International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-1011
Article

The Impacts of Climate Change on Temperate Forests in Europe and Adaptation Options

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Abstract: Vegetation phenology is a sensitive indicator of climate change, and its changes directly reflect the response of vegetation growth to climate change. The study of vegetation phenology is of great significance to understand the impact of global climate change on terrestrial ecosystems. In this paper, the impact of climate change on temperate forests in Europe was investigated using biased correlation analysis and multiple regression analysis based on NDVI extracted vegetation phenology parameters and climate data from the German Weather Service (DWD) observation network in the Hartz Mountains forest study area. It was found that the interannual variability of forest phenology in the Hartz Mountains from 2001 to 2020 was characterized by summer and fall temperatures as well as fall precipitation as the main factors affecting EOS in the study area. Changes in the sensitivity of forest vegetation EOS to temperature and precipitation were strongly correlated. The effects of both temperature and precipitation on forest EOS showed a trend from negative to positive, in which every 1 mm increase in precipitation from April to August would advance the forest by 0.15 d on average. The correlation between NPP and temperature and precipitation was gradually significant with the increase of time scale. In order to cope with the problem of climate change, it is reasonable to meet the urgent requirements of climate change adaptation by improving the corresponding forest legal system.

Keywords: climate change; European temperate forests; partial correlation analysis; multiple regression analysis; forest legal system

1. Introduction

It is an indisputable fact that the global climate is changing and has already caused significant impacts on socio-economic and natural ecosystems, and will threaten the survival of human beings, representing a long-term and serious challenge to the sustainable development of human society [1-2]. As one of the most widely distributed ecosystems in Europe, temperate forests cover large areas of land, and they are essential for maintaining ecological balance and human well-being in Europe [3]. However, with the increasing climate change, European temperate forests are also affected by climate change.

First, climate change has led to the loss of biodiversity in European temperate forests. Temperate forests are home to many species that provide abundant food and habitat. However, climate change has triggered issues such as increased temperatures and altered precipitation patterns, and these changes have negatively affected the survival and reproduction of many species [4]. This will lead to the breaking of the food chain in the ecosystem, further affecting the survival of other species. Secondly, climate change has had a significant impact on the growth and distribution patterns of temperate forests. Some temperate forests may be challenged by early drying and water scarcity as temperatures increase and precipitation patterns change [5]. This negatively affects the growth and regeneration of forest vegetation. At the same time, climate change is also having a significant impact on the ecosystem functioning of temperate forests. Temperate forests play an important role in the European and global carbon cycle by absorbing large amounts of carbon dioxide and releasing oxygen [6]. However, as droughts and pests increase due to climate change, temperate forests are inhibited in their growth and their ability to absorb carbon dioxide may diminish [7]. This will lead to a further increase in global greenhouse gas concentrations, exacerbating the worsening of climate change. In the face of the various impacts of climate change on temperate forests in Europe, it is necessary to take an effective countermeasure, such as strengthening the monitoring and research of forest resources, establishing a perfect monitoring system, and grasping the changes in forest ecosystems in a timely manner, so as to provide a basis for the development of scientific and reasonable protection strategies [8-10].

In the research on the impact of climate change on European temperate forests and adaptation strategies, Dobor et al. simulated eight climate and herbivory combinations through the iLand model and pointed out that maintaining the current high herbivory pressure would hinder the adaptive transformation of spruce forests to broadleaf forests and intensify disturbance intensity and vulnerability. In contrast, reducing herbivory could drive an increase in carbon storage and system stability within 120 years under RCP4.5, thereby emphasizing that regulating herbivory is a key lever for reshaping the resilience of temperate mixed forests and avoiding ecosystem mutations [11]. Nunes reviewed the response of Northwest Iberian forests to climate change and pointed out that their impacts are highly territorial and adaptive and vulnerable due to differences in species composition and topography, and emphasized that the ecological response mechanisms in this region are still weak and need to be explored in depth in order to formulate targeted coping strategies [12]. Kutnar et al. analyzed the effects of climate warming in Slovenia in combination with disturbances such as ice storms and insect infestations and showed that spruce stocking at low elevations declined significantly as a result of warming and salvage logging, whereas beech stocking trended upwards and the three dominant tree species generally declined, suggesting that silvicultural management in close proximity to nature has a key adaptive potential for mitigating the risks of future climate change and disturbances [13]. After constructing a generalized additive model and developing a decision support system for understory vegetation based on remeasurement data, Wen et al. pointed out through multi-scenario projections that climate warming and nitrogen depletion often drive species richness and the proportion of forest endemics to decrease, while woody and total cover to increase, and emphasized the unique value of maintaining a more closed forest canopy to buffer climatic stresses and to safeguard the biodiversity of the understory [14]. After reviewing the literature on forest transition zones in Western Europe, Fernández-Manjarrés et al. pointed out that broadleaf evergreen expansion and conifer dieback were the main climatic response characteristics, while fire frequency was correlated with land abandonment, and emphasized that agroforestry complexes, although regarded as adaptive options for drought and risk reduction, are of questionable acceptance in temperate zones, and that there is a strong need for proactive monitoring in unmanned zones in order to support natural adaptation [15]. After reviewing 126 remote sensing papers, Wegler and Kuenzer pointed out that multispectral time-series data are the most widely used in assessing climate responses in temperate forests and that drought and tree mortality are the most intensively researched extreme events and responses, and argued that current large-scale analyses still lack the ability to differentiate between the impacts of abiotic drivers at the species level, which is critical for the development of precise adaptation scenarios [16]. Schulze, taking the Central European Quercus robur forests as an example, pointed out after comparing the biodiversity of managed and unmanaged forests that clear-cutting management can increase the richness of forest endemics, deadwood fungi and soil bacteria without causing plant extinction. At the same time, based on long-term data of bird populations, it was indicated that sustainable management did not lead to a decline in diversity. He emphasized that under the pressure of climate change and tree diseases, it is not advisable to completely remove management from forests, but rather to avoid expanding the global ecological footprint through adaptive management [17].

In addition, Chivulescu et al. pointed out that the growth of Carpathian forests tends to increase with climate change and above-ground biomass will increase after calibration of the Landis-II model with annual tree rotation analysis and emphasized that there is a difference in the response of pure forests versus mixed forests, and that this sensitivity feature can provide a key basis for the development of adaptive management programs [18]. Analyzing the remodeling of canopy structure by climate change and forest decline, Sallé et al. showed that deadwood-feeding carrion-feeding insects may gain resource pulses while foliage-feeding taxa are negatively impacted, suggesting that there are gaps in current knowledge and that systematic insights into the adaptive mechanisms of insect community responses are needed to address the new challenges of conservation by means of long term collaborations and multidisciplinary interactions across scales [19]. Augustynczik et al. simulated the temperate forests in southwestern Germany by constructing a coupled ecological-economic partial equilibrium model and pointed out that by the end of this century, the consumption of wood and the supply of biodiversity will increase by up to 38.4% at most. The current management underestimates their social value and is inefficient. They emphasized that policy tools such as taxation should be used to internalize biodiversity in forest planning to achieve the socially optimal output under climate change [20]. Romeiro et al., after reviewing the correlation between natural disasters in European forests and climate change, as well as 39 disturbance models, pointed out that global warming exacerbates root rot and bark beetle damage by shortening the frozen soil period, while drought and an increase in combustible materials increase the risk of temperate wildfires. They emphasized that although probability models are widely used, there are still few models with the ability to influence predictions, and they need to be integrated into large-scale forest planning to improve the accuracy of adaptation decisions [21]. A hybrid assessment by Ding et al. synthesizing climate scenarios and productivity shocks showed that Mediterranean countries would experience significant welfare gains and Northern Europe high losses by shifting to an environmentally oriented pathway, providing a differentiated economic rationale for designing regional ecosystem-based adaptation responses [22]. Dyderski et al. integrated multi-source distributional data with the MaxEnt model to assess the distributional changes of 12 European tree species under three emission pathways up to 2080, revealing that late-successional species tend to expand, while pioneer and boreal populations face severe habitat contraction, which poses a serious challenge for adaptive management under limited migration scenarios [23]. The above studies show that the impacts of climate change on temperate forests in Europe are characterized by significant geographic, species-dependent and disturbance interactions, in which regulating herbivory pressure, maintaining a closed canopy, promoting near-natural silviculture and adaptive management, enhancing the value of biodiversity in forest planning, and strengthening cross-scale monitoring and modeling integration are the key adaptive levers for enhancing forest resilience and avoiding abrupt ecosystem changes. However, there are still research gaps such as insufficient analysis of abiotic driving mechanisms at the species level and weak knowledge of ecological responses in specific regions.

As one of the most important ecosystems on Earth, the impacts of climate change on temperate forests in Europe are of great importance for the conservation of the Earth's ecosystems. In this paper, we take the natural beech and remnant spruce forests in the Hartz Mountains in northern Germany, which is located in the temperate zone of Europe, as the study area, and take 2000~2020 as the study years, and analyze the temporal and spatial characteristics of SOS, EOS, and LOS with multivariate statistical analysis, using extracted forest NDVI data and climate data. Combined with the meteorological data of the same period, we analyzed the relationship between SOS and climate factors (temperature and precipitation), explored the response mechanism of SOS to climate change, and thus explored the adaptation options for temperate forests in Europe under climate change.

2. Data sources and research methodology

2.1. Overview of the study area

The Hartz Mountains are located in the north of Germany, about 110km long and 30km wide, with the highest peak, Brocken, at an altitude of 1,141 m. The climate is temperate and mountainous, with an average temperature of 2.5~8.0°C (decreasing with elevation) and an annual precipitation of 1,000~1,600 mm. The soils are characterized by acidic brown yellows and stony soils. The forests are composed of natural beech and remnant spruce at an altitude of more than 800 meters, and mixed spruce-beech forests at an altitude of 500-800 meters. At altitudes of less than 500 m, pure spruce forests (mostly planted in the 18th-20th centuries) were established. 2018-2020 drought led to a large-scale dieback of spruce at lower altitudes, followed by a large-scale outbreak of spruce eight-toothed waxwings.

2.2. Study data and pre-processing

2.2.1. NDVI data

The study used NDVI to extract vegetation phenology parameters.NDVI was derived from the land cover dynamics product (MOD13Q1 NDVI) monitored by the Moderate Resolution Imaging Spectroradiometer (MODIS) of the National Aeronautics and Space Administration (NASA) of the United States of America (USA), with a spatial resolution of 250 m and a temporal resolution of 16 d.Referring to the relevant literature, $NDVI_{\mathrm{mean}}$=0.05 was used as the exclusion threshold of the non-vegetation Threshold. The 16-d maximum synthesized NDVI data are then used for time series reconstruction to remove the noise, and the window size and rational polynomials are set to 3. Because the remote sensing images are greatly affected by clouds and the atmosphere when acquiring the images, it is necessary to reduce the noise and smoothen the NDVI time series data, and in this study, we utilize the Savitzky-Golay filtering method for the time series reconstruction of NDVI data to remove the noise. Firstly, the Spike Method is used to remove the invalid points of the original NDVI curve during the curve reconstruction process; secondly, the filtering window is constructed on the original NDVI data; finally, the fitting of the whole curve is realized by smoothing the window of the original NDVI time series data. The specific formula for comparing the data before and after filtering is:

$$Y_j = \frac{\sum_{i=-m}^{i=m} C_i Y_{j+i}}{N} \tag{1}$$

where: Y_j is the NDVI sequence data after fitting; Y_{j+i} is the original NDVI sequence data; C_i is the filter coefficient; and N is the size of the sliding window $(2m+1)$.

2.2.2. Climate data

Temperature and precipitation data are derived from the daily value dataset of the German Weather Service (DWD) and span the period 2000-2020. The seasonal climate is divided into the following categories: the months of December, January, and February are defined as winter (beginning of the year winter), March, April, and May are defined as spring (spring of the current year), June, July, and August are defined as summer (summer of the previous year and summer of the current year), and September, October, and November are defined as fall (fall of the previous year and fall of the current year), where beginning of the year winter, spring of the current year, summer of the current year, and fall of the current year data are used for the spatio-temporal analysis. Summer and current year fall data were used for spatial and temporal analysis of seasonal climate. Because considering that vegetation SOS in the Hartz Mountains mainly occurs from April to May, and vegetation EOS mainly occurs from September to October, a total of three sets of extreme and annual mean climate data are defined in this paper, the first: climate data from the beginning of June of the previous year to the end of May of the current year are used as the analysis of vegetation SOS in response to the extreme and annual mean climate, the second: climate data from the beginning of September of the previous year to the end of August of the current year are used as the analysis of the vegetation EOS response to climate extremes and annual mean climate, and third: climate data from the beginning of January of the current year to the end of December of the current year were used for the temporal and spatial analysis of climate extremes and annual mean climate. Regarding the calculation of the extreme climate indices, it was specified that firstly, the selected data were quality controlled according to RclimDex, and finally 13 meteorological stations in the study area were screened out, whereas the commonly used climatic indices recommended by the ETCCDMI were used, and the TXx index, TXn index, TNn index, TNx index, DTR index, RX1day index, and RX5day index were selected to reflect the marginal state of temperature events and extreme state of precipitation events, and the time series of each index were calculated using RclimDex and MATLAB 10.2 software. The annual scale and seasonal data were interpolated into a raster data set with a spatial resolution of 250 m using the professional meteorological interpolation software ANUSPLINE 4.2.

2.2.3. Climate validation data

Climate station data were obtained from the climatic observation network of the German Weather Service (DWD) and long-term observation records of the Brockenberg Botanical Garden in the Hartz National Park. Four representative climatic stations in the Hartz Mountains were selected: the Brockenberg Botanical Garden, Elbingrod, Blankenburg, and St. Andreasberg. The observed species were dominated by the European beech and the European spruce. Records whose recording time differed from other data by more than 30 days were excluded according to the recommendations of the Hus Society, and the emergence and dieback periods of the data from the three ground-based observation sites were defined as vegetation SOS and vegetation EOS.

2.2.4. Elevation data

The 30 m resolution digital elevation model (DEM) data were obtained from the DGM25 dataset published by the German Federal Agency for Cartography. The data were processed in ArcGIS Pro 3.0 using tools such as reclassification and extraction by mask to obtain a 500 m spatial resolution DEM for the Hartz Mountains region, which was used for interpolating covariates of meteorological data in the ANUSPLINE 4.2 software, as well as as being the basis for the calculation of the topographic factors (slope, aspect, and elevation band delineation).

2.3. Research methodology

2.3.1. Extraction methods for vegetation phenology

Although the NDVI data have been processed by the maximum value synthesis (MVC) method and other noise removal methods, they may still be affected by pollution such as clouds and snow. Therefore, before extracting the vegetation phenology, it is necessary to further remove the noisy points in the NDVI data that are polluted by clouds, snow, and water vapor, etc. The values of the noisy points in the NDVI data are generally lower than the NDVI values of the two periods before and after the point, because the NDVI in spring and autumn is characterized by monotonically increasing or decreasing. Simple linear interpolation was performed using the points in the two periods before and after the noise point, and the NDVI value obtained from the interpolation was substituted for the value of the noise point.

In this study, the Polyfit-Maximum (PM) method was used to extract vegetation phenology. This method uses the NDVI maximum rate of change and the NDVI minimum rate of change to extract SOS and EOS, respectively, and has been widely used to extract vegetation phenology in the mid- to high-latitude regions of the Northern Hemisphere. First, the relative rate of change of NDVI $\left(NDVI_{ratio}\right)$ on the 21-year average NDVI seasonal curve for each image element was calculated using Equation (2):

$$NDVI_{ratio}(t) = \frac{NDVI(t+1) - NDVI(t)}{NDVI(t)} \tag{2}$$

where t is the time (with a temporal resolution of 15d), $NDVI(t)$ is the NDVI value at the moment t, and $NDVI_{ratio}(t)$ is the rate of change of NDVI at the moment t. Next, the moment t corresponding to the maximum $NDVI_{ratio}(t)$ is searched for and the $NDVI(t)$ at the moment t is used as the threshold for extracting SOS; the moment t corresponding to the minimum $NDVI_{ratio}(t)$ is searched for and the $NDVI(t+1)$ at the moment $t+1$ is used as the threshold for extracting EOS. Then, the NDVI data points from January to September (SOS) and July to December (EOS) of each year are fitted using a one-dimensional sixth-degree polynomial function (Eq. (3)) to reconstruct the NDVI time series with a temporal resolution of 1 d. Finally, the SOS and EOS thresholds determined in the third step are utilized for each image to extract the SOS and EOS from the reconstructed daily NDVI time series curves :

$$NDVI = a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n \tag{3}$$

where x is the day of the year (Julian day), n is taken as 6, and $a_0, a_1, a_2, a_3, a_3, a_n$ are the coefficients of the regression fit.

2.3.2. Trend analysis of vegetation phenology

A one-way linear regression model (Eq. (4)) was used to calculate the trend of inter-annual changes in vegetation phenology (SOS, EOS and LOS). Least squares-based one-way linear regression models are widely used to analyze trends in interannual changes in metrics such as NDVI, water use efficiency (WUE), and biological productivity:

$$y = ax + b + \varepsilon \tag{4}$$

where y is the time series value of vegetation phenology (SOS, EOS, or LOS), x is the year (2000, 2001, ..., 2020), and ε is the residual of the regression fit. a and b are the coefficients of the regression fit, where coefficient a is the slope, i.e. the rate of change of vegetation phenology over time. A negative a indicates an advance trend in SOS (EOS); a positive a indicates a delay trend in SOS (EOS). In addition, a negative a indicates a shortening trend in LOS; a positive a indicates a lengthening trend in LOS. T-test was used to test the significance of regression coefficient a, and $P < 0.05$ was set as the significance level.

2.3.3. Biased correlation analysis between SOS and climate factors

Partial correlation analysis is the study of the correlation of one variable with another variable by removing the effects of the other variables (i.e., the other variables are used as control variables), and the partial correlation coefficient, R, indicates the degree of correlation. The method has been commonly applied to studies in ecology and geography, among others. In this paper, partial correlation analysis was used to study the correlation of SOS with temperature and precipitation:

$$R_{12(3)}=\frac{R_{12}-R_{13}R_{23}}{\sqrt{1-R_{13}^{2}}\sqrt{1-R_{23}^{2}}} \tag{5}$$

$R_{12(3)}$ is the partial correlation coefficient between the first and second variables obtained by setting the third variable as a control variable, and R_{12}, R_{13}, and R_{23} are the simple correlation coefficients between the two variables, respectively. The partial correlation coefficients were tested for significance using the T test, setting 0.05 as the significance level. In this paper, pre-season cumulative precipitation was set as a control variable when calculating the partial correlation coefficients between SOS and pre-season mean temperature; pre-season mean temperature was set as a control variable when calculating the partial correlation coefficients between SOS and pre-season cumulative precipitation. In order to analyze the relationship between preseason climate factors and SOS, this paper calculates the bias correlation coefficients of SOS with all preseason mean temperatures (preseason cumulative precipitation) and determines the most relevant preseason period corresponding to the climate factors. The most relevant pre-season period is the period corresponding to the largest (absolute value) bias correlation coefficient between SOS and pre-season climate factors (temperature and precipitation).

2.3.4. Multiple linear regression analysis

The slopes of multiple linear regressions of SOS on the mean temperature of the most relevant preseasonal period and the cumulative precipitation of the most relevant preseasonal period were taken as the sensitivities of SOS to preseasonal temperature and preseasonal precipitation (i.e., SOS temperature sensitivity and SOS precipitation sensitivity):

$$y=\alpha_0+\alpha_1x_1+\alpha_2x_2+\varepsilon \tag{6}$$

y is the SOS time series value, x_1 and x_2 are the mean temperature in the most relevant pre-season period and the cumulative precipitation in the most relevant pre-season period, and ε is the residual of the regression fit. α_0, α_1, and α_2 are the coefficients of the regression fit, where the regression coefficients α_1 and α_2 are the regression slopes, which indicate the magnitude of the SOS temperature sensitivity (d - °C^{-1}) and the SOS precipitation sensitivity (d-10mm^{-1}) magnitudes. A negative $\alpha_1(\alpha_2)$ indicates the number of days when SOS is advanced for a 1°C increase in preseason mean temperature (10 mm increase in preseason cumulative precipitation), while a positive $\alpha_1(\alpha_2)$ indicates the number of days when SOS is delayed for a 1°C increase in preseason mean temperature (10 mm increase in preseason cumulative precipitation).

2.3.5. Calculation of Trend Turning Points

In this paper, we only detect possible TPs in the SOS, EOS, and LOS time series for the years 1987-2010.Prior to the segmented linear regression, a 3-year moving average method is applied to smooth the SOS, EOS, and LOS time series to remove the statistical uncertainty caused by the first and the last data points, as well as by the individual outliers:

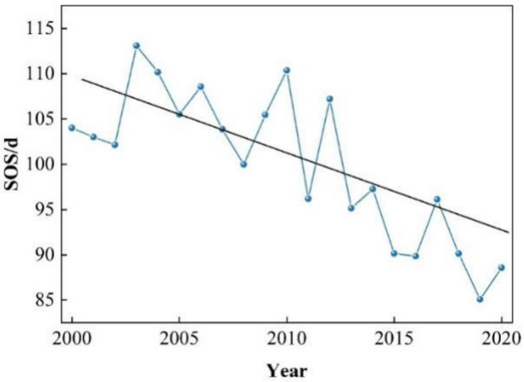
$$y=\begin{cases}\lambda_0+\lambda_1t+\varepsilon & t<\alpha\\ \lambda_0+\lambda_1t+\lambda_2(t-\alpha)+\varepsilon & t\geq\alpha\end{cases} \tag{7}$$

Here, t represents the sequence value of the year (2000, 2001, ..., 2020), y is the sequence value after the moving average of SOS, EOS and LOS for each climate zone, α is the year corresponding to TP in the trend of SOS, EOS and LOS, λ_0, λ_1 and λ_2 are the coefficients of the regression fit, and ε is the residual of the fit. λ_1 and $\lambda_1+\lambda_2$ denote the slopes before and after fitting the TP for SOS, EOS and LOS segments, respectively. To assess the necessity of introducing TP, a t-test was used to test the following null hypothesis: " λ_2 is not significantly different from 0" and $P<0.05$ was considered significant. If λ_2 at each point fails the significance test, it indicates that there is no TP in the trend; If there exists more than one point for which λ_2 passes the significance test, the point with the smallest P is taken as the TP.After obtaining the TP, the linear trends before and after the TP of the SOS, EOS, and LOS time series are computed using a one-dimensional linear regression model.

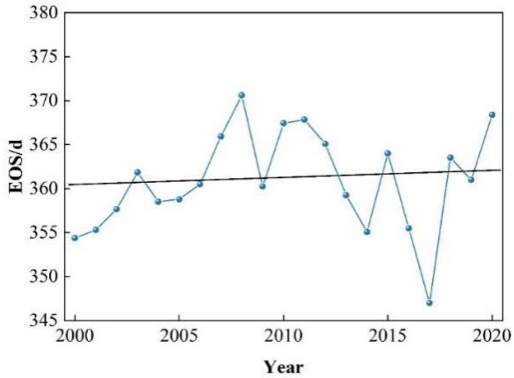
3. Results and analysis

3.1. General characteristics of inter-annual variability in forest phenology

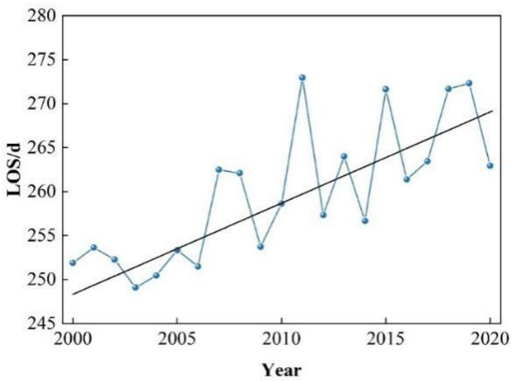
Figure 1 shows the calculated interannual variability characteristics of forest phenology in the Hartz Mountains from 2001 to 2020.The SOS had an advance trend and passed the test of significance (R^2=0.53, P=0.001<0.05), with an average of 1.15d(10a)-1. This trend was consistent with the global SOS phenology value trend, but smaller than the global -3.2d(10a)-1 during 1981-2003 and -(4±0.83)d(10a)-1 during 2000-2008 in the Northern Hemisphere.EOS showed a delayed trend, with an The average delay of 0.08 d(10a)-1 did not pass the test of significance (R^2 = 0.05, P = 0.759 > 0.05). The magnitude of change was also smaller than the global 0.48d(10a)-1 during 1981-2003 and the European temperate 2.5d(10a)-1 during 2000-2008. The LOS in the study area had a prolonged trend in 19a and passed the test of significance (R^2=0.48, P=0.001<0.05), with an average prolongation of 1.11d(10 a)-1, a trend that is consistent with the prolonged trend of the LOS in the global and temperate Europe.



(a)SOS



(b)EOS



(c)LOS

Figure 1. The trend of the forest in the year

3.2. Relationship between forest phenology and climate factors

In this paper, we analyzed the characteristics of forest phenology response to climate change in the study area by calculating the correlation coefficients of SOS, EOS, and LOS with climatic factors (temperature and precipitation) in quarterly and annual mean phases in the whole region and four eco-geographical subzones, and the correlation coefficients of SOS, EOS, and LOS with temperature and precipitation under different subzones are shown in Table 1.

From the correlation coefficients of SOS and temperature, SOS was negatively correlated with spring as well as annual mean temperature in different ecological zones, indicating that the beginning date of the vegetation growing season was advanced by increasing temperature. And it was positively correlated with the previous winter temperature, indicating that the beginning date of the forest growing season was delayed by the increase in temperature in the previous winter. From different seasons, the correlation coefficients between SOS and spring temperature were the largest in all subregions, indicating that higher spring temperatures greatly promoted vegetation sprouting, while higher winter temperatures in the previous year delayed the onset of the following spring phenological period.

The correlation coefficients between SOS and precipitation showed that spring precipitation as well as precipitation in the previous winter had the same effect on SOS in all sub-regions. For the natural beech and remnant spruce forest zones, spring as well as the previous winter precipitation had a depressing effect on their SOS, indicating that increased precipitation delayed the start date of the vegetation growing season in this zone. For the grassland zone in the southern section, spring as well as the previous winter precipitation had a facilitating effect on its SOS. However, overall, temperature affected SOS in the study area to a greater extent than precipitation, and there was a lag in the response of SOS to precipitation.

From the correlation coefficients between EOS and temperature in different subzones, EOS was positively correlated with summer, fall, and average annual temperature, indicating that they all had a promoting effect on EOS, among which, the correlation between EOS and fall temperature was the largest. It indicates that the increase in temperature in fall has the greatest delaying effect on EOS.

From the correlation coefficients between EOS and precipitation in different subzones, the correlation between EOS and fall precipitation was the largest in the whole study area as well as in the four ecological subzones, and except for the positive correlation between EOS and fall precipitation in the southern section of the forest area, EOS and fall precipitation in the other three ecological subzones were negatively correlated, which indicated that precipitation mainly played a promotional role for EOS in the southern section of the forest area, and played an inhibitory role for EOS in the rest of the forest area, that is to say, the increase of precipitation in the southern section of the forest area was mainly associated with the increase of precipitation in the southern section. Increased precipitation delayed the end date of the vegetation growing season in the southern forest zone, while the end date of the vegetation growing season in the other three subzones advanced. In summary, it can be seen that summer and fall temperatures as well as fall precipitation are the main factors affecting EOS in the study area.

From the correlation coefficients between LOS and different seasonal temperatures in different subzones, all subzones' LOS were significantly and positively correlated with summer, fall, and annual average temperatures, among which summer temperature had the largest correlation coefficients with the LOS of all subzones, which indicated that summer temperature was the main factor contributing to the length of the vegetation growing season in the area. Among them, the correlation coefficients between LOS and summer and fall temperatures in the western forest zone of the northern section were as high as 0.622 and 0.553, respectively, whereas the correlation coefficient between LOS and fall temperature in the forest zone of the southern section was the smallest, only 0.166, because it was located in a semiarid area in the mesophilic zone, which was insensitive to the response to fall temperature.

From the correlation coefficients between LOS and precipitation in different seasons in different subzones, except for the southern section of the forest zone, the other three subzones have negative correlation between LOS and fall precipitation, which indicates that fall precipitation has an inhibitory effect on the LOS in most of the zones, and promotes the LOS in the southern section of the forest zone, but the effect is extremely weak. Among them, the LOS of the mountainous deciduous-coniferous forest zone in the northern section and the forest zone in the western part of the northern section were significantly negatively correlated with fall precipitation, indicating that the increase of fall precipitation would shorten the length of the vegetation growing season. This may be due to the fact that these two subareas are located in humid and semi-humid areas, where rain and heat coincide with each other and precipitation is plentiful. Soil moisture increases rapidly with the increase of precipitation in summer and fall, which enhances photosynthesis by affecting the carboxylation of the vegetation, and the vegetation accelerates the growth and completes the growing season earlier than expected.

Table 1. The correlation coefficients of the SOS, EOS and LOS and climate factors

Factor	Region	SOS			EOS				LOS			
		Spr.	Win.	Mean	Spr.	Sum.	Aut.	Mean	Spr.	Sum.	Aut.	Mean
Temp.	O	-0.489***	0.207	-0.366**	-0.266	0.477***	0.515***	0.225	0.173	0.595***	0.565***	0.401**
	I	-0.555***	0.125	-0.355*	-0.118	0.318*	0.352*	0.157	0.305*	0.433**	0.381**	0.352*
	II	-0.356**	0.355*	-0.322*	-0.235	0.435**	0.518***	0.199	0.066	0.622***	0.553***	0.33*
	III	-0.333*	0.115	-0.255	-0.353	0.333*	0.247*	0.097	-0.008	0.481***	0.413**	0.235
	IV	-0.238	0.319*	-0.108	-0.278	0.445**	0.082	-0.051	-0.022	0.501***	0.166	0.042

Precip.	O	-0.075	0.045	-0.119	0.255	-0.108	-0.577***	-0.368**	0.222	0.078	-0.459***	-0.156
	I	0.358*	0.028	-0.148	0.201	-0.062	-0.493***	-0.333*	-0.107	0.143	-0.371**	-0.121
	II	-0.222	-0.085	0.065	0.242	-0.031	-0.523***	-0.325*	0.296	-0.065	-0.383**	-0.255
	III	0.041	0.021	-0.081	0.283	0.015	-0.346*	-0.113	0.161	0.006	-0.117	-0.023
	IV	-0.199	-0.245	-0.212	-0.115	-0.121	0.291	0.095	0.061	0.111	0.112	0.201

3.3. Sensitivity of forest phenology to climatic factors

Based on the analysis of related literature, it was found that nighttime air temperature in temperate regions of Europe has a stronger influence on vegetation phenology, so nighttime air temperature and cumulative precipitation were selected to conduct multivariate linear regression with phenology parameters to investigate the sensitivity of phenology parameters to climate factors, and the trend of the sensitivity of forest and grassland vegetation SOS to air temperature. The trends of forest and grassland vegetation SOS sensitivity to temperature and precipitation are shown in Figure 2. The results showed that forests responded to precipitation only in November and February during the SOS period, and every 1 mm increase in precipitation would advance by 0.33 d in November and delay by 0.65 d in February; precipitation in December would delay the onset of SOS in grasslands by an average of 2.66 mm^{-1}, while there was a clear trend of advancement in January and March to April, with an average of 0.77 d advancement for every 1 mm increase in precipitation (Figs. a, b). This indicates that spring precipitation has different mechanisms on forests and grasslands, and forest SOS is less sensitive to precipitation, while grasslands are more sensitive and advance with the increase of spring precipitation. The effect of temperature on vegetation phenology changed over time (Fig. c, d), with all months showing significant effects. Forest SOS had opposite response mechanisms in winter and spring, with warmer temperatures in winter delaying the arrival of SOS by an average of 1.15 d per 1°C of increase, while in spring it advanced by an average of 2.63 d per 1°C of increase.This was mainly because warming during the cold-driven phase would be detrimental to the low-temperature environment required by vegetation and delay SOS, whereas in the spring-driven phase the vegetation would need to build up heat in order to break through low-temperature limitations, and therefore Warming in spring will drive SOS earlier, and the opposite is true for warming in fall and winter. Notably, grasslands did not have a longer cold-driven phase compared to forests, with only a weak tendency to delay warming in February (0.67 d°C^{-1}), while all other months significantly advanced SOS, with an average rise of 1°C advancing by 3.44 d. The SOS of grasslands was also significantly earlier than that of forests.

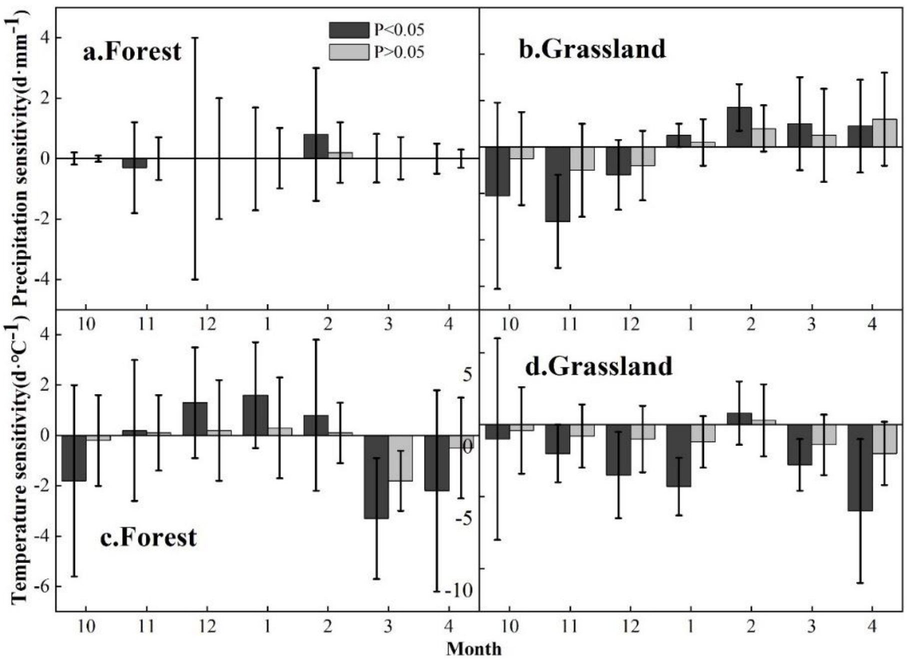


Figure 2. SOS trends in temperature and precipitation

The trends of forest vegetation EOS sensitivity to temperature and precipitation are shown in Figure 3. During the EOS period, the effects of precipitation on forest EOS all showed a trend from negative to positive (a).Each 1 mm increase in precipitation from April to August will advance the forest by 0.15 d on average, and then September to October will be delayed by 0.13, whereas the related study showed that the grassland EOS had a significant negative correlation with precipitation from April to June, and that an increase of 1 mm on average will advance the forest by 0.23 d, and the July to October would be delayed by 0.14 d. Forest EOS responded to temperature similarly to precipitation (c), with each 1 ℃ increase in April to August advancing by 1.39 d, and each 1 ℃ increase in September to October delaying by 2.78 d. Meadow EOS, however, showed a smaller and inconsistent response to temperature from April to August, with a consistent trend of delay (4.35 d $℃^{-1}$) only in September to October.

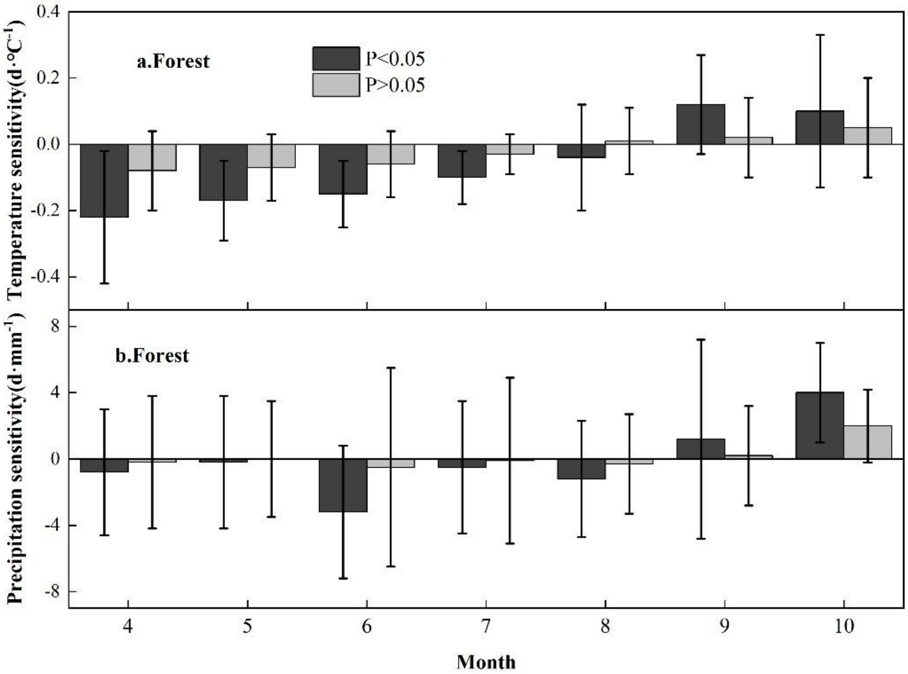


Figure 3. EOS change in sensitivity to temperature and precipitation

3.4. Relationship between NPP changes and climate change at different time scales

Table 2 shows the mean period of NPP change and its variance contribution at different time scales.NPP is decomposed into four IMF components, which are the fluctuating changes at 3, 6, 14, and 20-year time scales, respectively (Table 2). Among them, IMF1 has the largest variance contribution (39.38%), followed by IMF2 (16.15%). IMF3 and IMF4 have smaller variance contributions (11.92% and 3.52%, respectively), and thus these two components are not considered in the following analysis in this study. The trend term is consistent with the M-K results, both showing an increasing trend, and its variance contribution of 29.03% is second only to the 3-year time scale, but much larger than the other components. It can be seen that the vegetation NPP in the study area mainly shows 3-year cycle variation and long-term increasing trend.

Table 2. The average cycle of the growth season and its variance contribution

	IMF1	IMF2	IMF3	IMF4	Residual
Period / a	3	6	14	20	-
Standard deviation	0.35	1.11	4.85	10.25	-
Variance contribution / %	39.38	16.15	11.92	3.52	29.03
Standard deviation	0.18	0.13	0.11	0.08	0.23

Table 3 shows the mean period and its variance contribution of the mean growing season temperature and precipitation changes at different time scales. The mean growing season temperature is decomposed into four IMF components, which are the cycle changes at 3, 6, 15 and 21 years time scales.The variance contributions of the IMF components at 3 and 6 years time scales are 27.86% and 16.26%, respectively, which are larger than the variance contributions of the other components. Similar to the temperature M-K curve, the variance contribution of the EEMD trend term was 41.45%, which was higher than the other components, suggesting a significant trend of increasing temperatures during the growing season. Growing season precipitation was decomposed into fluctuating changes over 3, 6, 13, and 19 yr. The variance contributions of the 3 and 6 yr time scales were 67.39% and 16.06%, respectively, which were much larger than the other components. The variance contribution of the trend term was very low (6.23%) and this result is consistent with the M-K results, indicating that there is no significant increasing trend in growing season precipitation. This shows that the growing season precipitation is dominated by fluctuations on 3- and 6-year scales, with no significant long-term trend.

Table 3. Average cycle and its variance contribution

		IMF1	**IMF2**	**IMF3**	**IMF4**	**Residual**
Temperature	Period / a	3	6	15	21	-
	Standard deviation	0.36	1.29	3.82	7.11	--
	Variance contribution / %	27.86	16.26	10.45	3.98	41.45
	Standard deviation	0.12	0.12	0.07	0.02	0.18
		IMF1	IMF2	IMF3	IMF4	Residual
Precipitation	Period / a	3	6	13	19	-
	Standard deviation	0.29	0.84	3.89	6.41	--
	Variance contribution / %	67.39	16.06	6.91	3.41	6.23
	Standard deviation	0.01	0.1	0.08	0.03	0.07

4. Conclusion

Based on the vegetation index data from 2000 to 2020, the study explored the sensitivity of forest phenology to climate factors and the response of vegetation growth to climate factors at inter- and intra-annual scales in temperate forests of Europe in the last 20 years, and the main conclusions are as follows:

(1) The interannual variation of forest phenology in the Hartz Mountains is characterized by an advance trend in SOS, a delay trend in EOS, and a prolongation trend in LOS in 19a, which are basically consistent with the global and temperate European LOS prolongation trends.

(2) European temperate forests have a strong correlation with climate factors, both showing the sensitivity of vegetation spring phenology to temperature and the sensitivity of fall phenology to precipitation. During the SOS period temperature was the dominant factor in phenology, especially minimum temperature, and as far as climate sensitivity was concerned, spring phenology of forests was positively correlated with winter nighttime temperatures, and the effect of precipitation was only significant in individual months.

(3) As the main component of the terrestrial ecosystem, forests play a significant role in influencing climate change. In order to better protect the functions of the forest ecosystem, the revision of the forest legal system is becoming increasingly urgent due to the growing attention to the issue of climate change. In the current social context, it is necessary to strengthen the revision and improvement of the forest legal system, establish an effective legal framework, actively participate in the research on global climate change issues, and thereby maximize the ecological function of forests in adapting to climate change.

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