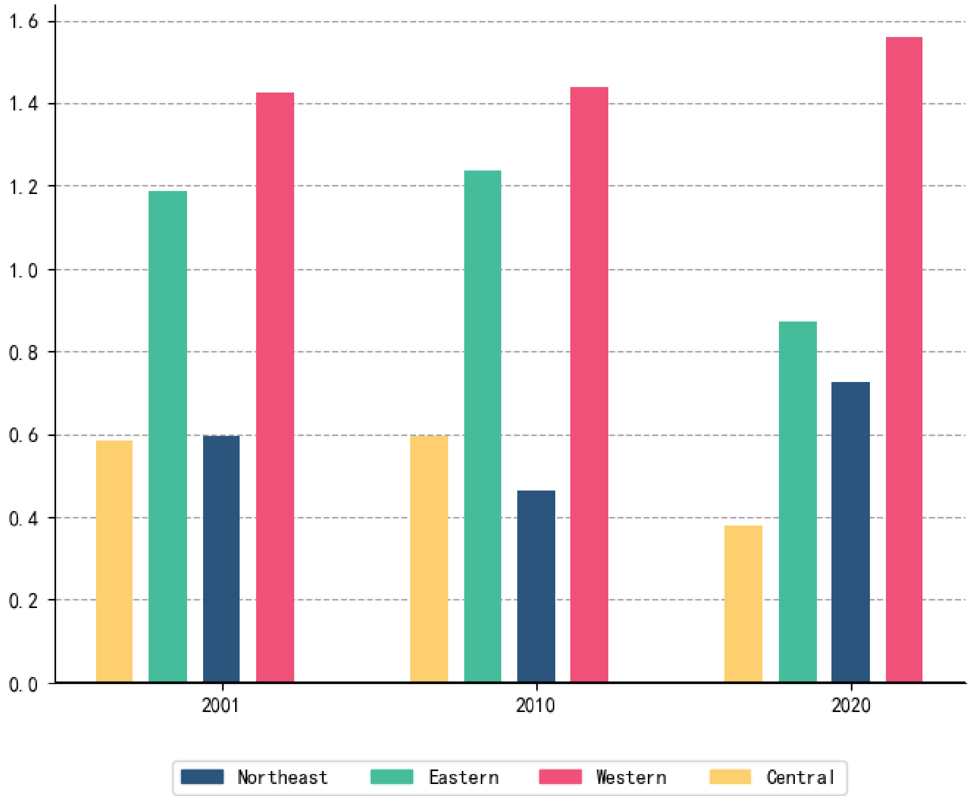


Figure 9 (a). The influence of PREC on NDVI, source: own elaboration

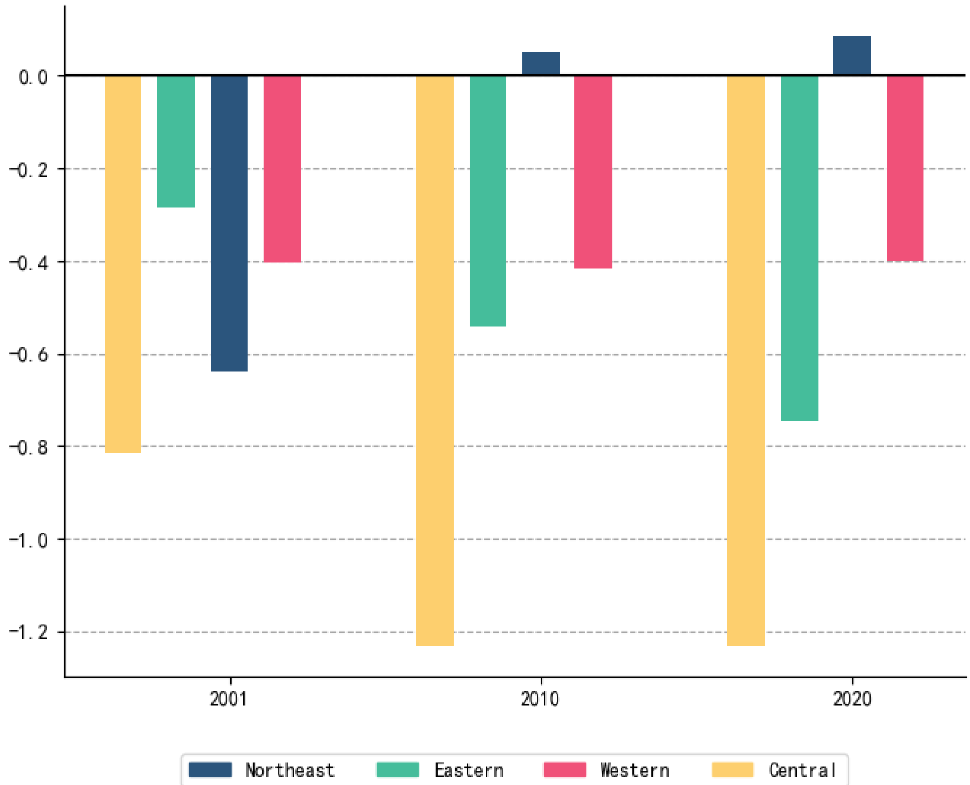


Figure 9 (b). The influence of SUN on NDVI, source: own elaboration

4.2.3. The influence of TEMP on NDVI

As shown in Figure 9(c), the impact of TEMP on NDVI exhibits significant spatial differences across regions. The northeastern region is heavily negatively impacted by TEMP, while the central region experiences the most significant positive impact from TEMP. The eastern and western regions maintain a stable positive impact from TEMP

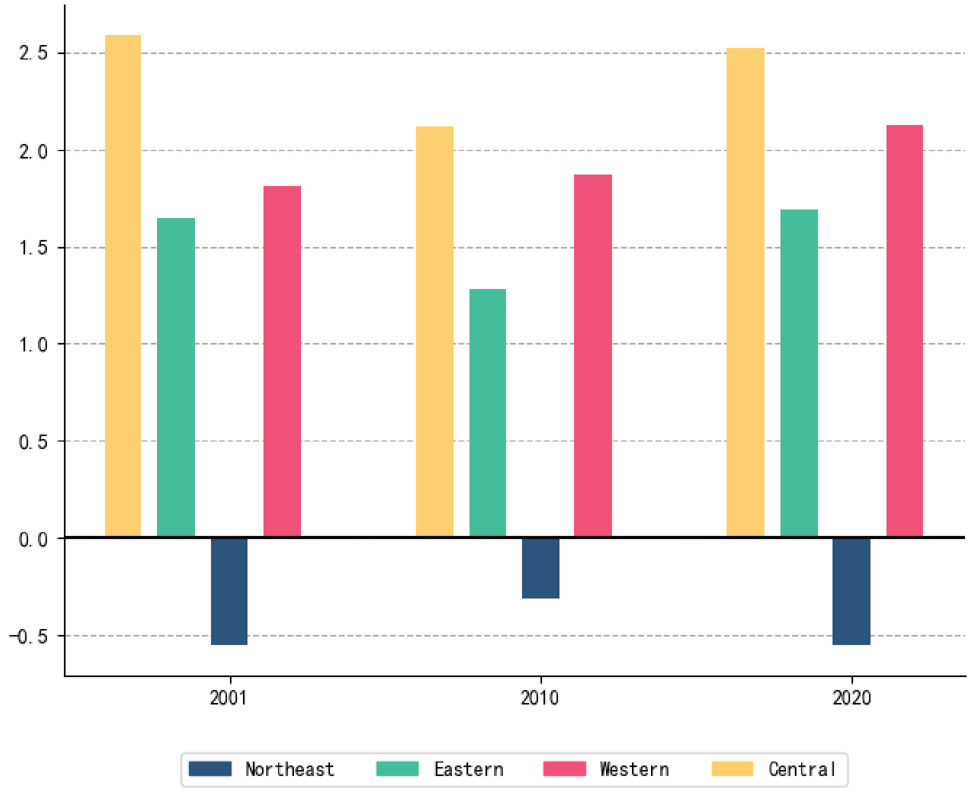


Figure 9 (c). The influence of TEMP on NDVI, source: own elaboration

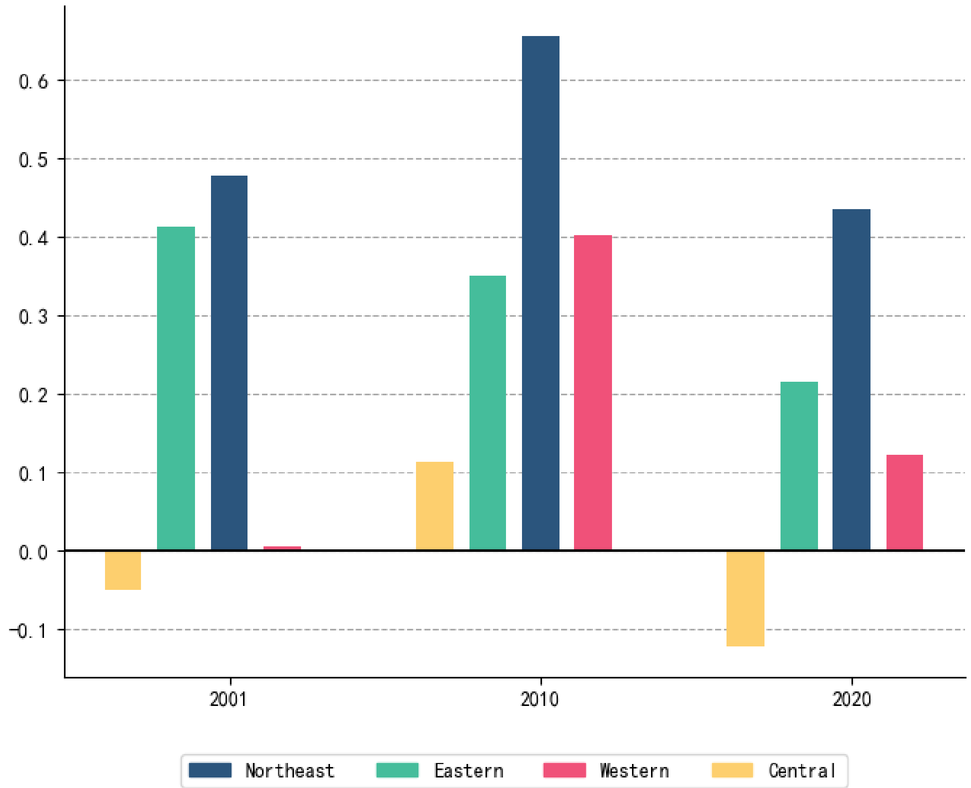


Figure 9 (d). The influence of BUILT on NDVI

on NDVI, with slight fluctuations. In response, the northeastern region should implement cooling measures or plant heat-tolerant vegetation to mitigate the negative effects of TEMP on vegetation. The eastern and western regions need to continuously monitor TEMP changes, optimize vegetation types, and fully utilize the positive effects of TEMP to promote vegetation growth. The central region should continue effective TEMP management to further leverage TEMP's positive impact on vegetation, enhancing the stability and adaptability of the ecosystem.

4.2.4. The influence of BUILT on NDVI

As shown in Figure 9(d), the impact of BUILT on NDVI exhibits significant spatial differences across regions. The overall impact of BUILT on NDVI is positive in the northeastern and eastern regions, although it fluctuates in the northeastern region. The positive impact of BUILT in the western region is gradually weakening, while the impact in the central region shows significant fluctuations between different years. To enhance vegetation cover and environmental quality, the following measures should be taken in each region: continue to optimize urban planning and green space layout in the northeastern and eastern regions to maintain the positive impact of BUILT on vegetation; improve urban greening levels in the western region to sustain the positive impact of BUILT on vegetation and prevent its weakening; and conduct in-depth research on the specific mechanisms of BUILT's impact on vegetation in the central region, developing targeted urban development and greening strategies to reduce negative impacts.

5. Conclusions

This study analyzed the spatiotemporal distribution of the Normalized Difference Vegetation Index (NDVI) in mainland China from 2001 to 2020, focusing on the influences of climate change and human activities. The research utilized the Geographically and Temporally Weighted Regression (GTWR) model to account for the spatial and temporal heterogeneity of NDVI changes. The findings reveal an overall increase in NDVI across mainland China, indicating an improvement in vegetation cover, particularly from 2015 to 2020. However, significant regional and seasonal variations were observed. Central and southern regions showed the highest NDVI growth, driven by favorable climate conditions such as sufficient rainfall and optimal temperatures. Conversely, the northeastern regions experienced slower growth due to delayed spring onset and cooler temperatures. The study highlights the predominant influence of precipitation and temperature on NDVI, with precipitation positively impacting vegetation cover across all regions. While temperature generally had a stable positive effect, extreme variations could lead to localized declines. Sunshine duration exhibited a negative impact on NDVI, likely due to excessive sunlight causing vegetation stress. Human activities, including urbanization and land use changes, also significantly affected NDVI, with urban expansion showing mixed effects depending on the region.

The study's findings underscore the importance of region-specific environmental policies to enhance vegetation cover and ensure sustainable development. In central and southern regions, continued efforts in managing water resources effectively and developing urban green spaces are essential to support the observed positive NDVI trends. For northeastern and western regions, strategies should focus on mitigating the negative impacts of temperature fluctuations and optimizing sunlight exposure for vegetation to foster growth. Policies should prioritize enhancing water use efficiency, improving irrigation practices, and implementing cooling measures or planting heat-resistant vegetation where necessary. Additionally, urban planning should aim to balance development with ecological preservation by optimizing green space layouts and integrating vegetation-friendly practices in urban areas. These targeted approaches can significantly contribute to sustainable ecological and urban development across China, addressing the diverse regional needs identified in the study.

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