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Study on the Response of Net Primary Productivity to Vegetation Phenology and Its Influencing Factors in Karst Ecologically Fragile Regions

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Abstract: Net primary productivity (NPP) is a crucial indicator of ecosystem function and sustainability. Quantifying the response of NPP to phenological dynamics is essential for understanding the impact of climate change on ecosystem processes. In this study, vegetation phenology data for Guizhou Province were extracted from the MCD12Q2 dataset, and NPP was estimated using the Normalized Difference Vegetation Index (NDVI) combined with meteorological data. Linear regression, trend analysis, and structural equation modeling were employed to clarify the spatiotemporal patterns of NPP and phenology as a basis for exploring the role of climatic factors in the NPP's response to phenological changes. The results indicate that 72.15% of Guizhou Province shows an increasing trend in vegetation NPP (slope = 5.0981, $p = 0.002$). The start of the growing season (measured as SOS) tends to advance (slope = -0.4004 , $p = 0.0528$), while the end of the growing season (measured as EOS) tends to delay (slope = 0.2747, $p = 0.1011$), resulting in an overall extension of the increasing length of the season (LOS) (slope = 0.64549, $p = 0.0065$). The spatiotemporal patterns of SOS, EOS, LOS, and NPP varied with elevation changes. For every 500 m increase in altitude, NPP decreased by 25.3 gC/m², SOS was delayed by 7.1 days, EOS advanced by 1.25 days, and LOS decreased by 8.36 days. These findings suggest that the response of NPP to phenological changes is primarily controlled by local climatic and topographical conditions. Additionally, the indirect effects of climate on NPP through phenological changes were more significant than the direct effects. Climatic factors play varying roles in the NPP response to phenological dynamics, highlighting the profound influence of climate in regulating the mechanisms by which NPP responds to phenological changes.

Keywords: net primary productivity (NPP); vegetation phenology; structural equation modeling; karst ecologically fragile region



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1. Introduction

As a fundamental biogeochemical process in the biosphere, the carbon cycle plays a crucial role in terrestrial ecosystems. It has become a focal point of research in ecology and related disciplines [1]. Net primary productivity (NPP), a significant component of the carbon cycle, is an essential indicator for assessing an ecosystem's carbon sequestration capacity and adaptability to climate change [2]. Vegetation phenology, regulated by climatic factors, influences ecosystem function and biological processes, altering physiological and biogeochemical cycles and thus significantly impacting the carbon cycle of terrestrial ecosystems [3]. Vegetation phenology is measured through indicators such as

the start of the growing season (SOS), end of the growing season (EOS), and length of the growing season (LOS), which are widely regarded as critical metrics for evaluating ecosystem functions and various biological processes, such as gross primary productivity, net primary productivity, and ecosystem respiration [3–5]. Therefore, it is paramount to clarify the impact of phenological changes on ecosystem productivity, their feedback to the climate, and the interrelationships among phenological changes, meteorological factors, and productivity.

Currently, two main methods are used in research on vegetation phenology: traditional ground-based monitoring and remote sensing. For large-scale studies, conventional ground-based monitoring methods are less frequently used because of limitations in observation stations, species coverage, and geographic area. The development of remote sensing technology has provided an effective platform for monitoring phenological information on regional and global scales [6,7]. Time series vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) [8], Enhanced Vegetation Index (EVI) [9], and Leaf Area Index (LAI), are commonly used in the remote sensing monitoring of vegetation phenology [10]. Most remote sensing-based vegetation phenology studies conducted in the mid- and high-latitude regions of the Northern Hemisphere over the past few decades have confirmed an advanced start and delayed end to the growing season, measured using the indicators SOS and EOS, respectively [11–13]. However, because vegetation phenology exhibits significant regional variation worldwide, the accurate quantitative assessment of phenological changes in different regions is crucial for understanding the carbon cycle in terrestrial ecosystems.

Guizhou Province, located in the eastern part of the Yunnan–Guizhou Plateau, is one of the most typical karst rocky desertification areas in southwest China, with highly fragile ecological conditions [14]. Since 1960, the temperature in Guizhou has shown an upward trend, that has been significant since 1990, when the rate of warming began notably increasing [15]. Changes in temperature and precipitation have affected the vegetation dynamics, with variability in both the magnitude and direction of phenological events [16]. Due to the lack of in situ observation data, evidence of the relationship between phenological changes and NPP in plateau regions remains scarce.

The objectives of this study were to investigate the temporal trends and spatial heterogeneity of vegetation phenology and net primary productivity (NPP) dynamics in Guizhou Province from 2001 to 2020 and to analyze the response mechanisms of NPP to phenological changes. Our research aimed to address the following important scientific questions: (1) What are the patterns of vegetation phenology and NPP in Guizhou Province over the past 20 years? (2) What is the relationship between vegetation phenology and NPP in this region? (3) What are the underlying mechanisms driving NPP and phenological changes, and how do they regulate NPP and influence phenological shifts? Answering these questions will deepen our understanding of the relationship between vegetation phenology and NPP and help quantify the magnitude and direction of NPP changes caused by phenological variations, providing critical scientific evidence for sustainable development.

2. Materials and Methods

2.1. Study Area Overview

Guizhou Province is located between 24°37' and 29°13' N latitude and between 103°36' and 109°35' E longitude, representing the core of southwest China's inland region (Figure 1). The topography of this province is characterized by a slope from high elevations in the west to lower elevations in the east, with a predominant subtropical monsoon climate of warm and humid conditions. The average temperature is approximately 15 °C, and the annual rainfall ranges from 1000 to 1400 mm. The region is notable for its well-developed karst landscape, which covers 61.9% of the total land area in the province, making it one of the world's largest areas of karst distribution [17]. The extensive karst distribution, with diverse morphological types and significant geographical variation, contributes to the formation of a unique karst ecosystem. Guizhou's distinctive karst environment

and climatic conditions support diverse vegetation types and abundant plant resources, including forests, grasslands, and cultivated land. Previous studies have indicated varying degrees of vegetation phenological changes in Guizhou, with spring phenology generally advancing and autumn phenology exhibiting a delaying trend [18].

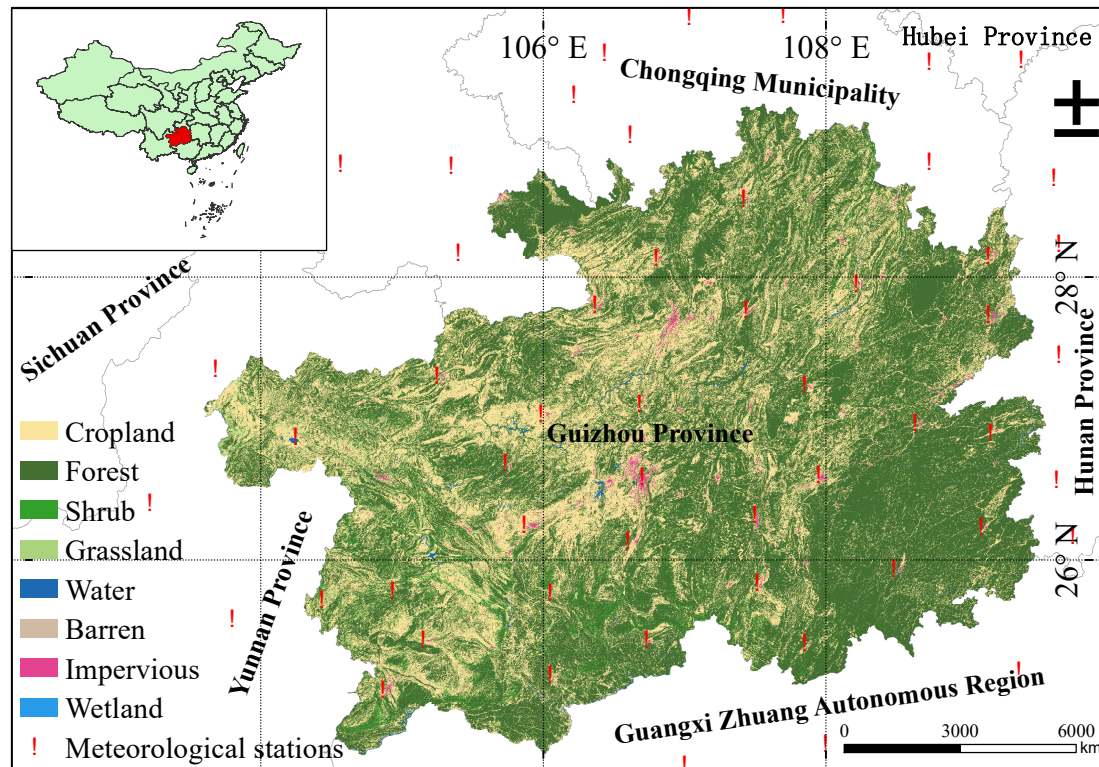


Figure 1. Study area, vegetation type distribution, and meteorological stations.

2.2. Data Source and Data Preprocessing

(1) **MODIS Data:** The MODIS MOD13A1 and MCD12Q2 datasets, released by NASA LP DAAC, were selected for extracting vegetation information. The MOD13A1 dataset was used to extract NDVI data, with a temporal resolution of 16 days. The MCD12Q2 dataset was employed to extract SOS, EOS, and LOS, with a temporal resolution of one year. The spatial resolution was unified to 500 m using resampling methods, and data were collected for the period spanning from 2001 to 2020.

(2) **Meteorological Data:** Meteorological data were used to estimate NPP and assess climate conditions related to phenological and NPP variations. The data were sourced from the China Meteorological Data Network (<http://www.nmic.cn/> (accessed on 27 March 2021)). To ensure the accuracy of spatial interpolation, 55 meteorological stations across Guizhou Province and its surrounding areas were selected (Figure 1), for determining 16-day averages of temperature, precipitation, and sunshine duration from 2001 to 2020. Due to the limited availability of solar radiation (SOL) monitoring stations, solar radiation data were calculated for each station using an empirical formula based on latitude and sunshine duration. All data were spatially interpolated using the Kriging method at a resolution of 500 m. The interpolation results were subjected to projection transformation and extracted for the study area in creating a raster dataset.

(3) **Land Use Data:** Land cover data for Guizhou Province were obtained from the CLCD_LULC dataset, which was generated by Yang Jie and colleagues from Wuhan University using a random forest classifier on the Google Earth Engine platform [19]. The temporal resolution is one year, and the spatial resolution is 30 m. The data covering the period from 2001 to 2020 were resampled to a 500 m resolution using resampling methods.

2.3. Research Methods

2.3.1. NPP Calculation

NPP is crucial for studying vegetation productivity, terrestrial ecosystems, and the global carbon cycle. Process-based models are considered a cost-effective alternative for NPP estimation since it is challenging to directly measure NPP on a regional scale. In recent years, many models have been developed to quantify NPP on regional and global scales. Among these models, the Carnegie Ames Stanford Approach (CASA) model, based on plant growth processes, has been widely applied in NPP estimation [20–22]. Therefore, the CASA model was employed in this study to estimate vegetation NPP. The calculation formulas for the CASA model are shown in Equations (1)–(3):

$$NPP(x, t) = APAR(x, t) \times \varepsilon(x, t) \quad (1)$$

where $APAR(x, t)$ represents the absorbed photosynthetically active radiation ($\text{MJ} \times \text{m}^{-2}$) by pixel x in month t and $\varepsilon(x, t)$ denotes the actual light use efficiency (gC/MJ) of pixel x in month t . The formulas for calculating $APAR$ and ε are given in Equations (2) and (3):

$$APAR(x, t) = SOL(x, t) \times FPAR(x, t) \times 0.5 \quad (2)$$

$$\varepsilon(x, t) = \varepsilon_{max} \times T_{\varepsilon1}(x, t) \times T_{\varepsilon2}(x, t) \times W_{\varepsilon}(x, t) \quad (3)$$

where $SOL(x, t)$ represents the total solar radiation ($\text{MJ} \times \text{m}^{-2}$) for pixel x in month t , and $FPAR$ is the fraction of photosynthetically active radiation (PAR) absorbed by the vegetation layer. Within a certain range, $FPAR$ is typically derived from the NDVI, due to their strong linear relationship. The constant 0.5 represents the fraction of total solar radiation that can be utilized by vegetation for photosynthesis [23]. $T_{\varepsilon1}(x, t)$ and $T_{\varepsilon2}(x, t)$ represent the effects of temperature on light use efficiency, while $W_{\varepsilon}(x, t)$ reflects the influence of water conditions. ε_{max} is the maximum light use efficiency under ideal conditions, and its value varies depending on vegetation type. In this study, we used the maximum light use efficiency values for various vegetation types as simulated by Zhu et al. [24].

2.3.2. Pearson Correlation Coefficient

The Pearson correlation coefficient [25,26] and significance tests were utilized to analyze the relationship between NPP and phenological changes from 2001 to 2020, as well as the impact of vegetation phenology on NPP trends. The Pearson correlation coefficient has a range of $[-1, 1]$, where a coefficient less than 0 indicates a negative correlation between the two variables, a coefficient of 0 indicates no correlation, and a coefficient greater than 0 indicates a positive correlation. Additionally, the t -test was used to assess the significance of correlations, with p -values of less than 0.1, 0.05, and 0.01 considered to indicate low, medium, and high levels of significance, respectively.

2.3.3. Structural Equation Modeling

AMOS (Analysis of Moment Structure) software is developed by IBM Corporation in Armonk, New York, USA, which was employed to analyze the data using a standardized structural equation modeling (SEM) approach to explore the direct and indirect effects of phenological and meteorological factors on NPP and their contributions. SEM is a statistical method used to estimate and test causal relationships, by analyzing the covariance matrix of variables and their interrelationships between them. In using this method, the relative contribution of each explanatory variable can be quantified through standardized path coefficients [27]. In this study, the initial structural equation model included all possible relationships. By setting up the model, testing it, and making revisions, relationships with lower correlations were gradually removed until only those with high correlations remained, resulting in optimal fit parameters [28]. The following indicators were considered to demonstrate model feasibility: a chi-square/degree of freedom ratio < 3 and $p > 0.05$.

(indicating that the data do not reject the model structure). The closer the values are to 1 for the Fit Index (GFI) and Normalized Fit Index (NFI), the more optimal the model structure.

3. Results

3.1. Validation of CASA Model Accuracy

In this study, the CASA model was used to calculate the 16-day mean NPP for Guizhou Province from 2001 to 2020. Cross validation was performed by comparing the NPP estimates from the CASA model with the NPP data product from MOD17A3HGF to evaluate the accuracy of the NPP calculations. Linear regression analysis was applied to determine the differences between the two datasets (Figure 2). The validation results confirm that the CASA model accurately reconstructed the spatial and temporal variations of MODIS NPP. The linear relationship between the NPP estimates from the CASA model and the MODIS NPP data product is expressed as $Y = 1.16638X - 139.22821$ ($R^2 = 0.6575$, $p < 0.01$), indicating that the CASA model effectively captures NPP variations within the study area.

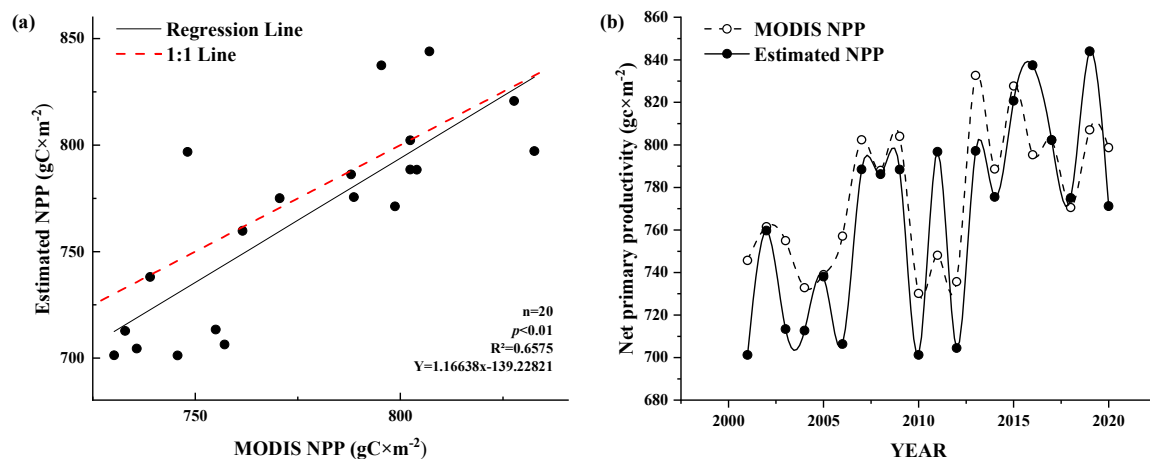


Figure 2. Comparison of CASA-estimated net primary productivity (NPP) and MODIS NPP ((a) comparison of CASA-estimated NPP and MODIS NPP for the same season across different years; (b) comparison of annual CASA-estimated NPP and MODIS NPP across various years). The solid line represents estimated NPP, while the dashed line represents MODIS NPP.

3.2. Spatial Patterns and Interannual Variability of Vegetation Phenology and NPP

Figure 3a–d illustrate the spatial patterns of vegetation phenology indicators (SOS, EOS, LOS) and NPP. Overall, SOS tends to advance gradually from west to east, while LOS and NPP are delayed in the same direction. These patterns reflect the influence of spatial heterogeneity in climate and topography on vegetation phenology within the study area and align with variations in humidity, temperature, and altitude gradients on the plateau.

Figure 3e–h present the spatial patterns of phenological indicators and NPP trends from 2001 to 2020. During this period, most of the plateau exhibited an advancing trend in SOS, with 94.61% occurring mainly in the southwestern and northcentral regions. A similar advancing trend in EOS was observed across 78.27% of the plateau. However, particular areas in the central and northeastern parts of the plateau showed a delay in EOS. Since the advancing EOS is smaller than that of SOS, the LOS indicated an extension in more than 61.35% of the study area over the research period. Unlike SOS, EOS, and LOS, the annual NPP showed a decreasing trend in the southeastern region, while increasing in the eastern, central, and northern regions. The areas where NPP increased (72.15%) outnumbered those where it decreased (27.85%), with the most pronounced positive trends observed in the northwestern part of the plateau.

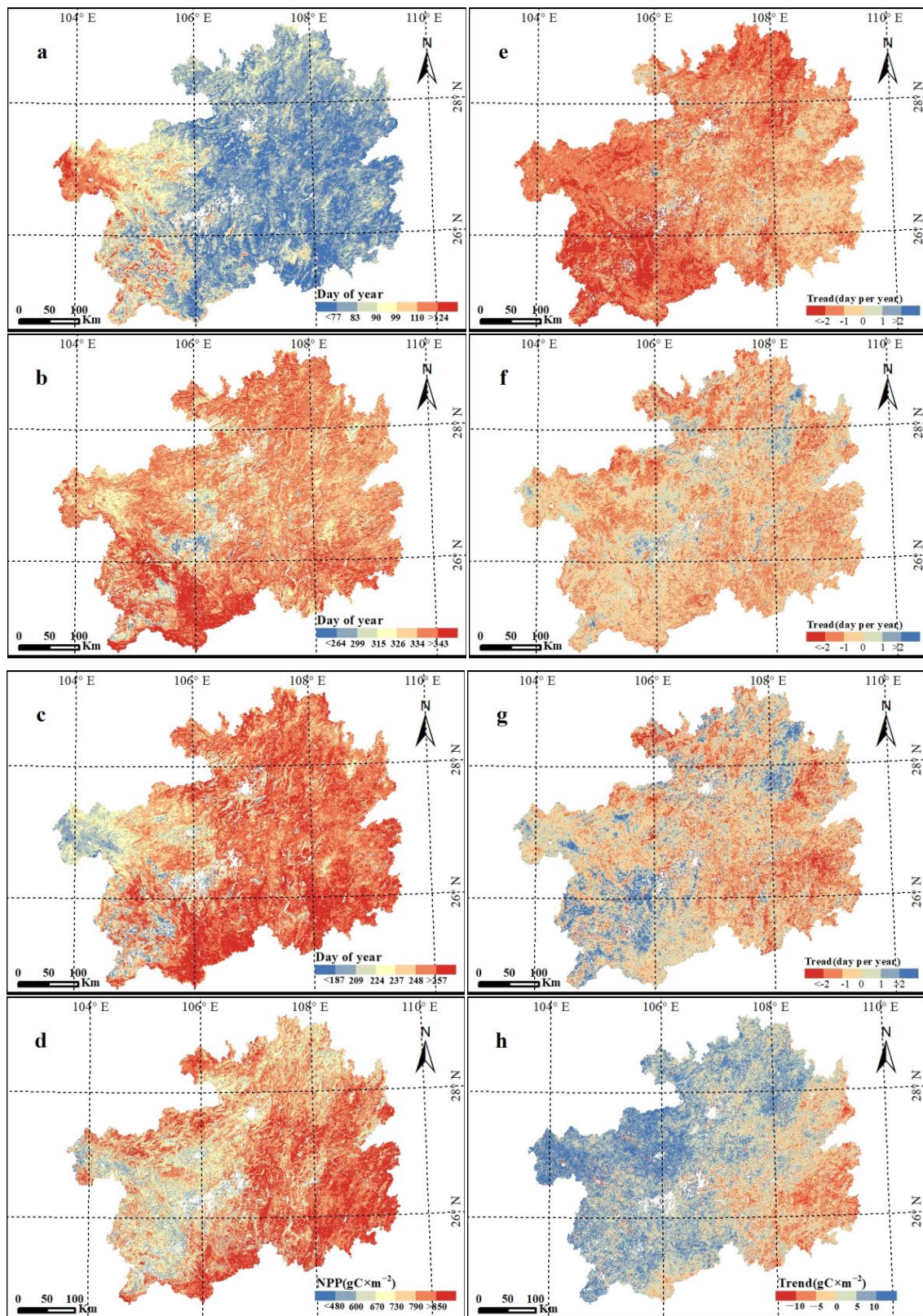


Figure 3. Spatial distribution of average phenological indicators, net primary productivity (NPP), and their trends in Guizhou Province from 2001 to 2020: (a) average Julian day of start of the growing season, (b) average Julian day of end of the growing season, (c) average length of the growing season, (d) average annual NPP, (e) start of the growing season trend, (f) end of the growing season trend, (g) length of the growing season trend, and (h) vegetation NPP trend.

At the provincial scale, NPP significantly increased over the 20-year study period ($p = 0.002$). The annual average NPP during 2001–2020 was 771.13 gC/m^2 , increasing from 701.2388 gC/m^2 in 2001 to 771.2261 gC/m^2 in 2020, corresponding to an average yearly increase of 3.5014 gC/m^2 (Figure 4a). Of the three phenological indicators, only LOS exhibited a significant increase during the study period ($p = 0.0065$) (Figure 4d), with no significant changes in SOS and EOS (Figure 4b,c). The mean SOS was 86 days, ranging from 78 days in 2013 to 99 days in 2010. The mean EOS was 334 days, ranging from 327 days in 2002 to 342 days in 2011. The mean LOS was 247 days, ranging from 236 days in 2001 to 249 days in 2015.

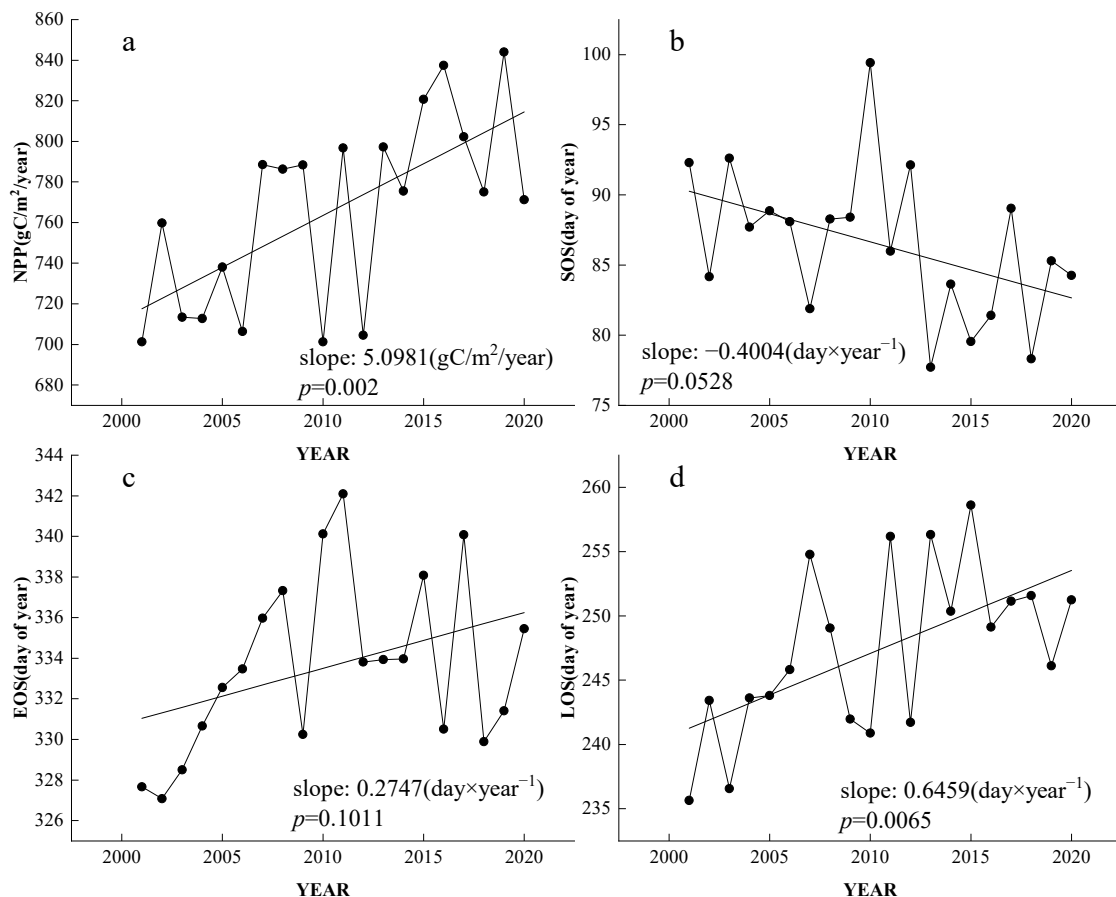


Figure 4. Changes in annual net primary productivity(NPP), start of the growing season, end of the growing season, and length of the growing season in Guizhou Province from 2001 to 2020: (a) Change in NPP, (b) Change in start of the growing season, (c) Change in end of the growing season, (d) Change in length of the growing season.

3.3. Vertical Spatial Changes in Vegetation Phenology and NPP

We further investigated the response of vegetation phenology and NPP to changes in elevation gradients. Figure 5 illustrates variations in the vertical gradient of vegetation phenology and the NPP in Guizhou Province from 2001 to 2020. With increasing elevation, the start of the growing season (based on SOS) was consistently delayed across the entire study area. In contrast, the end of the growing season (based on EOS) occurred significantly earlier, resulting in a gradual reduction in the magnitude of increases in the length of the season (LOS), corresponding to a clear pattern of change (Figure 5). According to Hopkins' Phenological Law, the spring phenology of vegetation is consistently delayed with increasing altitude [29], which aligns with our findings. Overall, for every 500 m increase in elevation, SOS indicated a delay of 7.1 days; EOS, an advancement of 1.25 days;

and LOS, a shortening of 8.36 days. NPP significantly decreased, at a rate of 25.3 gC/m² for every 500 m increase in elevation.

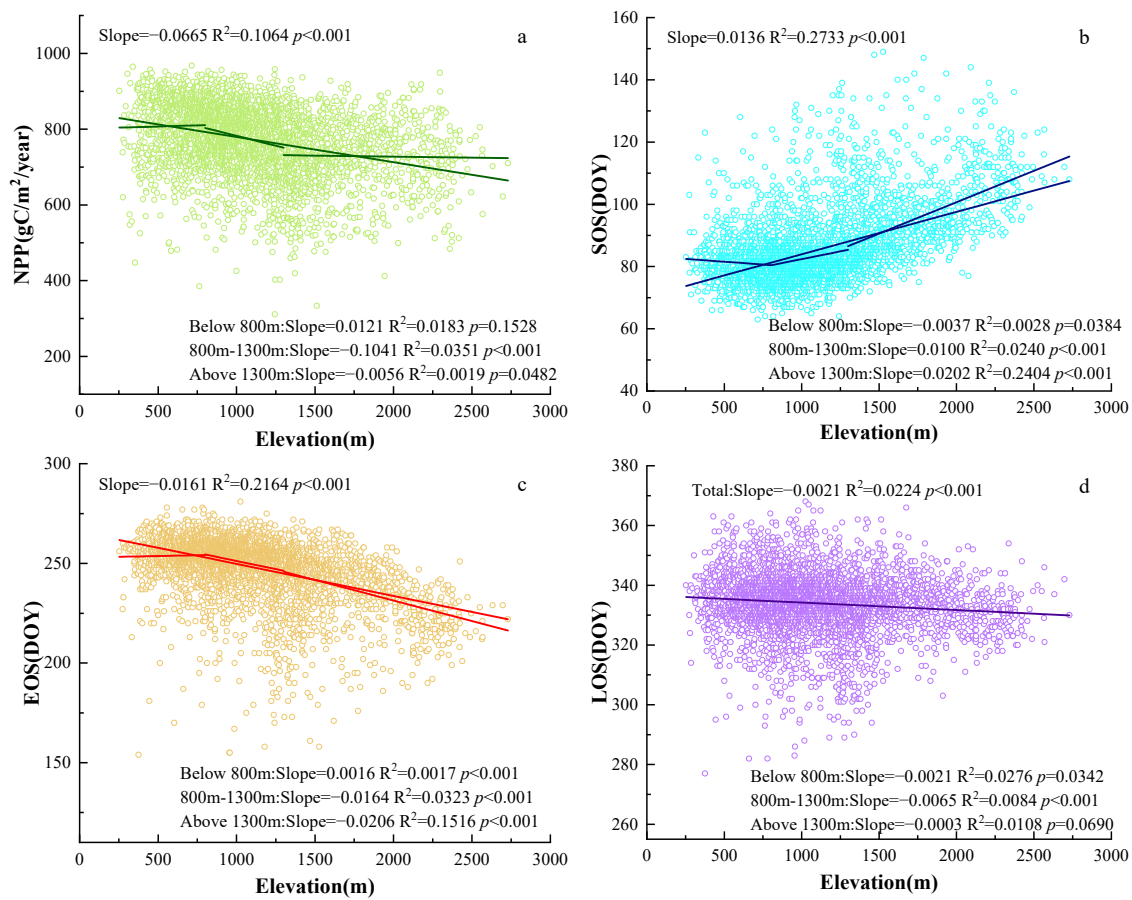


Figure 5. Vertical gradient changes in vegetation phenology and net primary productivity (NPP) in Guizhou Province from 2001 to 2020: (a) relationship between NPP and elevation; (b) relationship between start of the growing season and elevation; (c) relationship between end of the growing season and elevation; (d) relationship between length of the growing season and elevation.

As shown in Figure 5b–d, two distinct trends can be identified for SOS, EOS, and NPP along the elevation gradient. Below 800 m, SOS advanced (slope = −0.0037 d/m, R² = 0.0028, p = 0.0384), and EOS was delayed (slope = 0.0016 d/m, R² = 0.0017, p < 0.001). Above 800 m, SOS was delayed (slope = 0.01 d/m, R² = 0.024, p < 0.001), and EOS advanced (slope = −0.0164 d/m, R² = 0.0323, p < 0.001). NPP also exhibited similar trends along the elevation gradient. Below 800 m, NPP gradually increased (slope = 0.0121 gC/m²/m, R² = 0.0183, p = 0.1528); above 800 m, however, NPP decreased (slope = −0.0056 gC/m²/m, R² = 0.0351, p < 0.001). Regardless of the altitude range, the change in LOS with increasing altitude is insignificant. Although NPP and phenological indicators show trends that vary with altitude, their linear fit correlation with altitude is weak. This may be attributed to the fact that Guizhou Province, being a typical karst region with severe stone desertification and thin soil layers, makes the phenology and primary productivity of vegetation more susceptible to the influence of temperature and precipitation, leading to an indistinct vertical zonation of vegetation phenology and productivity [30].

3.4. Quantitative Indication of Vegetation Phenological Indicators on NPP Changes

To quantify the impact of phenological changes on vegetation NPP, we analyzed the quantitative relationships between the start of season (SOS), end of season (EOS), length of season (LOS), and NPP in Guizhou Province. Relationships between NPP and phenological

indicators were categorized into four groups: Group A, where an increase in NPP was associated with a delay in SOS (or EOS or an extension in LOS); Group B, where an increase in NPP was associated with advancement in SOS (or EOS or a shortening in LOS); Group C, where a decrease in NPP was associated with a delay in SOS (or EOS or an extension in LOS); and Group D, where a reduction in NPP was associated with advancement in SOS (or EOS or a shortening in LOS).

Figure 6a,d illustrate the spatial distribution of the response relationship and correlation coefficients between annual NPP and SOS. A significant negative correlation between NPP and SOS was observed in 79.72% of the region, particularly in the western and north-eastern parts of Guizhou Province. Correspondingly, 68.07% of the plateau area exhibited a notable early SOS, with an increase in NPP in the western and northern parts of Guizhou (Region B), where significant increases in temperature and precipitation were also observed. These climatic increases led to a notable advancement in SOS and an increase in NPP. For Region A, the second largest region in central and northern Guizhou's solar radiation and temperature were shown to be the primary climatic factors influencing vegetation growth, with correlation coefficients of 0.7155 and 0.6654, respectively. Despite a delay in SOS, NPP showed an upward trend with increases in solar radiation and precipitation. This finding contrasts with the majority of existing studies, which found that global warming leads to an earlier SOS [31–33]. This could be due to increased water demand when the growing season surpasses the temperature limitations on vegetation, leading to a delay in SOS [34]. These patterns indicate that although the climate in Guizhou is generally warming, the response of NPP to phenological changes remains complex.

Figure 6b,e display the spatial distribution of the response relationship and correlation coefficients between annual NPP and EOS. Most pixels (55.38%) exhibit a positive correlation, suggesting that a delayed EOS typically leads to an increase in annual NPP. Interestingly, despite the upward trend in NPP in Region B, the earlier EOS results in a shortening of LOS. The earlier occurrence of this phenological change in autumn, due to increased autumn temperatures, reflects the heightened sensitivity of these areas to climate warming. Furthermore, this also demonstrates the complex response of NPP to phenological changes in these areas.

Figure 6c,f show the spatial distribution of the response relationship and correlation coefficients between annual NPP and LOS. During 2001–2020, regions with increased NPP and extended LOS (Region A) are mainly located in Guizhou's western, central, and northeastern parts, where forest and arable land use types are predominant. Meanwhile, regions of increased NPP and significantly shortened LOS (Region B) are primarily found in northern Guizhou. This area, located in a subtropical humid climate zone, is sensitive to temperature changes and susceptible to the impacts of global warming. The correlation coefficients between the NDVI and temperature and solar radiation in this area were 0.6475 and 0.7005, respectively, higher than the correlation coefficient between precipitation and the NDVI (0.3602). Most areas with decreased NPP and shortened LOS (Region C) are mainly located in predominantly forest-covered southeastern Guizhou. In these areas, similar to Region B, the temperature remains the primary determinant of vegetation growth, with the correlation coefficients between the NDVI and temperature and solar radiation being 0.6070 and 0.6630, respectively, higher than the correlation coefficient between the NDVI and precipitation (0.2913). From 2001 to 2020, the advancement in EOS and shortening of LOS led to a $4.6637 \text{ gC/m}^2/\text{year}$ decline in NPP. The climatic conditions are poorer compared to Regions C and D. Due to reductions in the temperature, precipitation, and solar radiation, LOS was significantly shortened, leading to a $4.8300 \text{ gC/m}^2/\text{year}$ decrease in NPP.

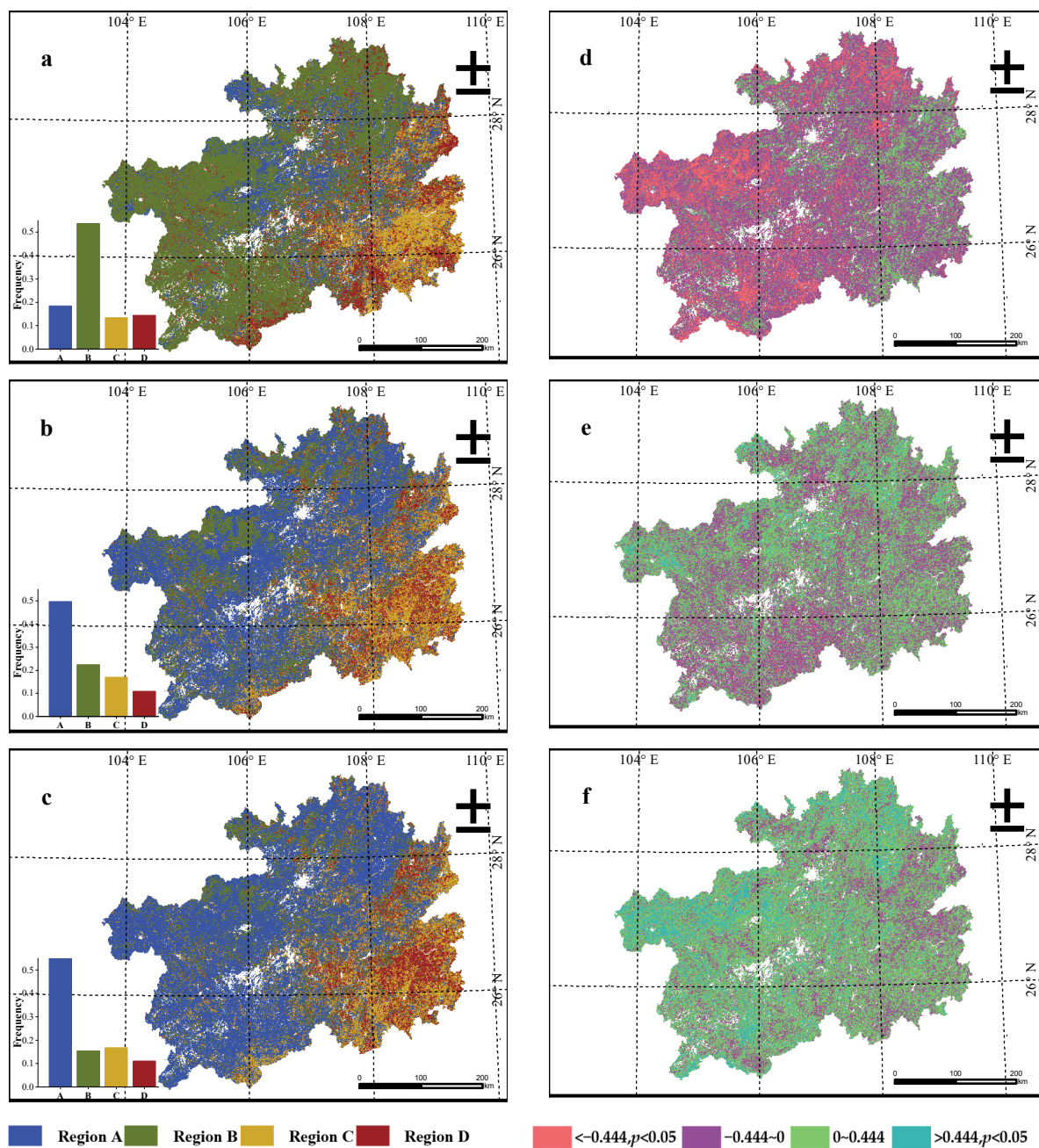


Figure 6. Spatial distribution of the response relationship and correlation coefficients between net primary productivity (NPP) and phenological indicators. (a) Response relationship between annual NPP and start of the growing season, (b) response relationship between annual NPP and end of the growing season, (c) response relationship between annual NPP and length of the growing season, (d) correlation coefficient between annual NPP and start of the growing season, (e) correlation coefficient between annual NPP and end of the growing season, and (f) correlation coefficient between annual NPP and length of the growing season. The inset shows the frequency of different response relationships (Regions A).

3.5. Coupling Effects of Phenological and Meteorological Factors on NPP

Vegetation undergoes regular phenological changes throughout the year, significantly impacting plant functions, ecosystem services, and their biophysical and biochemical feedback to the climate system [35]. Environmental conditions for vegetation growth, particularly climatic factors such as temperature and precipitation, play a critical role in phenology, providing reliable support for vegetation development. Changes in vegeta-

tion phenology result in adjustments to photosynthesis, respiration, and other ecosystem processes, impacting material cycles, energy transformation, and variations in vegetation NPP [6]. Some studies have shown that temperature has a primarily nonlinear impact on phenological changes [36,37]. Additionally, as a stress factor, precipitation significantly influences phenology, where insufficient water supply inhibits the utilization of light and heat by vegetation [38,39].

Depicted in Figure 7 is the SEM model used for calculations over the entire research period and spatial range in this study, with a maximum of seven iterations, chi-square-to-degrees-of-freedom ratio of 3, $p < 0.01$, GFI of 0.793, and NFI of 0.273. Annual precipitation and solar radiation have significant effects on SOS and LOS ($p < 0.05$), with SOS having a highly significant impact on NPP ($p < 0.001$). The effects of annual precipitation, average annual temperature, and solar radiation on EOS are insignificant; however, EOS has a highly significant positive impact on NPP. These three climatic factors indirectly influence NPP through phenology, with their indirect effects having a greater impact than their direct effects. The analysis results suggest that increases in temperature, precipitation, and solar radiation primarily lead to an earlier SOS and a delayed EOS, further promoting an increase in NPP.

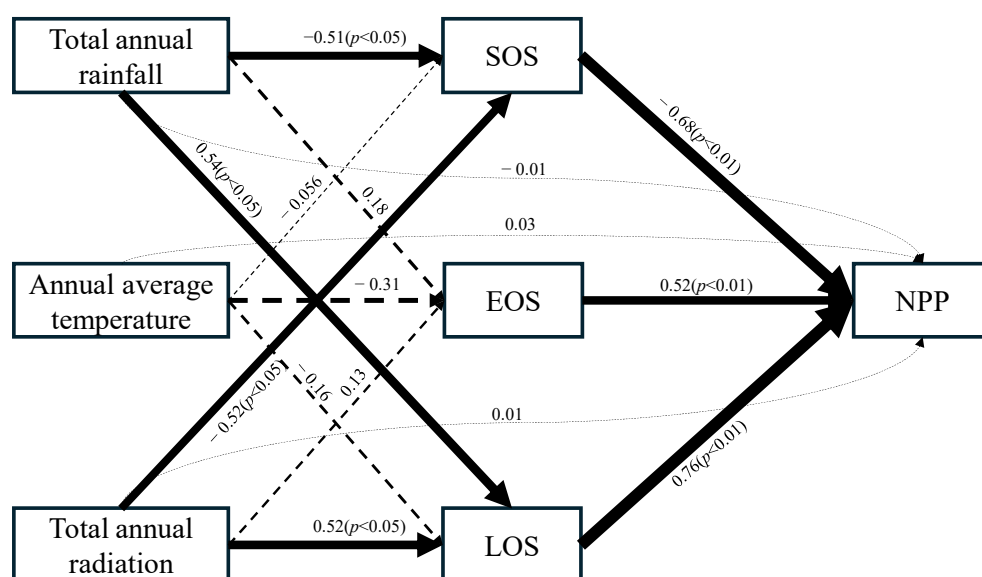


Figure 7. Structural equation model (SEM) representing the relationships between climatic factors, net primary productivity, start of the growing season, end of the growing season, and length of the growing season. Note: The values on the lines represent standardized path coefficients. The thickness of the arrows indicates the magnitude of the standardized coefficients. Solid lines represent significant relationships ($p < 0.1$), while dashed lines indicate nonsignificant relationships.

4. Discussion

4.1. Role of Climate in the NPP Response to Phenological Changes

To delve deeper into the effects of temperature and precipitation on vegetation productivity and LOS, we further analyzed the relationships between NPP, phenology, and climate across different temperature and precipitation zones based on historical climate data. As shown in Figure 8, the response of NPP to LOS varies with the temperature gradient. Although the increase in temperature enhances autumn respiration to a greater extent than autumn photosynthesis, it also advances the start of the growing season (SOS) and extends its length (LOS), thereby prolonging the period of vegetation photosynthesis. Consequently, as the temperature increases, the trend of NPP growth is intensified. When temperatures exceed 19°C , NPP increases from approximately 795 gCm^{-2} at 140 days to about 940 gCm^{-2} at 280 days. However, at temperatures below 13°C , NPP increases from about 725 gCm^{-2} at 140 days to approximately 780 gCm^{-2} at 280 days. At a fixed

temperature, NPP does not increase steadily with the extension of LOS but shows fluctuating growth. Across different precipitation zones, this growth trend of vegetation NPP with the extension of LOS is generally consistent. NPP increases relatively slowly during the first 200 days of the growing season, and then accelerates. This may be due to the fact that in the early stages of vegetation growth, neither temperature nor light reaches the optimal conditions for activating photosynthesis. Therefore, there is a relatively slow increase in vegetation NPP with increasing precipitation. However, when both temperature and light reach the conditions suitable for vegetation photosynthesis, there is a more rapid increase in vegetation NPP with increasing precipitation. The varying trends in NPP with LOS reflect the profound influence of climate on the response mechanisms of NPP to phenological changes.

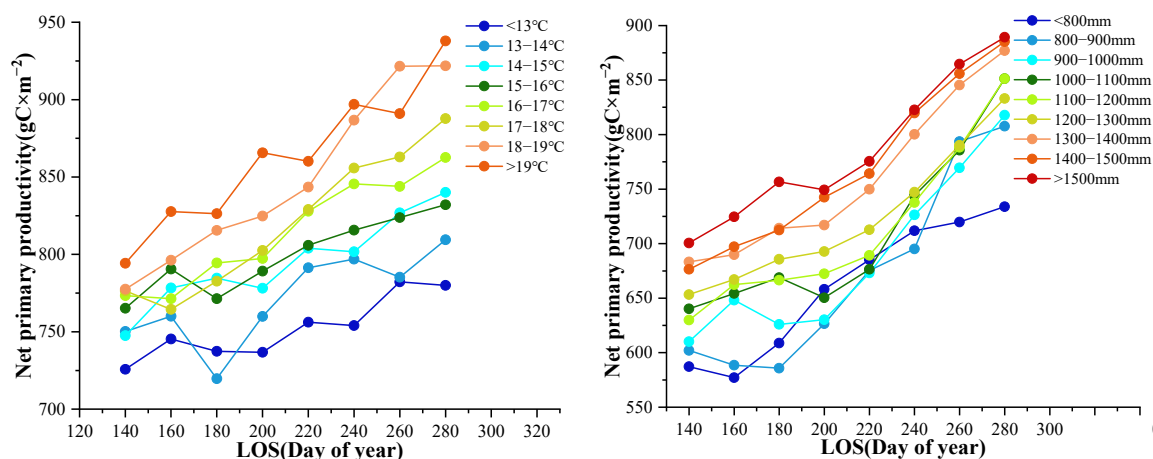


Figure 8. Response of net primary productivity to length of the growing season in different temperature and precipitation zones in Guizhou Province from 2001 to 2020.

4.2. Other Factors Influencing NPP's Response to Phenology

Vegetation NPP's response patterns to phenology vary across regions and are influenced by different factors. The Qinghai–Tibet Plateau, which is also in an ecologically fragile area, has a higher altitude, generally lower temperatures, and an extremely uneven distribution of water resources. During the period from 2000 to 2020, the vegetation NPP of the Qinghai–Tibet Plateau showed a slight decreasing trend under climate change caused by global warming [40]. In high-latitude forests, warmer winters may shorten the cold period, delaying the accumulation of cold units necessary for bud burst; conversely, warmer springs can accelerate heat accumulation, thus promoting plant growth [37,41,42]. In the arid and semiarid regions of the Mongolian Plateau, minor phenological changes induced by summer drought significantly impact the annual NPP, enough to offset the NPP dynamics driven by spring and autumn phenology [43]. In the snow-rich Colorado Rocky Mountains, snowpack reductions and temperature increases lead to earlier snowmelt, advancing the flowering period for most widely distributed species; communities composed of fewer, unique species are also primarily influenced by the timing of snowmelt [44]. Changes in soil resources support vegetation growth, and favorable hydrothermal conditions enhance the activity of photosynthetic enzymes and soil microbes, extending the LOS [22] and promoting the mineralization of soil organic matter, significantly increasing vegetation productivity [45]. Human activities also impact vegetation NPP and phenological dynamics. Since 2000, there has been some progress in Guizhou Province regarding ecological restoration through projects such as “Grain for Green,” “Comprehensive Treatment of Rocky Desertification”, and “Soil and Water Conservation” [46,47]. These ecological projects result in land cover changes, effectively restoring farmland, grassland, and forestland and significantly enhancing vegetation NPP. This may explain why the main factors of terrestrial ecosystems have a varying impact on vegetation productivity.

4.3. Uncertainties of the Results

In this study, remote sensing satellite technology was utilized to monitor vegetation phenology and estimate NPP; however, the spatiotemporal complexity and ecological intricacies of vegetation growth present certain limitations. Sufficient in situ phenological and NPP observational data were lacking for the research area, which restricted our ability to construct complete time series and deeply understand the response of NPP to phenological changes. The uncertainties inherent in satellite remote sensing data might introduce errors in the estimated NPP and phenology datasets, thereby impacting the research outcomes. Additionally, only NODIS was employed as a remote sensing data source, with no comparison to other data sources. In future research, the comparative differences between different types of remote sensing data should be considered [23]. In addition, we recommend that the existing data gaps in the current study be addressed by integrating MODIS data with higher-resolution remote sensing data, such as Landsat data, or utilizing high-resolution terrain data obtained from emerging technologies like drones. Additionally, field data, if available, could be used to further refine the CASA model, thereby minimizing the impact of limitations and uncertainties introduced into the research via the data. Moreover, this study relied solely on average temperature, solar radiation, and precipitation as meteorological variables, and the limitations of the meteorological interpolation methods might lead to errors in the results. Future studies should incorporate other climatic variables (such as extreme weather conditions and daily maximum temperatures) [48], land use changes [49], soil nutrients [50], human activities (such as graze logging) [51], and other natural disturbances as influencing factors to quantitatively analyze their impact on vegetation phenology and NPP.

5. Conclusions

In this study, the spatiotemporal characteristics of vegetation net primary productivity (NPP) were systematically quantified in Guizhou Province, China. We analyzed the response mechanisms of NPP to phenological dynamics and further explored the role of climate change in the NPP response to phenological dynamics. From 2001 to 2020, most regions in Guizhou Province experienced a significant advancement of -0.4 days for the beginning of the growing season and a reduction of 0.39 days at the end, leading to an extension of the growing season of 0.78 days and an annual increase in NPP of 3.5 gC/m^2 . With increasing altitude, NPP, EOS (end of season), and LOS (length of season) exhibited varying trends. Below an altitude of 800 m , NPP increased with altitude, EOS was delayed, and LOS was extended; above 800 m , NPP decreased with altitude, EOS was advanced, and LOS was shortened. The complex relationship between vegetation NPP and phenological dynamics in Guizhou, along with the different response patterns across various climatic zones, indicates that climatic factors have a greater indirect impact on NPP through vegetation phenology than direct effects. In the context of global climate change, it is imperative to consider the impact of seasonal climate changes on vegetation phenology and NPP. Given the complex terrain and climate conditions in Guizhou Province, our findings suggest the need for more detailed analyses across different climatic zones and vegetation communities to quantify the impact of NPP on phenological dynamics. The knowledge gained from this can be essential for land managers and restoration practitioners in karst regions, guiding decision making related to grazing management, reforestation efforts, and water resource management. For instance, the observed advancements and extensions in the growing season may necessitate adaptive strategies in land management to cope with these changes. For example, adjustments in grazing schedules may be required to prevent overgrazing and maintain ecosystem health. The increase in NPP also highlights the potential for enhanced carbon sequestration, which should be factored into reforestation and afforestation efforts. Furthermore, understanding the relationship between NPP and climate can inform strategies for water allocation and conservation during different seasons.

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References

1. Wang, K.; Wang, X.H.; Piao, S.L.; Chevallier, F.; Mao, J.F.; Shi, X.Y.; Huntingford, C.; Bastos, A.; Ciais, P.; Xu, H.; et al. Unusual characteristics of the carbon cycle during the 2015–2016 El Nino. *Glob. Chang. Biol.* **2021**, *27*, 3798–3809. [[CrossRef](#)] [[PubMed](#)]
2. Frank, D.; Reichstein, M.; Bahn, M.; Thonicke, K.; Frank, D.; Mahecha, M.D.; Smith, P.; Van der Velde, M.; Vicca, S.; Babst, F.; et al. Effects of climate extremes on the terrestrial carbon cycle: Concepts, processes and potential future impacts. *Glob. Chang. Biol.* **2015**, *21*, 2861–2880. [[CrossRef](#)] [[PubMed](#)]
3. DeForest, J.L.; Noormets, A.; McNulty, S.G.; Sun, G.; Tenney, G.; Chen, J.Q. Phenophases alter the soil respiration-temperature relationship in an oak-dominated forest. *Int. J. Biometeorol.* **2006**, *51*, 135–144. [[CrossRef](#)] [[PubMed](#)]
4. Noormets, A.; Chen, J.; Gu, L.; Desai, A. The Phenology of Gross Ecosystem Productivity and Ecosystem Respiration in Temperate Hardwood and Conifer Chronosequences. In *Phenology of Ecosystem Processes: Applications in Global Change Research*; Noormets, A., Ed.; Springer: New York, NY, USA, 2009; pp. 59–85.
5. Richardson, A.D.; Anderson, R.S.; Arain, M.A.; Barr, A.G.; Bohrer, G.; Chen, G.S.; Chen, J.M.; Ciais, P.; Davis, K.J.; Desai, A.R.; et al. Terrestrial biosphere models need better representation of vegetation phenology: Results from the North American Carbon Program Site Synthesis. *Glob. Chang. Biol.* **2012**, *18*, 566–584. [[CrossRef](#)]
6. Wu, L.Z.; Ma, X.F.; Dou, X.; Zhu, J.T.; Zhao, C.Y. Impacts of climate change on vegetation phenology and net primary productivity in arid Central Asia. *Sci. Total Environ.* **2021**, *796*, 149055. [[CrossRef](#)] [[PubMed](#)]
7. Beck, P.S.A.; Atzberger, C.; Hogda, K.A.; Johansen, B.; Skidmore, A.K. Improved monitoring of vegetation dynamics at very high latitudes: A new method using MODIS NDVI. *Remote Sens. Environ.* **2006**, *100*, 321–334. [[CrossRef](#)]
8. Zhang, X.; Jayavelu, S.; Liu, L.; Friedl, M.A.; Henebry, G.M.; Liu, Y.; Schaaf, C.B.; Richardson, A.D.; Gray, J. Evaluation of land surface phenology from VIIRS data using time series of PhenoCam imagery. *Agric. For. Meteorol.* **2018**, *256–257*, 137–149. [[CrossRef](#)]
9. Xie, Q.Y.; Moore, C.E.; Cleverly, J.; Hall, C.C.; Ding, Y.L.; Ma, X.L.; Leigh, A.; Huete, A. Land surface phenology indicators retrieved across diverse ecosystems using a modified threshold algorithm. *Ecol. Indic.* **2023**, *147*, 110000. [[CrossRef](#)]
10. Kang, S.; Running, S.W.; Lim, J.-H.; Zhao, M.; Park, C.-R.; Loehman, R. A regional phenology model for detecting onset of greenness in temperate mixed forests, Korea: An application of MODIS leaf area index. *Remote Sens. Environ.* **2003**, *86*, 232–242. [[CrossRef](#)]
11. Liu, Q.; Fu, Y.S.H.; Zeng, Z.Z.; Huang, M.T.; Li, X.R.; Piao, S.L. Temperature, precipitation, and insolation effects on autumn vegetation phenology in temperate China. *Glob. Chang. Biol.* **2016**, *22*, 644–655. [[CrossRef](#)]
12. Yang, Z.Y.; Shen, M.G.; Jia, S.G.; Guo, L.; Yang, W.; Wang, C.; Chen, X.H.; Chen, J. Asymmetric Responses of the End of Growing Season to Daily Maximum and Minimum Temperatures on the Tibetan Plateau. *J. Geophys. Res. Atmos.* **2017**, *122*, 13278–13287. [[CrossRef](#)]
13. Zhang, J.; Zhao, J.; Wang, Y.; Zhang, H.; Zhang, Z.; Guo, X. Comparison of land surface phenology in the Northern Hemisphere based on AVHRR GIMMS3g and MODIS datasets. *ISPRS J. Photogramm. Remote Sens.* **2020**, *169*, 1–16. [[CrossRef](#)]
14. Xue, X.; Wang, Z.J.; Hou, S.S. NDVI-Based Vegetation Dynamics and Response to Climate Changes and Human Activities in Guizhou Province, China. *Forests* **2023**, *14*, 753. [[CrossRef](#)]
15. Zhang, K.X.; Luo, J.J.; Peng, J.T.; Zhang, H.C.; Ji, Y.; Wang, H. Analysis of Extreme Temperature Variations on the Yunnan-Guizhou Plateau in Southwestern China over the Past 60 Years. *Sustainability* **2022**, *14*, 8291. [[CrossRef](#)]
16. Wang, S.Y.; Zhang, B.; Yang, Q.C.; Chen, G.S.; Yang, B.J.; Lu, L.L.; Shen, M.; Peng, Y.Y. Responses of net primary productivity to phenological dynamics in the Tibetan Plateau, China. *Agric. For. Meteorol.* **2017**, *232*, 235–246. [[CrossRef](#)]
17. Zhu, M.; Zhou, Z.; Jiang, Y.; Huang, D. Spatiotemporal Heterogeneity of Precipitation Based on Geomorphological Zoning in the Guizhou Plateau. *Res. Soil Water Conserv.* **2020**, *27*, 181–189.

18. Zeng, Y. Remote Sensing Monitoring of Forest Phenology in Guizhou and Its Response to Climate Change. Master's Thesis, Guizhou University, Guiyang, China, 2018.
19. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [\[CrossRef\]](#)
20. Potter, C.S.; Randerson, J.T.; Field, C.B.; Matson, P.A.; Vitousek, P.M.; Mooney, H.A.; Klooster, S.A. Terrestrial Ecosystem Production—A Process Model-Based on Global Satellite and Surface Data. *Glob. Biogeochem. Cycles* **1993**, *7*, 811–841. [\[CrossRef\]](#)
21. Yuan, W.P.; Cai, W.W.; Xia, J.Z.; Chen, J.Q.; Liu, S.G.; Dong, W.J.; Merbold, L.; Law, B.; Arain, A.; Beringer, J.; et al. Global comparison of light use efficiency models for simulating terrestrial vegetation gross primary production based on the La Thuile database. *Agric. For. Meteorol.* **2014**, *192*, 108–120. [\[CrossRef\]](#)
22. Sun, H.Z.; Chen, Y.B.; Xiong, J.N.; Ye, C.H.; Yong, Z.W.; Wang, Y.; He, D.; Xu, S.C. Relationships between climate change, phenology, edaphic factors, and net primary productivity across the Tibetan Plateau. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *107*, 102708. [\[CrossRef\]](#)
23. Zhang, X.Q.; Chen, Y.N.; Zhang, Q.F.; Xia, Z.H.; Hao, H.C.; Xia, Q.Q. Potential evapotranspiration determines changes in the carbon sequestration capacity of forest and grass ecosystems in Xinjiang, Northwest China. *Glob. Ecol. Conserv.* **2023**, *48*, e02737. [\[CrossRef\]](#)
24. Zhu, W.Q.; Pan, Y.Z.; He, H.; Yu, D.Y.; Hu, H.B. Simulation of maximum light use efficiency for some typical vegetation types in China. *Chin. Sci. Bull.* **2006**, *51*, 457–463. [\[CrossRef\]](#)
25. Sinhashthita, W.; Jearanaitanakij, K. Improving KNN Algorithm Based on Weighted Attributes by Pearson Correlation Coefficient and PSO Fine Tuning. In Proceedings of the 5th International Conference on Information Technology (IncIT), Chonburi, Thailand, 21–22 October 2020; pp. 27–32.
26. Lei, Z.; Liu, S.; Ge, Y.; Wen, Z. A High-Conflict Evidence Fusion Method Based on Average Evidence and Focal Element Distance. *Electron. Opt. Control* **2021**, *28*, 6–10.
27. Vehkalahti, K. Structural Equation Modeling with Mplus: Basic Concepts, Applications, and Programming by Barbara M. Byrne. *Int. Stat. Rev.* **2014**, *82*, 141–142. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Grace, J.B.; Pugsek, B.H. On the use of path analysis and related procedures for the investigation of ecological problems. *Am. Nat.* **1998**, *152*, 151–159. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Hopkins, A.D. The Bioclimatic Law. *J. Wash. Acad. Sci.* **1920**, *10*, 34–40.
30. Zhang, Y.; Tao, J.; Liu, P.; Xu, J. Spatial Differentiation of Forest Phenology in Guizhou Province Based on Time Series MODIS Data. *Resour. Environ. Yangtze Basin* **2015**, *24*, 1891–1897.
31. Zhang, G.L.; Zhang, Y.J.; Dong, J.W.; Xiao, X.M. Green-up dates in the Tibetan Plateau have continuously advanced from 1982 to 2011. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 4309–4314. [\[CrossRef\]](#)
32. Zheng, Z.T.; Zhu, W.Q.; Chen, G.S.; Jiang, N.; Fan, D.Q.; Zhang, D.H. Continuous but diverse advancement of spring-summer phenology in response to climate warming across the Qinghai-Tibetan Plateau. *Agric. For. Meteorol.* **2016**, *223*, 194–202. [\[CrossRef\]](#)
33. Wang, J.; Zhou, T.C.; Peng, P.H. Phenology Response to Climatic Dynamic across China's Grasslands from 1985 to 2010. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 290. [\[CrossRef\]](#)
34. Zhao, G.; Peili, S.; Ning, Z.; He, Y.; Zhang, X.-Z.; He, H.; Jing, Z. Declining Precipitation Enhances the Effect of Warming on Phenological Variation in a Semiarid Tibetan Meadow Steppe. *J. Resour. Ecol.* **2017**, *8*, 50–56.
35. Piao, S.L.; Liu, Q.; Chen, A.P.; Janssens, I.A.; Fu, Y.S.; Dai, J.H.; Liu, L.L.; Lian, X.; Shen, M.G.; Zhu, X.L. Plant phenology and global climate change: Current progresses and challenges. *Glob. Chang. Biol.* **2019**, *25*, 1922–1940. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Dai, J.; Wang, H.; Ge, Q.-S. The spatial pattern of leaf phenology and its response to climate change in China. *Int. J. Biometeorol.* **2014**, *58*, 521–528. [\[CrossRef\]](#)
37. Flynn, D.F.B.; Wolkovich, E.M. Temperature and photoperiod drive spring phenology across all species in a temperate forest community. *New Phytol.* **2018**, *219*, 1353–1362. [\[CrossRef\]](#)
38. Meng, L.; Zhou, Y.; Gu, L.; Richardson, A.D.; Peñuelas, J.; Fu, Y.H.; Wang, Y.; Asrar, G.; De Boeck, H.J.; Mao, J.; et al. Photoperiod decelerates the advance of spring phenology of six deciduous tree species under climate warming. *Glob. Chang. Biol.* **2021**, *27*, 2914–2927. [\[CrossRef\]](#)
39. Li, P.; Peng, C.; Wang, M.; Luo, Y.; Li, M.; Zhang, K.; Zhang, D.; Zhu, Q.A. Dynamics of vegetation autumn phenology and its response to multiple environmental factors from 1982 to 2012 on Qinghai-Tibetan Plateau in China. *Sci. Total Environ.* **2018**, *637–638*, 855–864. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Xu, Y.; Zheng, Z.; Dai, Q.; Guo, Z.; Pan, Y. Attribution Analysis of Vegetation NPP Changes in the Southwest Region Con-sidering Time Lag Effects. *J. Agric. Eng.* **2022**, *38*, 297–305+339.
41. Gao, M.D.; Wang, X.H.; Meng, F.D.; Liu, Q.; Li, X.Y.; Zhang, Y.; Piao, S.L. Three-dimensional change in temperature sensitivity of northern vegetation phenology. *Glob. Chang. Biol.* **2020**, *26*, 5189–5201. [\[CrossRef\]](#)
42. Yan, Z.J.; Xu, J.F.; Wang, X.Y.; Yang, Z.Y.; Liu, D.; Li, G.S.; Huang, H.B. Continued spring phenological advance under global warming hiatus over the Pan-Third Pole. *Front. Plant Sci.* **2022**, *13*, 1071858. [\[CrossRef\]](#)
43. Bao, G.; Chen, J.Q.; Chopping, M.; Bao, Y.H.; Bayarsaikhan, S.; Dorjsuren, A.; Tuya, A.; Jirigala, B.; Qin, Z.H. Dynamics of net primary productivity on the Mongolian Plateau: Joint regulations of phenology and drought. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *81*, 85–97. [\[CrossRef\]](#)

44. Winkler, D.E.; Butz, R.J.; Germino, M.J.; Reinhardt, K.; Kueppers, L.M. Snowmelt Timing Regulates Community Composition, Phenology, and Physiological Performance of Alpine Plants. *Front. Plant Sci.* **2018**, *9*, 1140. [[CrossRef](#)] [[PubMed](#)]
45. Sun, H.Z.; Wang, J.Y.; Xiong, J.N.; Bian, J.H.; Jin, H.A.; Cheng, W.M.; Li, A.N. Vegetation Change and Its Response to Climate Change in Yunnan Province, China. *Adv. Meteorol.* **2021**, *2021*, 8857589. [[CrossRef](#)]
46. Sun, Y.; Zhou, Z.; Zhao, Y.; Fang, M.; Wu, Y. Land Use Evolution and Rocky Desertification Distribution Patterns in Karst Mountainous Areas. *Bull. Soil Water Conserv.* **2022**, *29*, 311–318.
47. Liu, Y.; Zhou, Z.; Yan, L. Spatiotemporal Evolution of NDVI in Guizhou Province from 2001 to 2018 and Its Response to Climate Change and Human Activities. *Bull. Soil Water Conserv.* **2021**, *41*, 327–336.
48. Fu, Y.H.; Li, X.; Chen, S.; Wu, Z.; Su, J.; Li, X.; Li, S.; Zhang, J.; Tang, J.; Xiao, J. Soil moisture regulates warming responses of autumn photosynthetic transition dates in subtropical forests. *Glob. Chang. Biol.* **2022**, *28*, 4935–4946. [[CrossRef](#)]
49. John, R.; Chen, J.; Kim, Y.; Ou-Yang, Z.-T.; Xiao, J.; Park, H.-G.; Shao, C.; Zhang, Y.; Amarjargal, A.; Batkhshig, O.; et al. Differentiating anthropogenic modification and precipitation-driven change on vegetation productivity on the Mongolian Plateau. *Landsc. Ecol.* **2016**, *31*, 547–566. [[CrossRef](#)]
50. Shaukat, M.; Ahmad, A.; Khaliq, T.; Afzal, I. Organic and Inorganic Fertilization Changes the Phenophases of Rice (*Oryza sativa* L.) and Wheat (*Triticum aestivum* L.) by Modulating the Photosynthetic Capacity of Leaves. *Pak. J. Agric. Sci.* **2020**, *57*, 289–294.
51. Chen, J.; John, R.; Yuan, J.; Mack, E.A.; Groisman, P.Y.; Allington, G.R.H.; Wu, J.; Fan, P.; de Beurs, K.M.; Karnieli, A.; et al. Sustainability challenges for the social-environmental systems across the Asian Drylands Belt. *Environ. Res. Lett.* **2021**, *17*, 023001. [[CrossRef](#)]

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