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Disentangling Climatic Factors and Human Activities in Governing the Old and New Forest Productivity

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Abstract: Forest ecosystem plays a vital role in the global carbon cycle and maintaining climate stability. However, how net primary productivity (NPP) dynamics of different stand ages of forest respond to climatic change and residual (being other climate factors or human activities) still remain unclear. In this study, firstly, forests are divided into two categories based on their stand age: forests appeared before appeared before the research period (F_{old}), and forests appeared during the research period (F_{new}). Secondly, we improved a quantitative method of basic partial derivatives to disentangle the relative contributions of climatic factors, other climate factors, and human activities to the NPP of F_{old} and F_{new}. Then, different scenarios were simulated to identify the dominant drivers for forest restoration and degradation. In this study, we hypothesized the residual of F_{old} was other climate factors rather than human activities. Our results revealed that from 2000 to 2019, F_{old} and F_{new} of NPP in Yangtze River Basin showed a significant increment trend and precipitation was the major positive contributor among all of the climatic factors. We found that, in F_{old}, climate change and other climate factors contributed 9.77% and 28.33%, respectively, in explaining NPP. This finding unsupported our initial hypothesis and implied that residuals should be human activities for F_{old}. Furthermore, we found that human activities dominate either restoration or degradation of F_{new}. This result may be due to the attenuated human disturbances and strengthened forest management, such as ecological policies, forest tending, closing the land for reforestation, etc. Therefore, based on disentangling the two types of factors, we concluded that human activities govern the forest change, and imply that the environment-friendly forest managements may favorite to improving the forest NPP against the impacts of climate change. Thus, effective measures and policies are suggested implement in controlling forest degradation in facing climate change.

Keywords: residual; the old forest productivity; human activities; climate change; net primary productivity

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1. Introduction

The terrestrial ecosystem plays a vital role in sequestering carbon. As an important part of the terrestrial ecosystem, forests cover about 31% of the earth's surface area (4.06 billion ha) [1], and they have irreplaceable values for their ability to manage biodiversity, store carbon, and provide other ecosystem services [2]. Forest ecosystems are enormous carbon pools and hold almost 662 (GT C) in 2020 [1], therefore playing a great role in mitigating climate change [3].

Furthermore, as an important indicator of forest health states, forest net primary productivity (NPP), referring to the rate of net carbon fixed through photosynthesis by forestland, directly represents the production capacity of the forest [2]. NPP is widely applied in climate change research to analyze forest restoration or degradation trends in various climate zones and forest types in the past few decades [3]. NPP change trend is usually considered as a proxy for forest restoration or degradation [4,5]. An increasing NPP trend means forest restoration while a decreasing trend indicates forest degradation.

Generally, forests are primarily affected by both climatic factors and human activities. Precipitation, temperature, and solar radiation are three primary climate drivers for forest NPP [6]. Their effects vary across climate zones, geomorphic types, and forest types [3,7]. For example, the temperature is considered as a critical factor for forest restoration in high-latitudes and high latitude regions, precipitation in arid and semiarid areas, and solar radiation in tropical zones, respectively [3,7–9]. With climate change, climate factors such as extreme precipitation, drought, and high temperature can also lead to forest degradation [9,10]. In addition, human activities are another main driving force of forest dynamics. Some human activities (such as urbanization and huge population growth) may be the main driving forces for forest degradation [11], while other activities (such as returning farmland to forestland, mountain closure, and afforestation) promotes forest restoration [9,12,13]. However, the relative effects on NPP from climate change and human activities are still unclear, and it is still ambiguous which factors, natural factors or human factors, dominate forest restoration and degradation. Therefore, it is critical to separate the relative roles of the two drivers.

To date, Great efforts have been made to separately quantify the impacts of climate change and human activities on forest ecosystems. The most commonly used quantitative methods can be classified into three categories: the regression model method, the biophysical model method, and the residual trend method [9,14]. The regression model method is the simplest, but it is hard to distinguish the complex interactions between forest and internal and external influence factors such as climate factors and human activities [14]. The biophysical model method can study the driving mechanism of vegetation change [13]. Its idea is to simulate the potential and actual NPP, then by their difference for the separation of the relative role of human activities and climate change to forest dynamics. But the model needs a lot of forest physiological and ecological parameters, which may cause the uncertainty of the model to increase [15]. The residual trend method is to construct an NDVI-climate model, then to predict NDVI which is considered undisturbed by human activities [12,16]. However, this method is primarily applicable to these regions that precipitation is the main restrictive factor for vegetation growth such as arid and semi-arid climate zones [17]. Both the residual method and the biophysical mode regard the difference between the predicted value and the simulated value as the impact of human activities on vegetation.

However, for forests, far away from residential areas and poor accessibility (such as primary forests), they are less directly disturbed by human activities and hold long stand periods [1]. Under these conditions, this residual should be regarded as the influence of other climatic factors (such as forest fire, natural disasters). But a large number of regarding the impacts of climate and human activities on forest changes, they all are considered residuals as the impact of human activities on them, and they do not classify the forest [12,16]. This could overestimate the impact of human activities on vegetation. But with the protection and management of primary forests strengthened in China, human activities, such as the implementation of the natural forest conservation program and prohibition of commercial logging in natural forests, have a positive effect on forests. There exists a knowledge gap to deal with residuals when we study the causes of forest changes.

Against this background, in this study, the quantitative method based on the partial derivative was applied to evaluate the relative contribution of climatic factors, other climate factors, and human activities to forest net primary productivity in the Yangtze River Basin (YRB). To better clarify whether the residuals should refer to human activities or other climatic factors, forests are divided into two categories: old forests (F_{old}) and new forests (F_{new}). Old forests refer to those that have existed before our research, while new forests are those that only appeared during our research period (such as the conversion of grassland into forestland). We assume that old forests (F_{old})were dominated by climate and the residual of old forests referred to other climatic factors. The objectives were as follows:

(1) to investigate two types of forest variations; (2) to quantify the contribution of climatic and human drivers to forest restoration or degradation; (3) to explore whether climate factors or human activities dominate the restoration and degradation of old forests and new forests.

2. Data and Methods

2.1. Study Area

The Yangtze River, with its source in the Qinghai-Tibetan Plateau, flows eastward, through 19 provinces in China, to the East China Sea. The length of the river is 6300 km and its drainage area is 1.8×10^6 km^2 and accounts for 18.75% of land area in China. The Yangtze River Basin, located between 90°33′–122°25′ E and 24°30′–35°45′ N, has a subtropical monsoon climate. The annual average temperature is 12.6–18.0 °C with a mean annual precipitation of 476 mm. The study area has a large altitudinal difference from Northwest Tibet Plateau (over 4000 m a.s.l.) to lowland areas such as the Yangtze River Delta Plain (below 50 m a.s.l.) (Figure 1). The region has diverse landforms. The superior climate and natural conditions are suitable for forest growth and forest resources are very abundant. The forest area of YRB is about 7.53×10^5 km^2 and the forest coverage rate is 40.49% [18]. The area of natural forest is about 4.72×10^5 km^2, and the area of artificial forest is 2.33×10^5 km^2 [18].

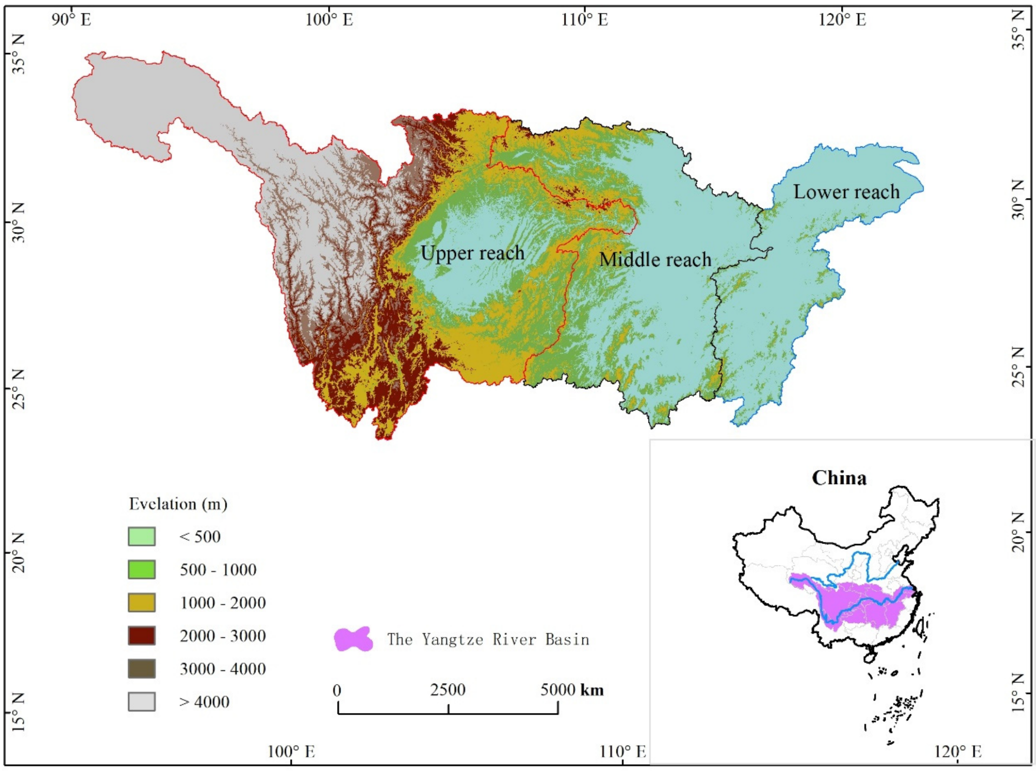

Figure 1. Location of the study area.

2.2. Datasets

The Moderate Resolution Imaging Spectroradiometer (MODIS) Net Primary Production (MOD17A3HGF) was chosen to analyze the long-term NPP dynamics, which was applied to explore the contribution of climate and human activities on forest dynamics during 2000–2019. This dataset was provided by the United States Geological Survey (USGS) (https://lpdaac.usgs.gov/products/mod17a3hgfv006/, accessed on 15 September 2021). The NPP of MOD17A3 was calculated by the BIOME-BGC model with 500 m spatial resolution and 1a temporal resolution [19,20]. NPP dataset was widely used to explore vegetation ecosystem variation [9,19,21]. Hence, we applied the nearest neighbor method to resample the NPP dataset to 1 km, with the same spatial resolution as the forest dataset.

Monthly meteorological data consists of precipitation, temperature, and solar radiation from 2000 to 2019, which are available in the National Earth System Science Data Center (http://www.geodata.cn/, accessed on 15 September 2021) [22,23]. With a 1 km spatial resolution, the average temperature, total precipitation, and solar radiation during the growing season (from April to October) (2000–2019) were calculated. To evaluate the impact of climate on forest NPP more comprehensively, annual values of the Standardized Precipitation Evapotranspiration Index (SPEI) were applied [24]. Annual SPEI of different time scales were considered such as 1, 3, 6, 9, and 12 months. The SPEI data were obtained from the website https://digital.csic.es/handle/10261/202305 (accessed on 15 September 2021). Its spatial resolution is 0.5°.

To attain the distribution of old and new forests, 2000 forest data and 2017 forest data were applied. The forest dataset was retrieved from the National Earth System Science Data Center (http://loess.geodata.cn/index.html, accessed on 15 September 2021). In this study, F_{old} and F_{new} were separated based on the 2000 and 2017 forest images. The old and new forest distributions are illustrated in Figure 2. The forests include the coniferous forest, broadleaf forest, and coniferous and broad-leaved mixed forest. Forests are mainly distributed in two climate zones: subtropical zone and plateau climate zone. Coniferous forests are characterized by drought-tolerant and barren-tolerant and are dominated by Masson pine, larch, and fir species. And broadleaf forest has the characteristics of high-temperature resistance and are dominated by camphor wood, oak and cypress species. In addition, forest volume stock and forest areas of different stand ages were obtained from the China Forest Inventory data (2014–2018).

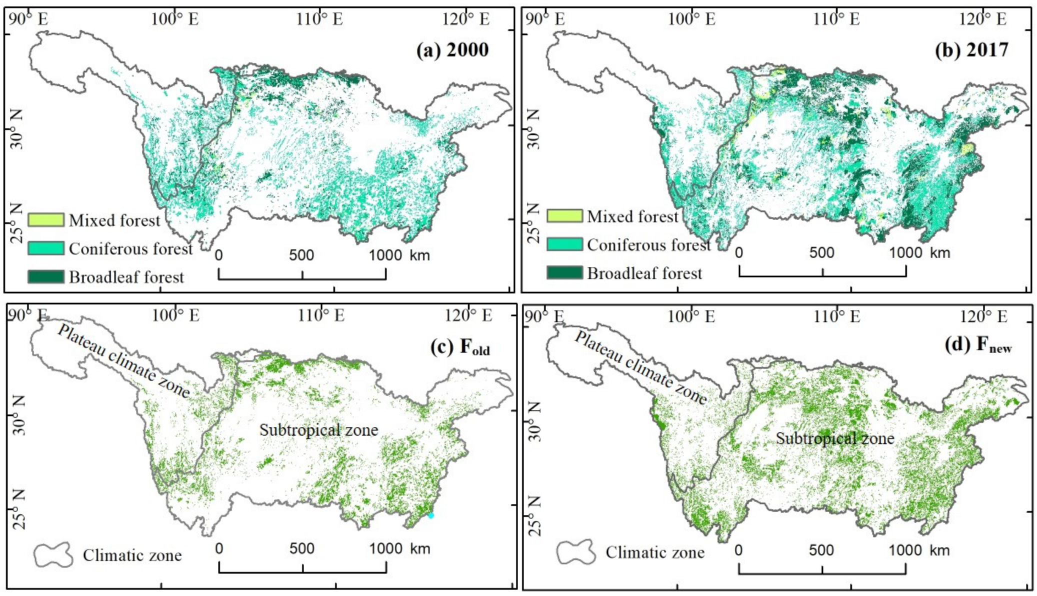

Figure 2. The distributions of (**a**) 2000 forest, (**b**) 2017 forest, (**c**) old forest (F_{old}), and (**d**) new forest (F_{new}) in Yangtze River Basin, China.

2.3. Methods

2.3.1. Chang Trends of NPP

A linear regression analysis was conducted to explore the long-term trends of NPP in YRB from 2000 to 2019, the formula is as follows (Equation (1)). The trend slope of regression represents inter-annual NPP change, and the slope indicates the direction and magnitude of the interannual variation in NPP. A positive slope shows that climate change is conducive to forest growth, while a negative slope represents that climate change hinders forest growth. In addition, a slope of zero means that climate change does not affect forest net primary productivity. Moreover, the significance of variation is investigated using *t*-tests to represent the confidence level of variation ($p < 0.05$).

$$Slope = \frac{n \times \sum_{j=1}^{n} j \times \mathrm{NPP}_j - \sum_{j=1}^{n} \mathrm{NPP}_j \sum_{j=1}^{n} j}{n \times \sum_{j=1}^{n} j^2 - \left(\sum_{j=1}^{n} j\right)^2} \quad (1)$$

where *Slope* is the inter-annual variation rate of NPP; n is the study period, from 2000 to 2019; and NPP_j is the forest NPP in the jth year. The correlation between NPP sequences and time sequences(year) is used to determine the significance of interannual variation in NPP.

2.3.2. Contributions of Climate Factors and Human Activities to Forest Dynamics

In the study, to better explore the impacts of human activities and climate changes on forests of different ages, forests were separated into two parts using the forest maps in 2000 and 2017. $\mathrm{F_{old}}$ refers to the forests that have already existed during 2000–2019, while $\mathrm{F_{new}}$ refers to those that only appeared after 2000. Figure 2 shows the separation of $\mathrm{F_{old}}$ and $\mathrm{F_{new}}$. Forests in YRB that are disturbed by anthropogenic factors from 2000 to 2019 are identified as $\mathrm{F_{new}}$, including plantations and secondary forests and covering 62.17% of forest area in YRB. $\mathrm{F_{old}}$ accounts for 37.83% of the forest area in YRB, and is mainly distributed in areas with rich primary forest.

Secondly, NPP dynamic is the function of climate factors (including temperature, precipitation, and solar radiation) and other variables such as ecological projects, winds, natural disaster, etc.; therefore, the contribution of each factor to the interannual variation rate of NPP can be estimated for each pixel using Equation (2). Equation (2), based on partial derivatives, has been widely employed to assess the effects of various climatic factors on evaporation or hydrological dynamics [12,25,26].

$$\begin{aligned} \mathrm{slope}_{NPP} &= \mathrm{C}_{con} + UF = \mathrm{T}_{con} + \mathrm{P}_{con} + \mathrm{R_{con}} + UF \\ &= \partial NPP/\partial T \times dT/dn + \partial NPP/\partial P \times dP/dn + \partial NPP/\partial R \times dR/dn + UF \end{aligned} \quad (2)$$

where slope_{NPP} refers to the inter-annual variation trend of NPP. C_{con}, T_{con}, P_{con}, and R_{con} represent the contributions of climate, temperature, precipitation, and solar radiation to the inter-annual NPP changes, respectively; C_{con} is the sum of T_{con}, P_{con}, and R_{con}. T_{con} can be calculated as $\partial \mathrm{NPP}/\partial \mathrm{T}$ which is the partial correlation coefficient between NPP and temperature without the effects of precipitation and solar radiation. dT/dn is the inter-annual variation rate of temperature, and T_{con} is calculated as the product of $\partial \mathrm{NPP}/\partial \mathrm{T}$ and $\mathrm{dT/dn}$. The calculation of P_{con} and R_{con} is the same as T_{con}. *UF* is equal to the residual between the slope_{NPP} and C_{con}. In this study, *UF* indicates the change rate of the contribution of unknown factors to NPP. Both human activities and some uncertain natural factors (such as wind, natural disaster, et al.) are contained in *UF*. As expressed in previous studies [12,16], *UF* of $\mathrm{F_{new}}$ represents the impact of human activities on NPP, namely, H_{con} (such as ecology projects and urbanization). Nevertheless, for $\mathrm{F_{old,}}$ disturbances of human activities are minimal and can be ignored by selecting an unaltered natural forest. Hence, *UF* of $\mathrm{F_{old}}$ represents the effects of other climatic factors (such as vapor pressure deficit, drought, and snowstorm) on forest dynamics, namely, O_{con}. Besides, the impacts of climate on all forest variations in YRB were achieved by adding the effects of climate factors to $\mathrm{F_{old}}$ and $\mathrm{F_{new}}$.

2.3.3. Contribution Proportions of Climate Factors and Human Activities to Forest Restoration and Degradation

Generally, increased NPP is considered as an indicator of forest restoration, while decreased NPP represents forest degradation [15]. Based on Section 2.3.1, a positive slope_{NPP} represents forest restoration, whereas a negative slope_{NPP} stands for forest degradation. Positive C_{con}, O_{con}, and H_{con} represent that climate, other climate factors, and human activities that are conducive to forest growth, whereas the negative C_{con}, O_{con}, and H_{con} represent that climate, other climate factors, and human that inhibits forest growth. Furthermore, six scenarios were designed (Tables 1 and 2) based on $slope_{NPP}$, C_{con}, H_{con}, and O_{con} to assess the contribution proportions of climate, human, and other climate factors to forest restoration and degradation.

Table 1. Six scenarios for quantifying the contribution proportions of climate and humans to F_{new} of restoration and degradation.

Scenario		C_{con}	H_{con}	Contribution		Relative Role
				Climate (%)	Human (%)	
S > 0	1	>0	>0	$\frac{\lvert C_{con}\rvert}{\lvert C_{con}\rvert+\lvert H_{con}\rvert}\times 100$	$\frac{\lvert H_{con}\rvert}{\lvert C_{con}\rvert+\lvert H_{con}\rvert}\times 100$	Both, when climate contribution is greater than human contribution, climate dominates, and vice versa.
	2	>0	<0	100	0	Climate change
	3	<0	>0	0	100	Human activities
S < 0	1	<0	<0	$\frac{\lvert C_{con}\rvert}{\lvert C_{con}\rvert+\lvert H_{con}\rvert}\times 100$	$\frac{\lvert H_{con}\rvert}{\lvert C_{con}\rvert+\lvert H_{con}\rvert}\times 100$	Both, when climate contribution is greater than human contribution, climate dominates, and vice versa.
	2	<0	>0	100	0	Climate change
	3	>0	<0	0	100	Human activities

Table 2. Six scenarios for quantifying the contribution proportions of climate and humans to F_{old} of restoration and degradation.

Scenario		C_{con}	O_{con}	Contribution		Relative Role
				Climate (%)	Other Climatic Factors (%)	
S > 0	1	>0	>0	$\frac{\lvert C_{con}\rvert}{\lvert C_{con}\rvert+\lvert O_{con}\rvert}\times 100$	$\frac{\lvert O_{con}\rvert}{\lvert C_{con}\rvert+\lvert O_{con}\rvert}\times 100$	Both, when climate contribution is greater than other climatic factors contribution, climate dominates, and vice versa.
	2	>0	<0	100	0	Climate change
	3	<0	>0	0	100	Other climatic factors
S < 0	1	<0	<0	$\frac{\lvert C_{con}\rvert}{\lvert C_{con}\rvert+\lvert O_{con}\rvert}\times 100$	$\frac{\lvert O_{con}\rvert}{\lvert C_{con}\rvert+\lvert O_{con}\rvert}\times 100$	Both, when climate contribution is greater than other climatic factors contribution, climate dominates, and vice versa.
	2	<0	>0	100	0	Climate change
	3	>0	<0	0	100	Other climatic factors

In this study, when the contribution proportion of climate to forest restoration or degradation was higher than that of human activities, it was considered as "climate-dominated restoration or degradation". Conversely, it would be defined as "human-dominated restoration or degradation".

3. Results

3.1. Spatiotemporal Characteristics of NPP Dynamics

Figure 3 shows the inter-annual variations of NPP of F_{old} and F_{new} from 2000 to 2019 in YRB. The annual average NPP of the two kinds of forest showed a significantly increasing trend (p < 0.0001). However, in 2016–2019, the NPP value changed very little. Besides, the annual average NPP of F_{old} was higher than that of F_{new} because of the less disturbance to F_{old}. However, the significant increasing rate of F_{new} was higher than that of F_{old}. The increasing rate of F_{new} and F_{old} was 3.77 g C m^{-2} $year^{-1}$, 3.28 g C m^{-2} $year^{-1}$, respectively.

The spatial variations of NPP from 2000 to 2019 were shown in Figure 4. The annual average NPP of F_{new} in YRB ranged from 100.80 g C m^{-2} to 1419.50 g C m^{-2}. Besides, the annual average NPP of F_{old} and F_{new} exhibited different spatial variations. For F_{old}, the higher regions were mainly distributed in the upper of YRB. For F_{new}, it markedly increased from the northwest to the southeast of the upper of YRB (Figure 4b). More specifically, the higher NPP values were distributed in Sichuan and Yunnan (>800 g C m^{-2} year^{-1}, Figure 4). Conversely, the lower NPP values were in the northwest of the YRB (<200 g C m^{-2} year^{-1}, Figure 4).

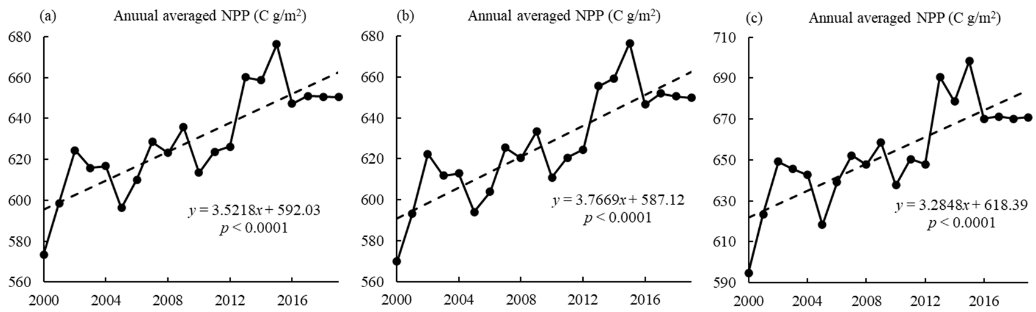

Figure 3. Changes in annual net primary productivity (NPP) of (**a**) all forest, (**b**) the new forest, and (**c**) the old forest.

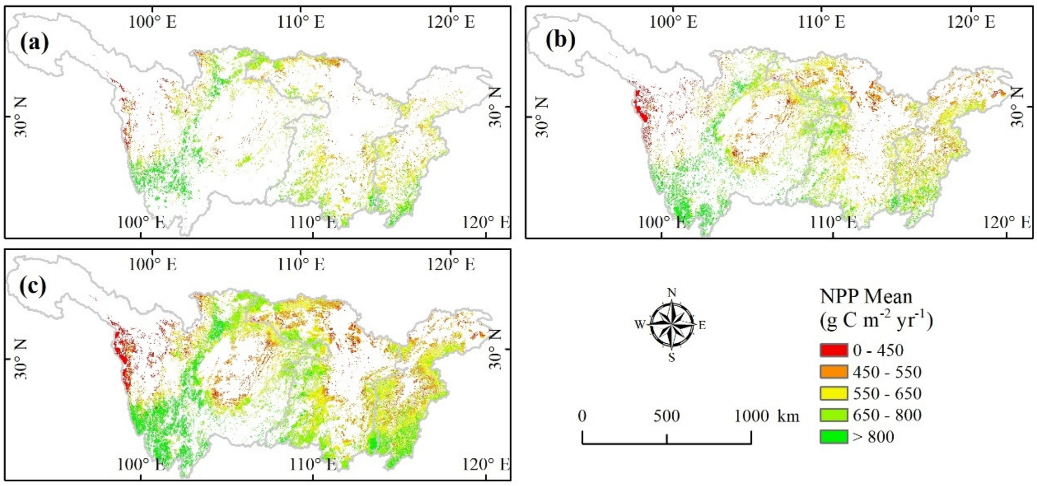

Figure 4. Annual averaged net primary productivity (NPP) of (**a**) the old forest; (**b**) the new forest; (**c**) all forest.

The spatial distribution of the forest NPP change trend was obvious regarding regional differences (Figure 5). The overall trends of F_{new} and F_{old} ranged from −61.10 g C m^{-2} year^{-1} to 36.40 g C m^{-2} year^{-1}, and −56.93 g C m^{-2} year^{-1} to 31.94 g C m^{-2} year^{-1}, respectively. Besides, trends of F_{old} and F_{new} displayed similar spatial characteristics, with increasing trends in most regions of the study areas. NPPs of F_{old} and F_{new} increased in 29.24% and 52.05% of the forest area, respectively (Figure 5b,d), and the significant increasing trend of F_{old} and F_{new} ($p < 0.05$) accounted for 14.36% and 30.65% of this area, respectively (Figure 5b, d). In contrast, the significant decreasing trend ($p < 0.05$) in NPP was only accounted for 3.14% of the forest area (Figure 5f) (1.39% of F_{old}, and 1.75% of F_{new}, respectively).

3.2. Contributions of Climate and Human Activities to NPP

To quantitatively evaluate the contributions of climatic factors to NPP changes, the method based on partial derivatives was applied to calculate the contributions of temperature, precipitation, and solar radiation to NPP variations. From 2000 to 2019, T_{con}, P_{con}, and R_{con} in YRB were 0.002 g C m^{-2} year^{-1}, 0.93 g C m^{-2} year^{-1}, and 0.16 g C m^{-2} year^{-1}, respectively (Figure 6). Precipitation achieved the greatest positive contribution among all of the climate factors, followed by solar radiation and temperature. Furthermore, the results of T_{con}, P_{con}, R_{con} were applied to require the contributions of C_{con} (Figure 6a–c,f). Both climate and human activities positively contributed to forest NPP changes in YRB, and the contribution of human activities was 2.41 g C m^{-2} year^{-1}, while the contribution of climate was 1.09 g C m^{-2} year^{-1}. In addition, for each type of forest, F_{old} and F_{new}, the contributions of climate and human activities to NPP share the same pattern as that of the forests as a whole. The contributions of climate to F_{old} and F_{new} NPP were 0.8553 g C m^{-2} $year^{-1}$, 1.2526 g C m^{-2} $year^{-1}$, respectively. And the contributions of human activities to F_{old} and F_{new} NPP were 2.4210 g C m^{-2} $year^{-1}$, 2.4932 g C m^{-2} $year^{-1}$, respectively.

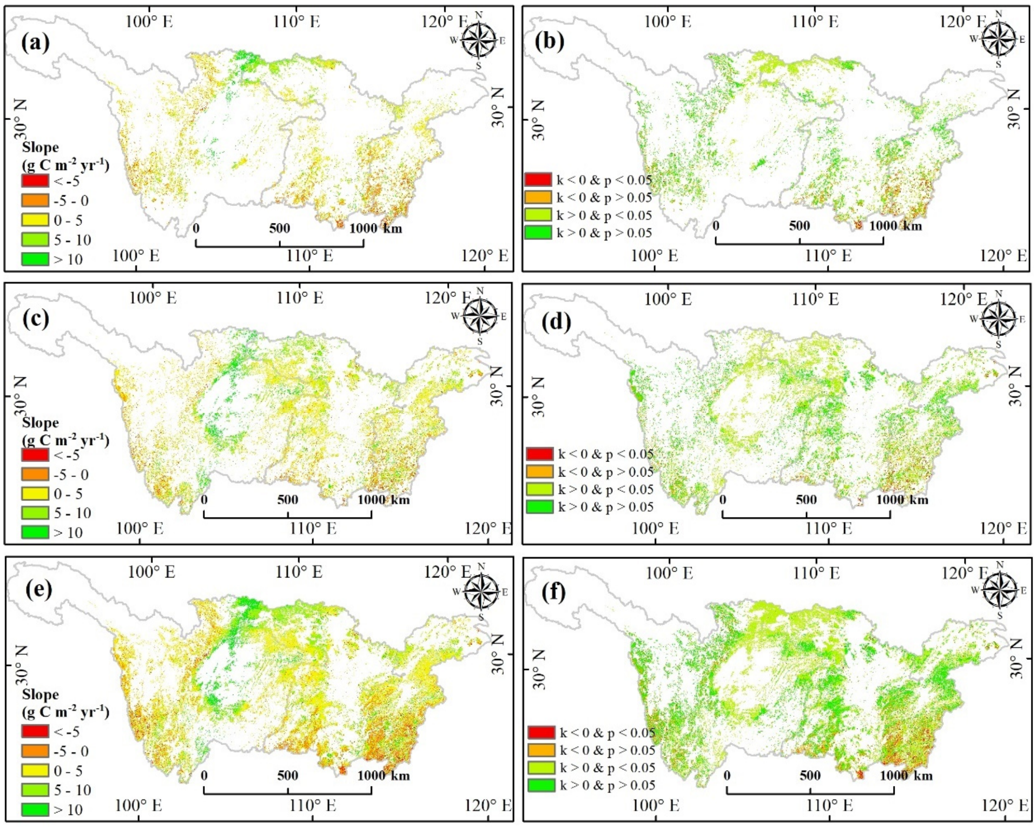

Figure 5. Net primary productivity (NPP) trend of (**a**) the old forest, (**c**) the new forest, and (**e**) all forest, (**b**,**d**,**f**) their corresponding.

As shown in Figure 6a, temperature positively contributed mainly in the upper of YRB, while it had a negative contribution in the middle and lower reaches. Precipitation had positive contributions in the west of 110 east longitude, whereas its negative contributions were mainly distributed in the east of 110 east longitude. Additionally, the positive contributions of solar radiation to NPP were distributed in most of YRB (57.20%). All in all, contributions of climatic factors to NPP were found to be positive in the upper of the YRB, but negative in the Jiangxi Province. Besides, for F_{old}, *UF*, representing the contributions of other climate factors, accounted for 38.11% (negative impacts: 10.12%; positive impacts: 27.99%). For F_{new}, *UF* represents the contributions of human activities. In 48.48% of YRB, human activities were beneficial to forest growth (Figure 6e). However, negative contributions of human activities to NPP were scattered in the southern areas of YRB.

3.3. Contributions Proportions of Climate Change and Human Activities to Forest Restoration or Degradation

According to scenario analysis, the contribution proportions of climate and humans to forest restoration and degradation are evaluated. Based on this, the regions of climate-dominated and human-dominated forest restoration and degradation were attained (Figure 7). For F_{old} the climate-dominated forest and other climate factors-dominated forest accounted for 9.77% and 28.33%, respectively (Figure 7). For F_{new}, the climate-dominated forest and the human-dominated forests are 17.56% and 44.34%, respectively (Figure 7). Obviously, for F_{new}, the impacts of humans on forest restoration or degradation were larger than those of climate in YRB (37.22% vs. 14.35%; 6.62% vs. 3.21%) (Figure 8). However, for F_{old}, the other climate factors dominated the forest restoration and degradation.

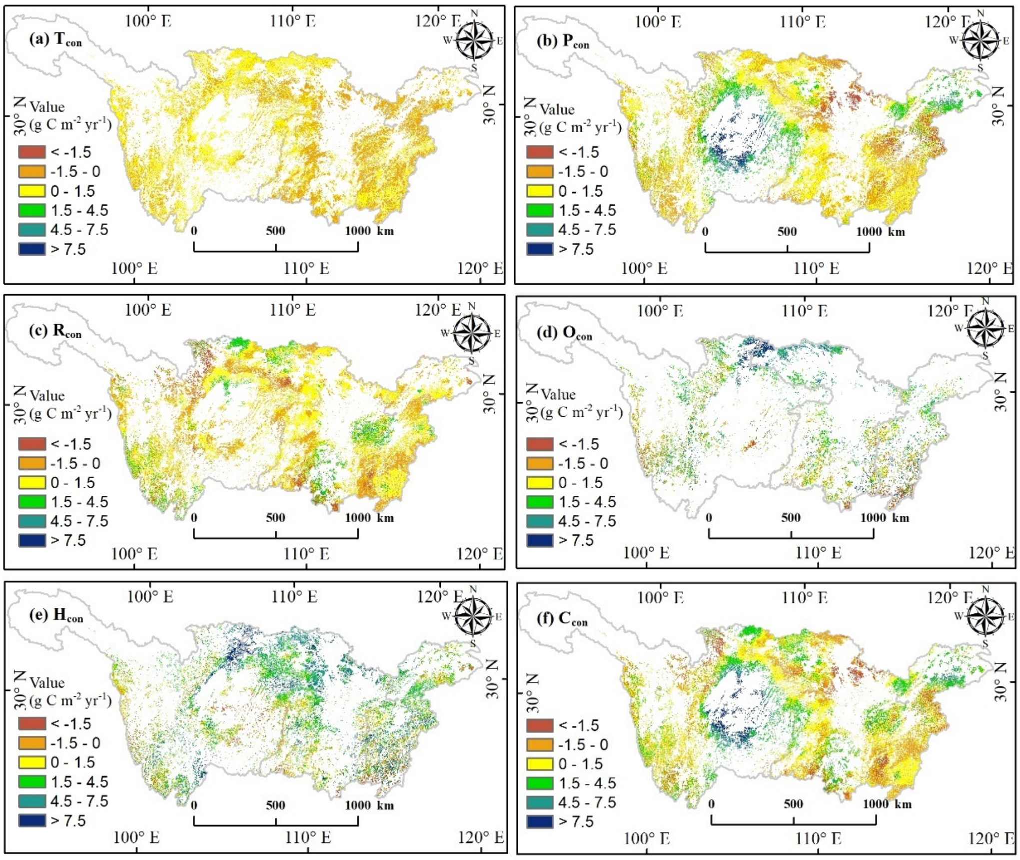

Figure 6. The contributions of climate factors and human activities to net primary productivity (NPP) trend from 2000 to 2019 in YRB, China. (**a**) temperature, (**b**) precipitation, (**c**) solar radiation, (**d**) other climate factors, (**e**) human activities, and (**f**) climate.

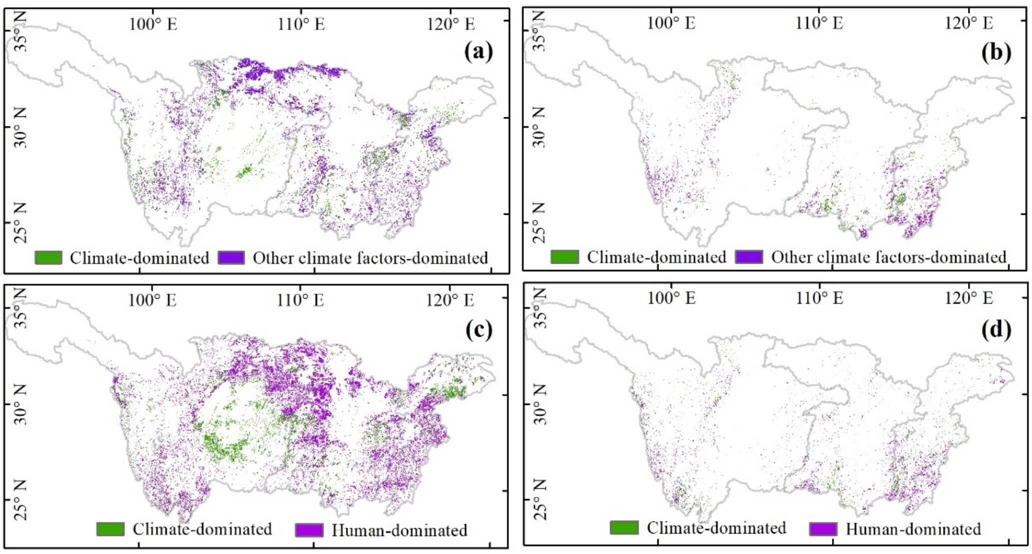

Figure 7. Spatial distribution of the climate-dominated, and other climate factors-dominated (**a**,**b**) new forest restoration and degradation areas, respectively; and the climate-dominated, and human-dominated (**c**,**d**) old forest restoration and degradation areas, respectively.

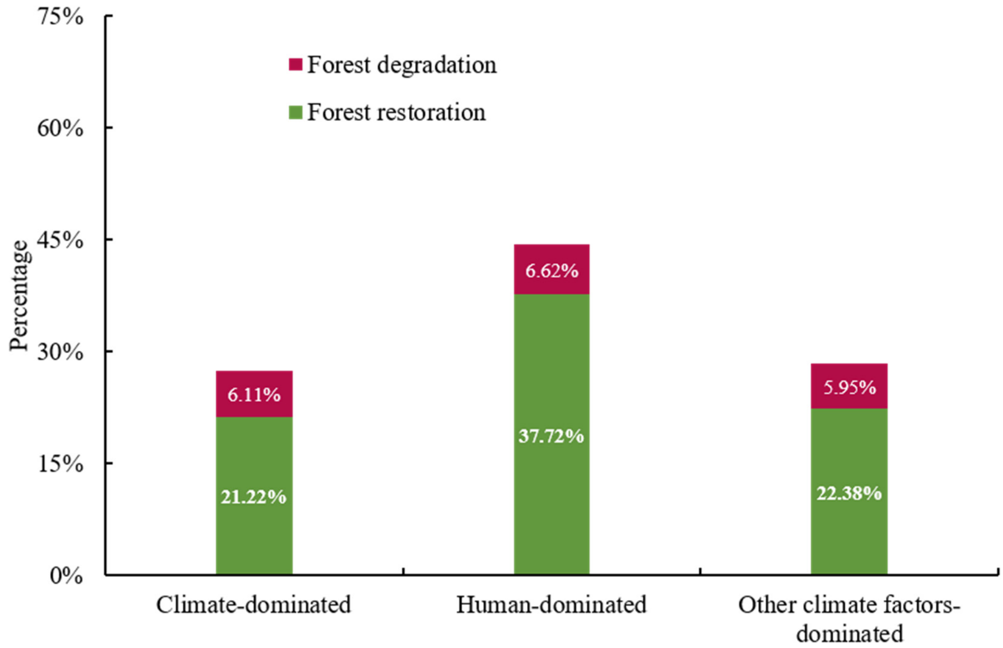

Figure 8. Statistical analysis of the percentages of climate-dominated, human-dominated, and other climate factors-dominated forest restoration and degradation.

4. Discussion

4.1. NPP Difference between F_{old} and F_{new}

The old forest NPP was higher than the new forest NPP, but the NPP growth rate of F_{old} and F_{new} showed the opposite trend because the stand ages of F_{old} and F_{new} are very different and most F_{old} is natural forest while F_{new} is converted from reforestation or afforestation during the study period. The young forest and middle-aged forest areas accounted for approximately 70% and the forest stock was less than half of the total forest stock (Figure 9). Besides, F_{old} does not grow as fast as $F_{new,}$ and the carbon sequestration capacity of F_{old} decreased (Figure 9). We found that the high-value NPP is mainly distributed in the upper reaches of YRB. The essential reason can be the fact that the natural forests of YRB are mainly distributed in the upper YRB [18].

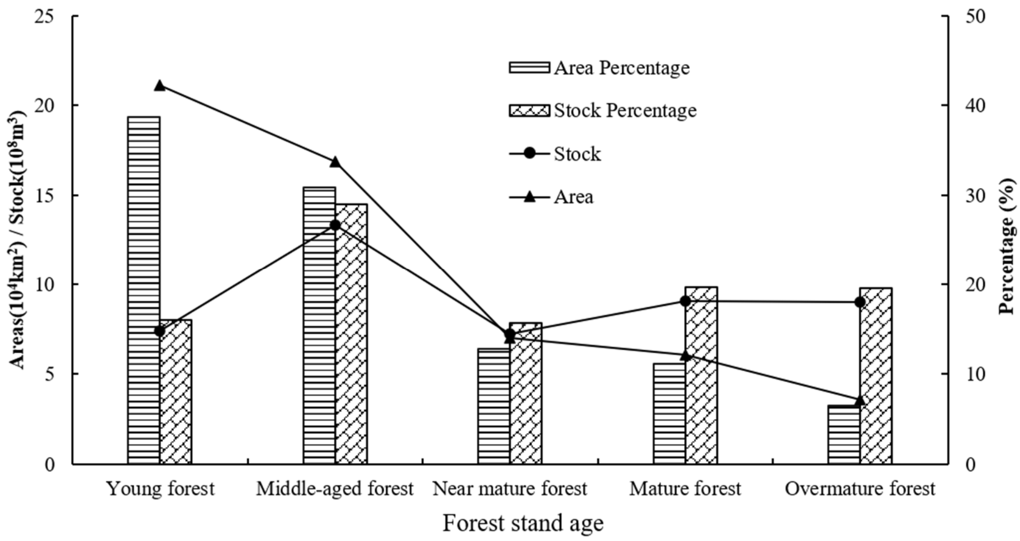

Figure 9. Forest area, forest volume stock, and their corresponding percentage in the YRB.

4.2. Impacts of Climate on Forest Productivity

The contribution of climate factors to forest NPP is different. Precipitation presented the greatest positive contribution to forest NPP changes than solar radiation and temperature in YRB, probably due to an increasing trend of precipitation in most regions of YRB (Figure 10d). Besides, climate factors have spatial heterogeneities in the impact of forest net primary productivity. Temperature and precipitation have a positive contribution to NPP in the upper YRB, but a negative effect on NPP in some regions of the middle and lower YRB, and solar radiation is mainly negative in the whole YRB. For the upper YRB, where precipitation is usually low, the increase in precipitation would improve the water available for forest plants, and therefore be beneficial to forest growth. Adequate precipitation would enhance the carbon uptake ability to boost forest NPP [5]. More importantly, the temperature in this area is also rising and which is very vital for the upper reaches of YRB with an average altitude of 4000 m a.s.l. Due to low temperature inhibiting forest growth, increasing temperature can boost the plant photosynthesis and respiration rates to enhance the carbon storage capacity. Therefore, the increasing trend of temperature and precipitation could greatly promote forest growth between 2000 and 2019. Solar radiation is also a vital driving factor for forest NPP. Although the average solar radiation showed a decreasing trend in the study area (Figure 10d), its change was very small in the upper of YRB (Figure 10a,c). Solar radiation enhances the chlorophyll content of plant leaves, strengthened photosynthesis, and promotes the carbon sequestration capacity of vegetation [2]. More importantly, temperature, precipitation, and solar radiation all have positive effects on the forest dynamics in the upper reaches of YRB (Figure 6a–c).

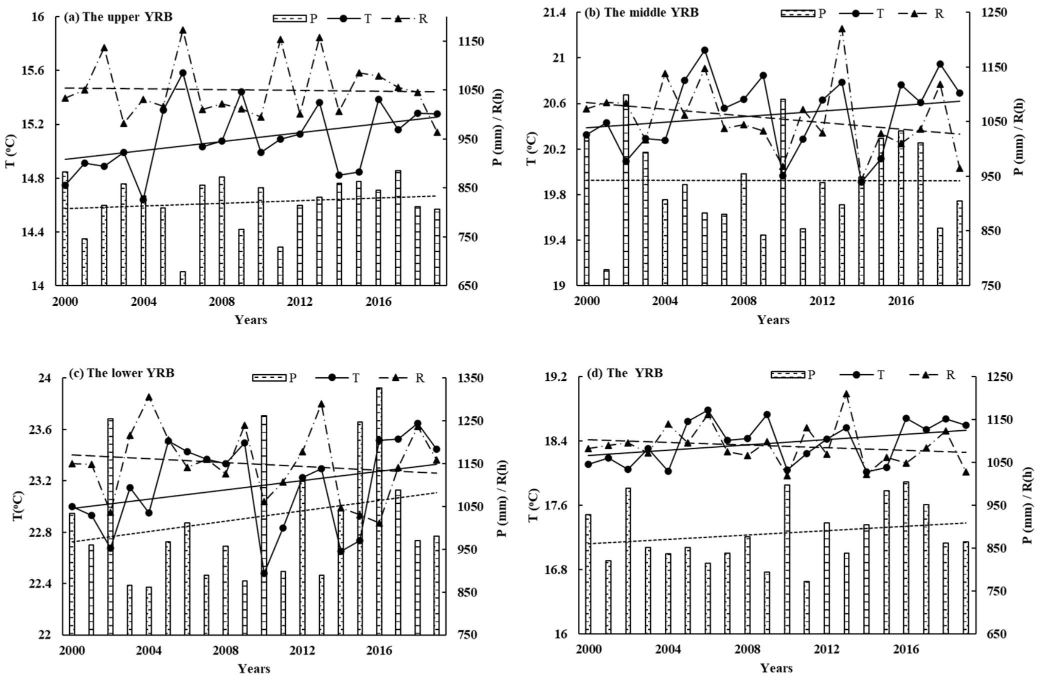

Figure 10. Changes in annual of T, P, and R in (**a**) the upper of Yangtze River Basin, (**b**) the middle of Yangtze River Basin, (**c**) the lower of Yangtze River Basin, and (**d**) the Yangtze River Basin. (T: temperature, P: precipitation, R: solar radiation).

However, in the middle YRB, the climate has a warming-drying trend (Figure 10b) and the temperature has a negative effect because the temperature is too high to exceed the limitation [27]. With region warming, the vapor pressure deficit could cause plants to close stomata, resulting in decreasing intercellular CO_2 concentration in the leaves and a lower photosynthesis rate [28]. Yuan et al. indicated the warming-induced elevated vapor pressure deficit induced the most substantial negative effect on GPP [29]. This is the reason why warming will not be conducive to the increase in NPP in some regions of the middle and lower of YRB. Besides, although the precipitation in the YRB has shown an upward trend as a whole, the precipitation has declined in some years, such as after 2016. It would increase evaporation and cause SPEI to drop (Figure 11). Extreme precipitations are likely to have an adverse effect on plant growth [30]. Persistent extreme precipitation happened in the lower YRB in May 2016 due to the super EI Niño [31] and heavy rainfall events often occur in summer due to the monsoon climate [32]. This is the possible reason why precipitation has a negative contribution to the NPP of the lower YRB. This result is consistent with many previous studies [5,27,30]. We found that from 2016 to 2019, NPP showed a flat development and a small value. It may be that after the entire YRB experienced extreme precipitation in 2016, the precipitation has shown a downward trend in recent years, and the temperature has risen and solar radiation has been higher than in previous years. Which has increased evapotranspiration and enhanced the effect of drought (Figure 11). This showed that climate warming may exacerbate the impact of drought on forest growth. As Marin et al. (2021) indicated that drought is becoming a considerable constraint for tree growth [33].

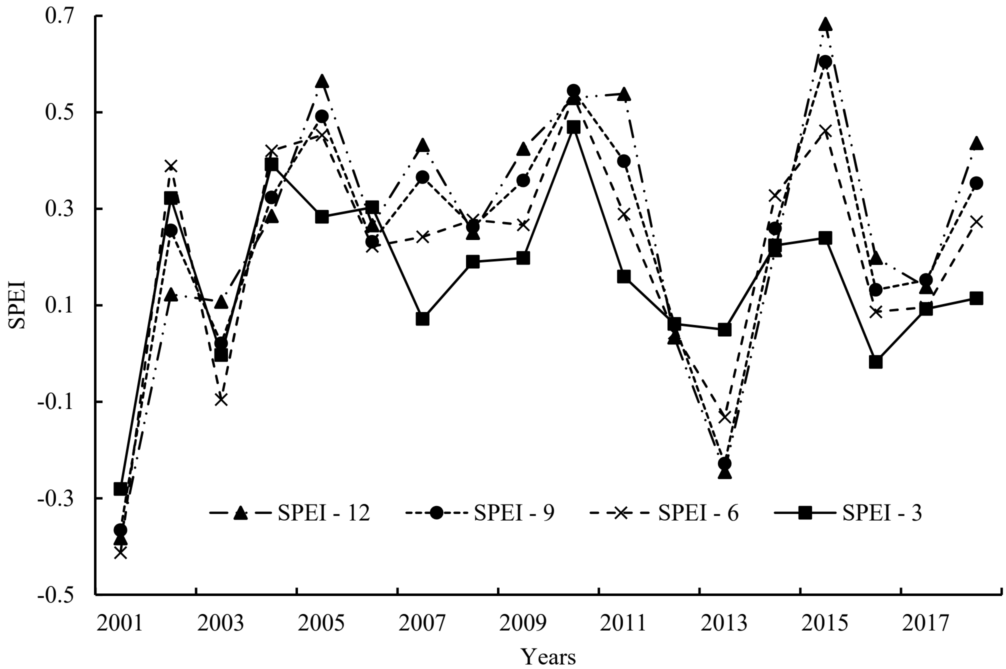

Figure 11. Interannual changes of SPEI at different time scales in YRB.

Overall, the contribution of climate to NPP dynamics was positive in YRB. This finding is consistent with those of Yan et al. and of Zhu et al. [13,34], both of which have demonstrated that climate is favorable for forest growth. Forest restorations dominated by climate were mainly distributed in the upper YRB (Figure 7a,c). This result is similar to Wang et al. [5]. The reason is as mentioned above. the climate-dominated forest degradation was distributed in the middle YRB. Temperature and precipitation made the greatest negative effects on NPP changes in the middle YRB (Figure 6a,b). The temperature in the middle YRB increased (Figure 10b), while precipitation decreased (Figure 10b); which inhibited forest growth.

4.3. Impact of UF on Forest NPP

4.3.1. Impact of UF on F_{old} NPP

For the forest ecosystem, the climate is the internal driving force, and human activities are the external driving force that can either intensify or mitigate the role of climate on forests [2]. For F_{old}, O_{con} accounted for 22.38% for the restoration, exceeding the proportion of C_{con} (6.87%). And, the residual contribution made by other climate factors was

2.4210 g C m^{-2} year^{-1} (climate contribution of 0.8553 g C m^{-2} year^{-1}). This result sounds interesting because temperature, precipitation, and solar radiation are the fundamental driving force of forest growth, therefore implying that it is unreasonable to express *UF* (residual) as the other climate factors for the F_{old}. The residual should be indicated as human activities rather than other climate factors. This may be several reasons as follows. Firstly, Natural Forest Protection Project were implemented in the whole upper YRB for 20 years [21] and many nature reserves have been built. Additionally, ecological policies have been implemented from the prohibition of commercial logging in the natural forest to the total ban on logging [35]. Human disturbance to natural forests has been greatly reduced to promote the natural recovery of forests and the positive effects are gradually strengthening. Secondly, ecological management measures, such as forest tending and closing the land for reforestation, have been implemented. Thirdly, economic development has changed the energy structure and demand, reducing fuelwood demand, especially in rural areas [36]. Besides, rural labor has migrated to cities, thereby reducing the human disturbance of forests. For F_{old}, human activities have affected it indirectly, which has promoted the ecology process of old forests. In addition, this could show that when analyzing the impact of climate on vegetation, we not only need to consider temperature, precipitation, and solar radiation, but also nitrogen deposition and CO_2 fertilization effects. They can explain 70% of the observed global vegetation greening trend [37].

4.3.2. Impact of UF on F_{new} NPP

Human activities play a major role in forest degradation in YRB. This result is consistent with that of Ge et al. [9], which showed that human activities are the main driving force for forest degradation in China. The rapid urban expansion has decreased terrestrial NPP [38], and the urbanization of the Yangtze River Delta has developed rapidly in two decades causing a negative effect on NPP. Fortunately, since the 1990s, a series of forest conservation and restoration projects have been implemented such as the Grain to Green Project, the Natural Forest Protection Project, and the Yangtze River Shelter Forest Project. These ecological programs increased forest areas through various initiatives, such as afforestation, reforestation, and returning farmland to forestland, and these programs have effectively accelerated the restoration process of forest. For example, Zhu et al. claimed that afforestation contributes to the increase in forest productivities observed in southeast China [37]. Qu et al. reported that ecological restoration projects are the main driving factors improving forest growth in the YRB [16]. Afforestation promotes the enhancement of forest net primary productivity in China, particularly the southwest regions [21]. Our study demonstrated that human-dominated forest restorations are disturbed in the east part of YRB and the east side of Hengduan mountain, which also confirms that these forest restoration projects have a positive contribution to the increase in forest productivity.

4.4. Limitations

In this study, the methodology based on partial derivatives was applied to quantitatively assess the contributions of climate and human activities to forest dynamics by NPP indicator. There are still some limitations. First, the method itself neglects the interaction between climate and human activities and merely considers the linear relationship between forest productivity and impact factors [4]. Second, in addition to temperature, precipitation, and solar radiation, other climatic factors, such as evapotranspiration and relative humidity, also affect forest dynamics. It requires further in-depth research. Therefore, more accurate quantitative methods, which can separate the contributions of climate from human activities to forest restoration and degradation, need to be further quested.

5. Conclusions

In this study, we employed NPP as an evaluation indicator for forest restoration and degradation, and a quantitative method of basic partial derivatives was improved by separating F_{old} and F_{new} for the relative contributions of climate change and human activities to NPP variations in YRB. Our study finds that from 2000 to 2019, 81.29% of forest NPP in YRB exhibited an increasing trend, while only 18.71% of forest NPP showed a decreasing trend. Moreover, precipitation made the greatest contribution to forest NPP variations among all climate factors, followed by solar radiation and temperature. The contribution of climate and human activities to all forest NPP changes were 1.09 g C m^{-2} $year^{-1}$ and 2.41 g C m^{-2} $year^{-1}$, respectively. For F_{old}, contributions of climate and other climate factors to forest variations were 9.77% and 28.33%, respectively. We concluded that for the F_{old} of YRB, the residual should refer to human activities. So, human dominated the F_{old} restoration or degradation. Dominated driving forces of forest restoration and degradation showed great spatial heterogeneity in YRB. Regarding forest restoration, climate played a dominant role in upper YRB. Humans played a major role in middle and lower YRB. In the terms of forest degradation, the impacts of humans were larger than those of climate in YRB.

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