

## Article

# Identifying the Main Factors Influencing Significant Global Vegetation Changes

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**Abstract:** Understanding the dynamics of vegetation change is crucial for comprehending ecosystem functioning and its response to anthropogenic activities and climate change. This study investigates significant vegetation changes worldwide and aims to identify the dominant factors responsible for these changes. By analyzing long-term data on vegetation dynamics and climatic factors, this research identifies regions with significant global vegetation changes and determines the main factors leading to such changes at the grid scale. The results reveal important insights into the drivers of vegetation change. Firstly, the study finds that the area experiencing significant browning from April to July is larger than the area exhibiting significant greening. Secondly, on an annual scale, anthropogenic activity emerges as the main factor driving significant vegetation greening, while climate change becomes the primary factor causing vegetation browning from July to September. Thirdly, in regions dominated by climate change, temperature is identified as the primary climatic factor contributing to significant vegetation greening. Additionally, the study reveals that the primary climatic factors causing significant vegetation browning are temperature followed by soil moisture, with temperature being the main factor in most months. These findings contribute to a deeper understanding of the mechanisms driving global vegetation changes and have implications for sustainable development and climate action.

**Keywords:** vegetation; anthropogenic activity; climatic factors; remote sensing; global change; NDVI



**Citation:** Zhang, Y.; Lu, Y.; Song, X. Identifying the Main Factors Influencing Significant Global Vegetation Changes. *Forests* **2023**, *14*, 1607. <https://doi.org/10.3390/f14081607>

Academic Editor: Giorgio Alberti

Received: 27 July 2023

Accepted: 7 August 2023

Published: 9 August 2023



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## 1. Introduction

Vegetation serves as a crucial indicator of the overall health and well-being of terrestrial environments [1]. It not only contributes to the aesthetics of landscapes, but also plays a vital role in supporting various ecological processes. Understanding the growth patterns and distribution of vegetation is essential for comprehending the structure and functioning of ecosystems [2]. It provides valuable insights into the dynamics of carbon and water cycles, as well as the absorption of solar radiation [3–5]. Consequently, continuous and long-term monitoring of vegetation is of utmost importance for ongoing scientific study.

Vegetation change is shaped by two primary factors: anthropogenic activity and climate change [6–9]. Anthropogenic activity is widely acknowledged as a significant driver of vegetation changes, contributing to the decline in vegetation greenness and accelerating global vegetation transformations. Anthropogenic activities have a substantial impact on approximately 75% of non-snow-covered land surfaces [10]. However, accurately predicting the consequences of anthropogenic actions on specific ecosystem processes can be challenging, often requiring retrospective assessments. Simultaneously, climatic factors, including rainfall and temperature, have also been identified as influential factors impacting vegetation change [11–14]. Nonetheless, relying solely on these factors is insufficient for accurately predicting the Normalized Difference Vegetation Index (NDVI) under diverse

climatic conditions. The relationship between anthropogenic activity and climatic factors is complex, exhibiting variations across different time scales and regions. To gain a more comprehensive understanding of the underlying dynamics, researchers have employed residual analysis, which examines the relative contributions of temperature, precipitation, and anthropogenic activity to vegetation changes [15,16]. Although temperature and precipitation are primary factors influencing the NDVI, the predictions derived from residual analysis are influenced by the intricate interactions among climatic factors [17–20]. Thus, while residual analysis allows for the determination of the relative contributions of anthropogenic activity and climate change, it cannot precisely identify the primary climate factors responsible for vegetation changes. Currently, there have been studies revealing the response of global vegetation to human activities and climate change [21,22]. However, many of these studies have chosen different influencing factors and tend to focus more on human activities. It is urgent to identify the primary climate factors driving global vegetation changes from the perspective of climate change.

Droughts have become more frequent and severe worldwide, largely due to the combined effects of rising temperatures and reduced precipitation resulting from climate change [23–26]. These prolonged dry spells have significant negative consequences for vegetation, impacting its growth and development in various ways. Droughts inhibit photosynthesis, the vital process by which plants convert sunlight into energy, and disrupt other essential physiological processes such as respiration [27–29]. In extreme cases, severe drought events can even lead to increased vegetation mortality, further exacerbating the ecological impact [16,30–33]. While temperature and precipitation play crucial roles in vegetation changes, other climate factors also contribute significantly. Soil moisture levels, for instance, directly influence the availability of water resources for plant uptake and usage. Similarly, the duration of sunshine affects the amount of energy available for photosynthesis. Both soil moisture and sunshine duration have been identified as influential factors in global vegetation changes [34–37]. However, despite these insights, our current understanding of the primary climate drivers behind global vegetation changes remains limited. Gaining a deeper understanding of the mechanisms and driving forces behind climate-driven vegetation change is of paramount importance for achieving sustainable development goals, as well as targets related to carbon peaking and carbon neutrality [33,38–40]. By unraveling the complex interplay between climatic factors and vegetation dynamics, we can develop more effective strategies to mitigate the adverse impacts of climate change on ecosystems. This knowledge will also contribute to the development of sustainable land management practices and inform policymakers in their efforts to enhance climate resilience and ecosystem conservation.

Therefore, the objectives of this study were threefold. Firstly, it aimed to identify regions worldwide that are experiencing significant changes in vegetation. This identification is crucial for targeting conservation and restoration efforts effectively. Secondly, the study aimed to determine whether the dominant factor causing these significant vegetation changes is anthropogenic activity or climate change. Understanding the primary driving force behind vegetation changes is essential for developing appropriate mitigation strategies. Lastly, the study aimed to identify the primary climatic factors responsible for significant vegetation changes in regions affected by climate change. By identifying these key factors, policymakers and scientists can better predict and manage the impact of climate change on vegetation.

## 2. Materials and Methods

### 2.1. Data

We utilized remote sensing vegetation data and climatic factors data spanning from 1981 to 2015. Additionally, land use data from 2000 to 2015 were incorporated. Our analysis encompassed various widely used indicators of global vegetation change, such as the NDVI, vegetation area, temperature, precipitation, soil moisture, and sunshine duration (Table 1).

**Table 1.** Remote sensing vegetation, climatic factors, and land use data.

Category	Index	Time Duration	References
GIMMS NDVI 3 g	NDVI	1981–2015	[41]
ERA	Temperature	1981–2015	[42]
	Precipitation	1981–2015	[43]
	Soil Moisture	1981–2015	[35]
	Sunshine Duration	1981–2015	[44]
MODIS land cover type product	Vegetation	2000–2015	[45]

### 2.1.1. NDVI

We employed the GIMMS NDVI3g dataset generated by AVHRR, which features a spatial resolution of  $1/12^\circ$  and a time resolution of 16 days. In our data processing, we took into account adverse factors such as calibration loss, volcanic eruptions, and orbital offsets. To synthesize monthly values and exclude values below 0.1, we applied the maximum value composite (MVC) method. Subsequently, the data were resampled to a resolution of  $0.25^\circ$  to align with the parameters of the climatic factor data.

### 2.1.2. Climatic Factor Data

In addition to temperature and precipitation, soil moisture and sunshine duration are often analyzed to determine their influence on vegetation [46,47]. We analyzed these climatic factors utilizing data from the European Center for Medium-Range Weather Forecasts (ECMWF) fifth generation Reanalysis (ERA5) dataset. This dataset has been widely used to study the factors impacting vegetation change [47,48]. The spatial resolution of temperature, precipitation, and soil moisture was  $0.25^\circ$ , and the spatial resolution of sunshine duration was  $0.75^\circ$ . To match the spatial resolution of the data, we uniformly resampled the resolutions to  $0.25^\circ$ .

### 2.1.3. Land Use Data

We used land cover classification data provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) (MCD12C1) product, which has a spatial resolution of  $0.05^\circ$ . In this dataset, which has been widely used for land use analysis, land use type was divided into 17 categories. We analyzed areas where there had been no change in vegetation from 2000 to 2015 (Figure 1).

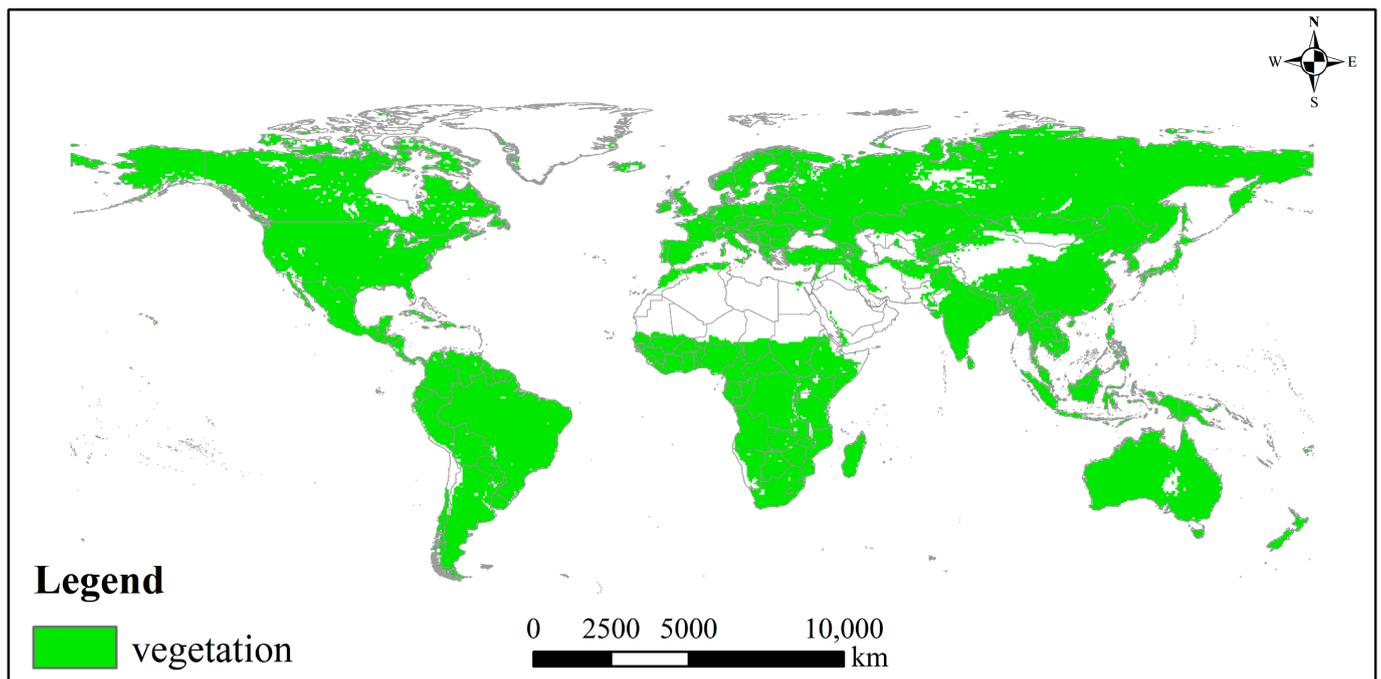
## 2.2. Methods

### 2.2.1. NDVI Trend Analysis

The ordinary least squares (OLS) method was employed to analyze the long-term data by minimizing the sum of squared errors between the predicted and observed values [49]. This method is commonly utilized for detecting trends in vegetation changes [50]. In our study, we applied the OLS model to analyze the monthly variation trends of ecosystem NDVI values from 1981 to 2015. To assess significance, we utilized the Mann–Kendall (MK) test, a non-parametric and rank-based method widely used for evaluating trends in time-series data [51]. The MK test enables the accurate identification of areas exhibiting significant ecosystem changes [52]. This study refers to vegetation changes identified through MK test as significant vegetation changes. The OLS formula is expressed as follows [53]:

$$t_i = I_0 + I_i(V_i) + \delta, \quad (1)$$

where  $t_i$  = dependent variable (NDVI),  $I_0$  = intercept,  $I_i$  = estimated coefficient,  $V_i$  = independent variable (climate factors), and  $\delta$  = error.



**Figure 1.** Areas consistently classified as vegetation according to the MODIS land cover type product from 2000 to 2015.

### 2.2.2. Determination of the Dominant Factor

Residual analysis was conducted to predict the monthly variation trend of NDVI values, taking into account the effects of climate change. Additionally, the impact of anthropogenic activity was assessed by calculating the difference between the predicted and actual NDVI values [54]. Through residual analysis, we determined the influence of anthropogenic activity and climate change on the monthly variations in ecosystem NDVI. The relative contributions of anthropogenic activity and climate factors were used to determine the dominant factors (refer to Table 2) [55]. The formula for this analysis is as follows [56]:

$$NDVI_{RS} = NDVI_{OB} - NDVI_{PR} \quad (2)$$

where  $NDVI_{RS}$  is the residual value of NDVI,  $NDVI_{OB}$  is the observed NDVI value, and  $NDVI_{PR}$  is the predicted value of NDVI.

**Table 2.** Determination of the dominant factor.

Slope <sub>OB</sub>	Driver	Driver Division		Contribution Rate (%)	
		Slope <sub>NI</sub>	Slope <sub>AI</sub>	NI	AI
>0	NI and AI	>0	>0	Slope <sub>NI</sub> /Slope <sub>OB</sub>	Slope <sub>AI</sub> /Slope <sub>OB</sub>
	NI	>0	<0	100	0
	AI	<0	>0	0	100
<0	NI and AI	<0	<0	Slope <sub>NI</sub> /Slope <sub>OB</sub>	Slope <sub>AI</sub> /Slope <sub>OB</sub>
	NI	<0	>0	100	0
	AI	>0	<0	0	100

OB means observed NDVI, NI means influence of climatic factors, AI means influence of anthropogenic activity.

### 2.2.3. Determination of the Dominant Climatic Factors

Partial correlation analysis simplifies the intricate interactions among multiple variables and focuses solely on calculating the correlation coefficient between two variables [57]. In our study, we employed partial correlation analysis to identify the primary climate factors influencing vegetation. This method unveils the dominant climate factors that impact monthly variations in NDVI [58]. The formula for this analysis is as follows:

$$R_{123} = (R_{12} - R_{13}R_{23}) / \left( \sqrt{(1 - R_{13})^2} \sqrt{(1 - R_{23})^2} \right) \quad (3)$$

where 1, 2, and 3 represent three different factors.  $R_{123}$  is the correlation between factors 1 and 2 after the interference associated with factor 3 is excluded.  $R_{12}$  reflects the linear correlation coefficient between factors 1 and 2, and  $R_{13}$  and  $R_{23}$  have similar meanings.

## 3. Results

### 3.1. Monthly Variation Trend of NDVI

The global NDVI data show an increasing trend (Figure 2). The monthly variation in the NDVI ranged from  $-0.03$  to  $0.03$ . The significant change area ( $p < 0.05$ ) in February was the lowest, accounting for 28.8% of the total vegetation area, while that in September was the highest, accounting for 56.34% of the total vegetation area. From January to March and from August to December, the monthly variation trends that passed the significance test ( $p < 0.05$ ) predominantly ranged from 0 to 0.01, and the significant change area ( $p < 0.05$ ) accounted for 55%–88% of the total vegetation area. However, from April to July, the monthly variation trends that passed the significance test ( $p < 0.05$ ) mostly ranged from  $-0.01$  to 0, with the significant change area ( $p < 0.05$ ) accounting for 52%–60% of the total vegetation area. Except for April to July, the area showing a significant increase ( $p < 0.05$ ) in the NDVI was larger than the area showing a significant decrease ( $p < 0.05$ ).

### 3.2. Contribution of Anthropogenic Activity and Climate Change to Areas with Significant Vegetation Changes

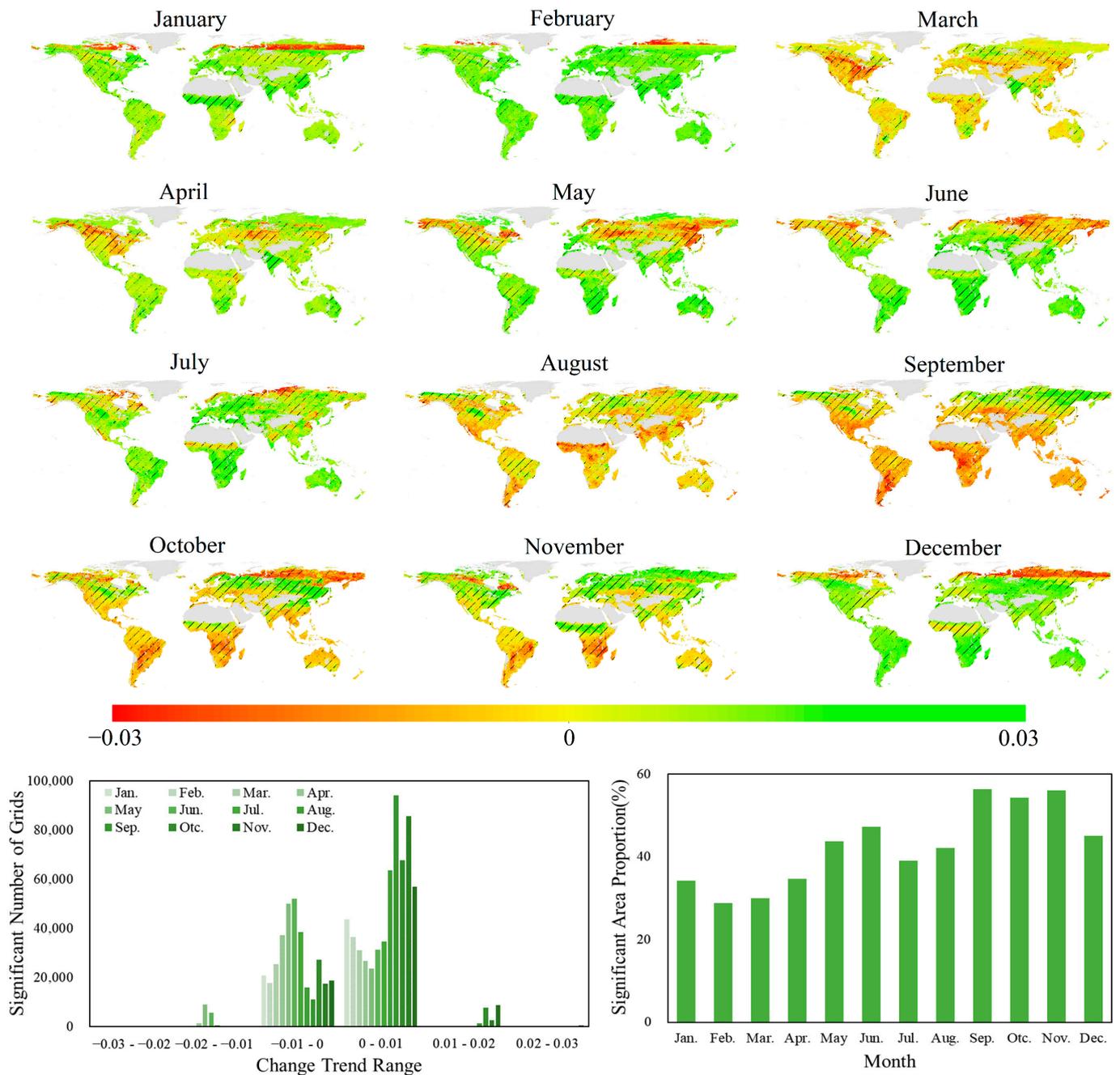
Over the past 34 years, anthropogenic activity has been a more significant driver ( $p < 0.05$ ) of vegetation changes compared with climatic factors (Figure 3). Throughout all months, anthropogenic activity had a greater positive influence ( $p < 0.05$ ) on vegetation compared with climatic factors. Similarly, the negative impact of anthropogenic activity outweighed that of climatic factors, except during the period from July to September. It is important to note that anthropogenic activity and climatic factors collectively contribute to vegetation change, with their combined effects being predominantly positive ( $p < 0.05$ ). However, there were specific months where the negative impact ( $p < 0.05$ ) of anthropogenic activities surpassed the positive impact ( $p < 0.05$ ) of climatic factors, particularly in April and May.

In regions experiencing significant vegetation changes, the monthly influence range of anthropogenic activity and climatic factors exhibited notable variations (Figure 4). The positive impact ( $p < 0.05$ ) of anthropogenic activity ranged from 49% to 80%, with September having the highest positive impact ( $p < 0.05$ ) and May exhibiting the lowest. On the other hand, the negative impact ( $p < 0.05$ ) of climatic factors ranged from 1% to 9%, with July having the highest negative impact ( $p < 0.05$ ) and November showing the lowest. These findings demonstrate the diverse magnitudes of influence exerted by anthropogenic activity and climatic factors on vegetation changes across different months and regions.

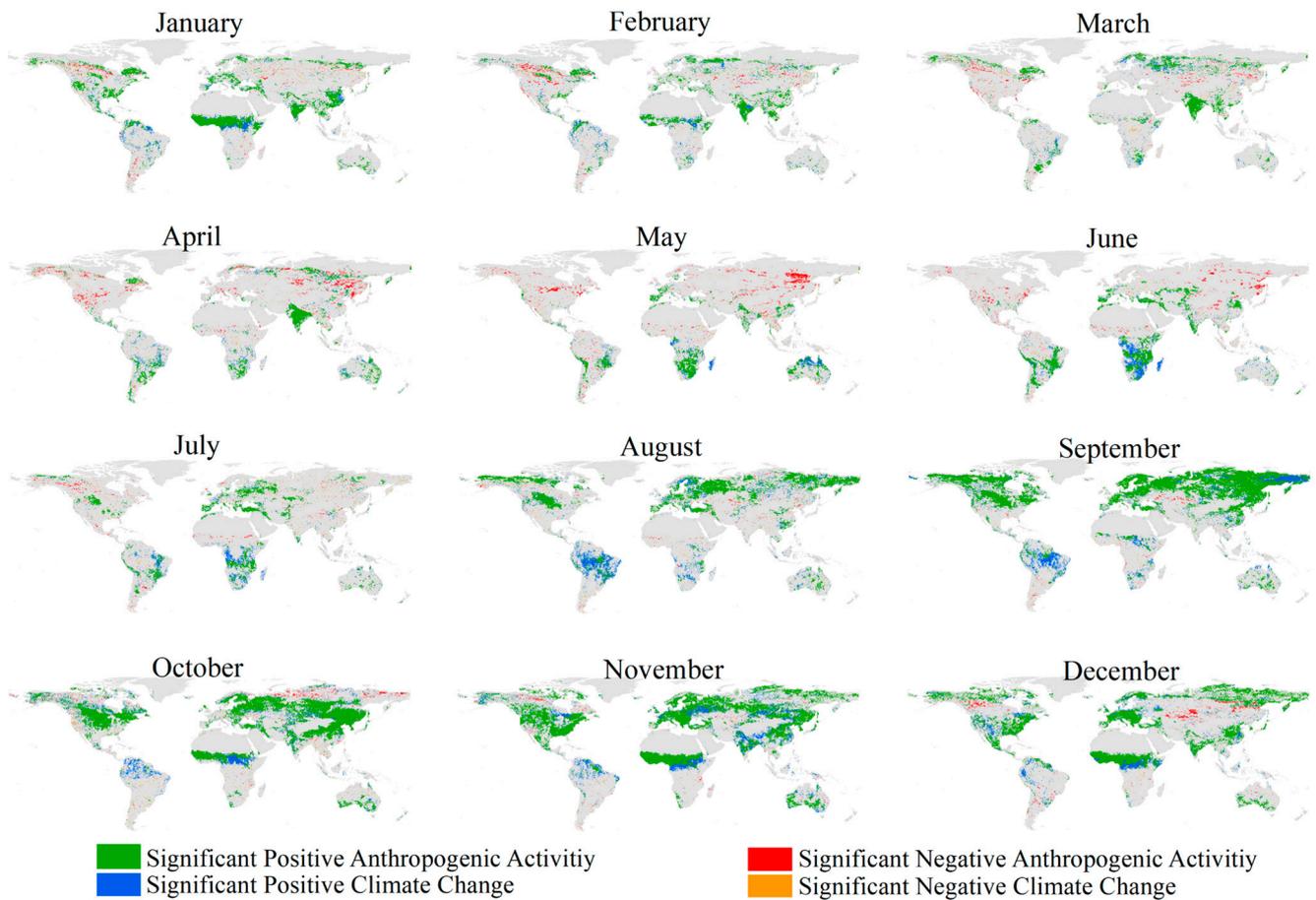
### 3.3. Dominant Climatic Factors Causing Significant Changes in Vegetation

The dominant climatic factor varied across different months and regions with significant vegetation changes ( $p < 0.05$ ) (Figure 5). In regions exhibiting significant vegetation greening ( $p < 0.05$ ), temperature emerged as the dominant climatic factor throughout the year. However, in regions experiencing significant vegetation browning ( $p < 0.05$ ), soil moisture took precedence in January. In February, March, June, July, October, and Novem-

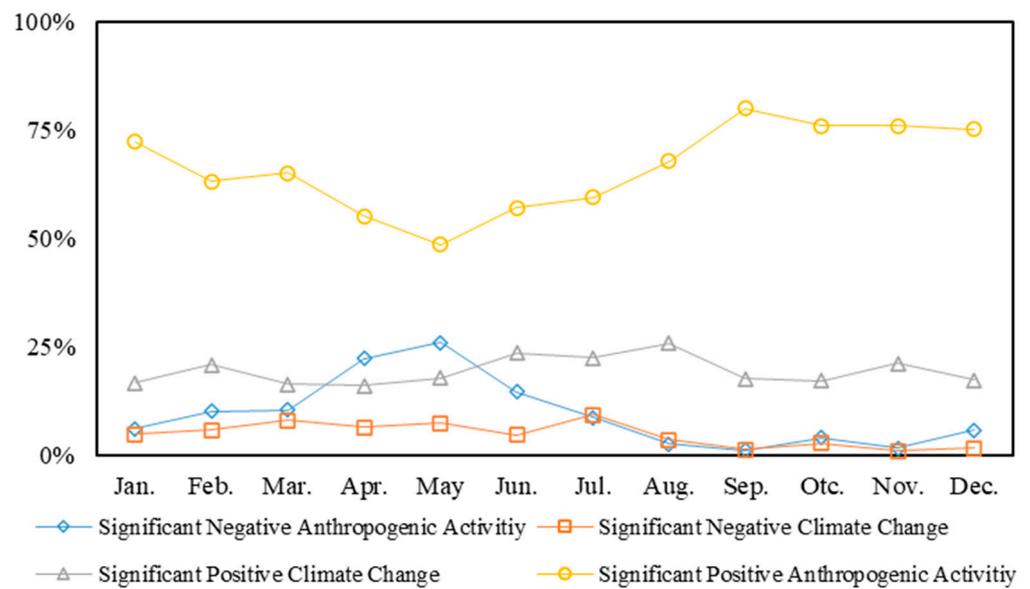
ber, temperature remained the dominant factor. April witnessed a combination of sunshine duration and temperature as the dominant variables, while sunshine duration alone played a major role in May. Soil moisture regained dominance in August, and in September, both temperature and soil moisture were the main determinants. Finally, precipitation, soil moisture, and temperature had the most significant influence ( $p < 0.05$ ) in December. These findings illustrate the varying importance of climatic factors in different months, highlighting the complex interplay between temperature, soil moisture, sunshine duration, and precipitation in driving significant vegetation changes ( $p < 0.05$ ).



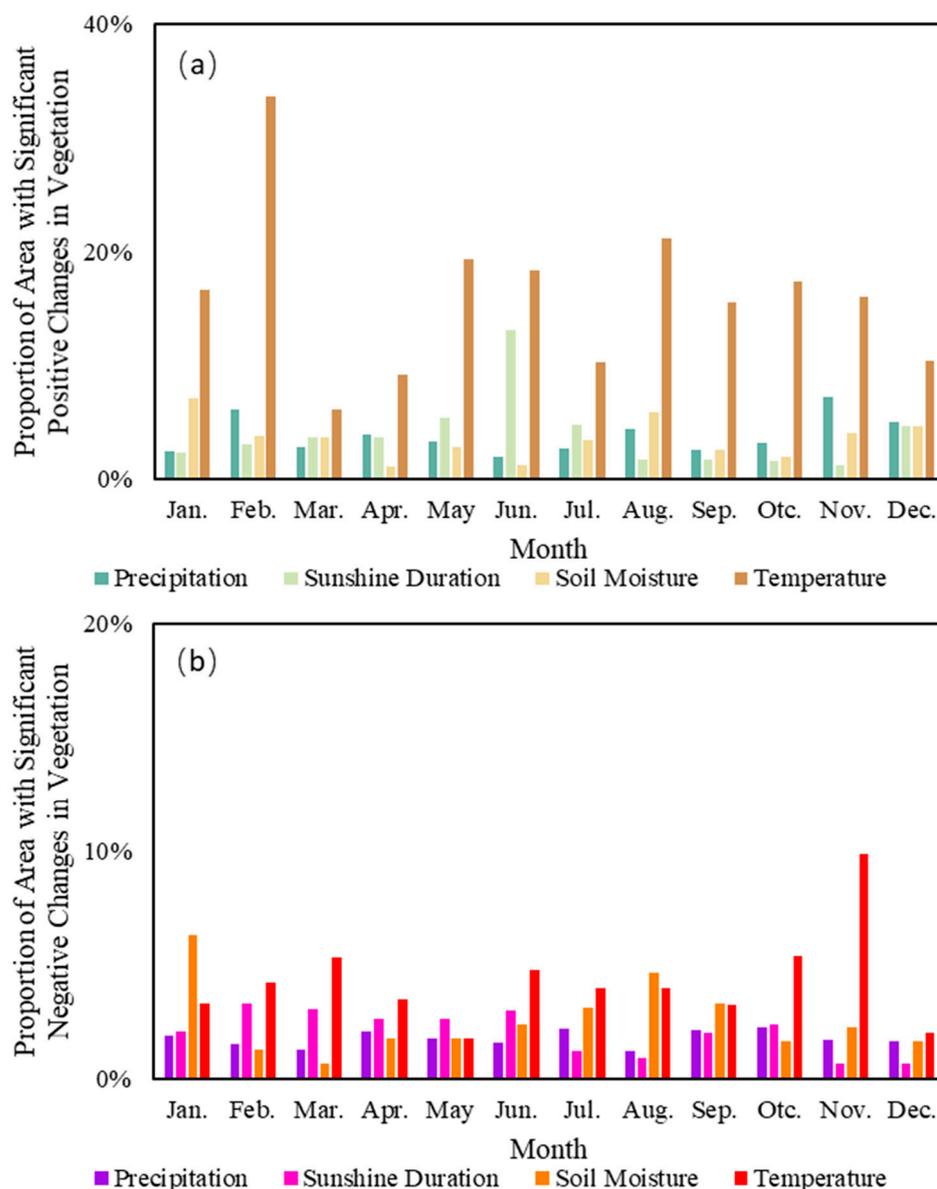
**Figure 2.** Monthly variation trends of NDVI from 1981 to 2015 (the shaded areas on the graph represent regions with significant vegetation changes that passed the MK test ( $p < 0.05$ )).



**Figure 3.** Significant changes ( $p < 0.05$ ) in vegetation due to anthropogenic activity and climate change.



**Figure 4.** Proportion of areas with significant changes ( $p < 0.05$ ) in vegetation due to anthropogenic activity and climate impacts.



**Figure 5.** Proportion of areas experiencing significant changes ( $p < 0.05$ ) in vegetation caused by dominant climatic factors, (a) positive impacts ( $p < 0.05$ ) and (b) negative impacts ( $p < 0.05$ ).

## 4. Discussion

### 4.1. Changing Trends in Global Vegetation

Analysis of global vegetation trends from 1981 to 2015 revealed an overall greening trend ( $p < 0.05$ ), except for the months of April through July, during which a browning trend ( $p < 0.05$ ) was observed. Previous studies also identified a global greening trend [19,59]. The GIMMS NDVI3g dataset exhibited a significant trend in more than half of its seasonal variation [60]. In our study, we examined the variation trend of the NDVI data at a monthly scale. There have been few studies on monthly scale vegetation changes previously, which can provide more detailed characteristics. We found that the area experiencing significant vegetation browning ( $p < 0.05$ ) from April to July accounted for 52% to 60% of the total area, while the area experiencing significant greening ( $p < 0.05$ ) accounted for 55% to 88% of the total area in other months. It is worth noting that our study observed more areas with significant greening and browning of vegetation ( $p < 0.05$ ) compared with the previous studies conducted by Eastman, Sangermano, Machado, Rogan and Anyamba [60], and

Fensholt and Proud [61]. These discrepancies could be attributed to differences in data collection methods and analysis techniques.

In particular, our study highlighted the prevalence of vegetation browning ( $p < 0.05$ ) from April to July, covering a significant portion of the total area analyzed. The magnitude of this browning trend accounted for 52% to 60% of the total vegetation area ( $p < 0.05$ ), indicating a substantial decline in vegetation greenness during these months. These findings align with the research conducted by Lamchin, Wang, Lim, Ochir, Pavel, Gebru, Choi, Jeon, and Lee [20], who reported pronounced browning from March to May, particularly during the spring season in the Northern Hemisphere. This anomaly in vegetation dynamics during the transitional period between winter and spring further supports the notion of delayed spring onset in various regions worldwide [20].

By analyzing the monthly variation trends, our study provides a more detailed understanding of the temporal dynamics of vegetation changes. The observed greening and browning trends ( $p < 0.05$ ) during specific months highlight the complex and dynamic nature of vegetation response to environmental factors. These findings contribute to our knowledge of vegetation dynamics and can support informed decision making for land management and conservation efforts. It is important to consider these variations in vegetation trends to accurately assess ecosystem health and respond effectively to environmental changes.

#### *4.2. Impact of Anthropogenic Activity Was Not Always Greater Than Impact of Climatic Factors*

Previous studies have often concluded that anthropogenic activity was the primary causal factor in significant vegetation changes [62], emphasizing its role in the decline of vegetation greenness [20]. Yang, Wang, Bai, Tan, Li, Wu, Tian, Hu, Li, and Deng [19] specifically highlighted rainfall as the most influential climatic factor affecting vegetation change. Anthropogenic activity has been shown to accelerate vegetation changes [17]. However, many studies have not initially distinguished regions where vegetation changes are primarily driven by human activities or climate change [63,64]. Instead, they directly use both human activity and climate factors in their research, making it difficult to identify the main factors causing vegetation changes. Therefore, it is necessary to conduct region-specific analysis to disentangle the contributions of human activities and climate change on vegetation dynamics. Our research provides new insights by examining the positive and negative effects ( $p < 0.05$ ) of these factors on a monthly basis.

Contrary to the prevailing notion, our findings revealed that during the months of July to September, the negative impact ( $p < 0.05$ ) of climatic factors outweighed that of anthropogenic activity. This period coincides with the transition from winter to spring in the Southern Hemisphere and from summer to autumn in the Northern Hemisphere. We observed a significant vegetation browning area ( $p < 0.05$ ) in the Northern Hemisphere, where temperature and soil moisture were identified as the primary climatic factors driving these changes. Alterations in temperature and soil moisture levels can lead to water scarcity and drought, which in turn cause vegetation browning ( $p < 0.05$ ).

Furthermore, our research indicated that the range of positive effects leading to significant vegetation changes ( $p < 0.05$ ) was not always greater than the negative effects. Over the course of 34 years, we observed an overall greening trend ( $p < 0.05$ ), suggesting that the positive impact of anthropogenic activity and climatic factors outweighed the negative impact on an annual timescale [18]. However, when examining the data on a monthly scale, we found that from April to May, the negative impact of anthropogenic activity ( $p < 0.05$ ) surpassed the positive impact of climatic factors ( $p < 0.05$ ). This highlights the complex interplay between anthropogenic activity and climatic factors, with specific months and regions exhibiting varying dynamics in the magnitude of their effects on vegetation.

While anthropogenic activity has been recognized as a significant driver of vegetation change, our research highlights the importance of considering climatic factors and their temporal dynamics. The complex interactions between anthropogenic activity and climatic

factors play a pivotal role in shaping vegetation patterns. Different months and regions may experience varying degrees of influence from these factors, emphasizing the need for a comprehensive understanding of their interplay to effectively manage and mitigate the impacts of vegetation change.

#### *4.3. Temperature Was the Main Climatic Factor*

Our research aims to investigate factors driving changes in vegetation globally. In regions where climate change primarily drives vegetation changes, we found that temperature is the predominant climatic factor responsible for significant greening of vegetation on a global scale ( $p < 0.05$ ). Moreover, our research highlights the temporal variations in the main climatic factors influencing vegetation changes ( $p < 0.05$ ), an aspect that has received limited attention in previous studies.

Temperature and precipitation are generally recognized as the primary climatic factors in many regions, and our findings align with this understanding [65,66]. During the longer months, temperature emerges as the key determining factor, while soil moisture also plays a significant role in vegetation browning in specific months like January, August, September, and December. This confirms the findings of Neilson and Drapek (1998), who identified temperature as the climatic factor with the highest influence range. Severe droughts often occur when high temperatures coincide with low soil-moisture levels [67].

Anthropogenic activity emerges as a primary driver of vegetation change, exerting both direct and indirect effects on ecosystems. Anthropogenic activities such as land use changes, deforestation, and urbanization directly influence vegetation cover and composition. These activities can result in the loss of natural habitats, fragmentation of ecosystems, and modifications to land surface properties, profoundly impacting vegetation patterns.

The intricate relationship between anthropogenic activity, temperature, and vegetation dynamics is crucial to understand the complex mechanisms underlying vegetation responses to climatic conditions. Changes in temperature resulting from anthropogenic activities can have direct influences on vegetation physiology, while the indirect effects mediated through processes like the heat island effect and modifications in land surface properties can further shape vegetation dynamics.

Temperature, as the predominant climatic factor driving global vegetation changes, influences various physiological processes in plants, including photosynthesis, respiration, and water use efficiency. Rising temperatures can stimulate plant growth and productivity in certain regions, but can also induce stress and negatively impact vegetation health during extreme heat events. Moreover, the interplay between temperature and soil moisture as drivers of vegetation browning is crucial for comprehending the complex mechanisms underlying vegetation responses to climatic conditions.

By shedding light on the temporal variations in the main climatic factors influencing vegetation changes, our study provides valuable insights for predicting and mitigating the impacts of droughts and other climate-driven phenomena on global vegetation dynamics. This holistic understanding enhances our ability to manage and mitigate the effects of climate change on vegetation, contributing to the broader understanding of the complex interplay between anthropogenic activity, temperature, and vegetation.

#### *4.4. Research Limitations*

In our research, we investigated the influence of four commonly studied climatic factors—temperature, precipitation, soil moisture, and sunshine duration—on vegetation changes. However, it is important to acknowledge that our analysis did not explicitly consider data uncertainty and limitations in remote sensing data quality, which can impact the accuracy and reliability of vegetation change analyses [68]. Future studies should incorporate methods that account for uncertainties and biases in the data, enabling a more comprehensive understanding of the relationships between climatic factors and vegetation dynamics.

Furthermore, considering the temporal and spatial scales of analysis is crucial for capturing the complexity of vegetation responses to climatic factors. Vegetation changes can exhibit different patterns and drivers at different time scales and spatial levels. Future research should explore these factors to gain a nuanced understanding of the dominant drivers of vegetation change.

By addressing data uncertainties, incorporating a broader range of factors, and considering temporal and spatial scales, future research can contribute to a more comprehensive understanding of the dominant factors driving vegetation change. This knowledge will facilitate more accurate predictions and effective management strategies for terrestrial ecosystems.

## 5. Conclusions

This study aimed to provide a comprehensive understanding of the factors driving global vegetation changes by analyzing long-term data on vegetation dynamics and climatic factors. The findings shed light on the complex interactions between anthropogenic activity, climate change, and vegetation, and offer insights into the dominant drivers of vegetation changes at different temporal scales. The results contribute to our understanding of ecosystem functioning, sustainable development, and climate mitigation efforts.

The analysis revealed an overall greening trend ( $p < 0.05$ ) in global vegetation, with localized browning patterns ( $p < 0.05$ ) observed during specific months. Anthropogenic activity was identified as the primary driver of vegetation changes ( $p < 0.05$ ), except during the transition from summer to autumn, when climatic factors had a greater negative impact ( $p < 0.05$ ). Temperature emerged as the dominant climatic factor influencing vegetation changes ( $p < 0.05$ ), with soil moisture, precipitation, and sunshine duration also playing significant roles.

These findings have important implications for predicting and managing vegetation responses to climate change and anthropogenic activities. By recognizing the influence of temperature and other climatic factors on vegetation dynamics, policymakers and land managers can develop more effective strategies for sustainable land use, carbon neutrality, and achieving sustainable development goals. Furthermore, the study highlights the need to consider uncertainties in remote sensing data and explore the effects of different temporal and spatial scales on vegetation responses to better inform future research.

To enhance our understanding of the complex mechanisms underlying vegetation changes, future studies should incorporate additional climatic factors, address data uncertainties, and consider the temporal and spatial scales of analysis. By doing so, we can advance our knowledge of the dominant drivers of vegetation change, improve prediction models, and develop more targeted and effective management approaches for terrestrial ecosystems.

**Author Contributions:** Conceptualization, Y.Z.; methodology, Y.Z.; software, Y.Z.; validation, Y.Z.; formal analysis, Y.Z.; resources, Y.L. and Y.Z.; data curation, Y.L., Y.Z. and X.S.; writing—original draft preparation, Y.Z., Y.L., and X.S.; writing—review and editing, Y.Z., Y.L. and X.S.; visualization, Y.Z.; supervision, Y.L.; project administration, Y.L. and X.S.; funding acquisition, Y.L. and X.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study was supported by the National Science Fund for Distinguished Young Scholars of China (41925030), the Youth Innovation Promotion Association of the Chinese Academy of Sciences (2020370), and the Applied Basic Research Project of the Science Technology Department of Sichuan Province (2020YJ0428), and the Innovation Capacity Improvement Program of Chengdu University of Information Technology (KYTD202219).

**Data Availability Statement:** The data that support the findings of this study are available from the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.

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