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Diverse Roles of Previous Years' Water Conditions in Gross Primary Productivity in China

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Abstract: Gross primary productivity is one of the most important indicators of ecosystem function, which is related to water conditions and shown high interannual variation. Due to the time-lag effect, not only the current water condition but also the previous water conditions (e.g., one year before) impact the gross primary productivity (GPP). Revealing the impacts of current and previous years' water status is currently a hot topic. In this study, we designed a series of water deficit scenarios based on the meteorological dataset of the Climatic Research Unit (CRU) and then analysed the responses of the remote sensing-based moderate resolution imaging spectroradiometer (MODIS) gross primary productivity (GPP) in China, from which the role of water deficit in time periods was evaluated. The results indicate that the impact of climate factors (i.e., water, temperature and radiation) on GPP has a high spatial heterogeneity and that water-limited regions that are primarily distributed in North and Northwestern China show a stronger water-GPP relationship than water-unlimited regions. The water deficit that occurred in different periods had a variable impact on GPP. Specifically, GPP was primarily controlled by the current year's water conditions in the water-limited regions, with the importance value of 52.8% (the percentage of Increased Mean Square Error, %IncMSE) and 3.8 (the mean decrease in node impurity, IncNodePurity), but at the same time, it was conditionally affected by the water status in the previous year, with the importance value of 20.4% (%IncMSE) and 0.6 (IncNodePurity). The role of water in previous years is multifarious, which depends on the water conditions of the current year. The results revealed by the scenarios indicate that the influence of water conditions in the previous year was not statistically significant when the water conditions of the current year were in a drought. In contrast, when the current year's water conditions were normal or wetter, the water conditions in the previous year (i.e., one-year time lag) were also important and the increase of GPP significantly depended on the water condition ($p < 0.05$). The diverse roles of water conditions in previous years on GPP and its non-ignorable time-lag effect revealed in this study imply that not only the current year's water condition but also its dynamic changes in previous years should be considered when predicting changes in GPP caused by climate change.

Keywords: gross primary productivity; vegetation response; water deficit; time-lag effect; random forest; China



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1. Introduction

The frequency of extreme weather events such as drought, heatwaves and heavy precipitation gradually increases under global climate change [1–4], which seriously affects the composition, structure, function and biodiversity of terrestrial ecosystems [5–8]. Gross primary productivity (GPP), which is the total amount of organic matter produced per unit time and unit area by green plants through photosynthesis using water and carbon dioxide as raw materials [9], plays an important role in the carbon cycle of terrestrial

ecosystems [10]. Water is indispensable in this process and is also the main component of plant cells. Once water levels fall below a certain threshold, the resulting drought often causes food shortages in agricultural systems [11,12] and affects the stock volume [13], leaf area index [14] and biomass of forest ecosystems. It is also possible that water stress leads to hydraulic failure and carbon hunger that reduces vegetative productivity and increases the risk of forest fires [15], thus changing the carbon budget of terrestrial ecosystems [4,16]. Therefore, studying the response of GPP to water deficit is of great significance for understanding the carbon absorption process of terrestrial ecosystems and estimating ecosystem productivity with a land surface carbon cycle model.

Previous studies have shown that abiotic factors (temperature, precipitation, etc.) and biological factors (forest age, tree height, stock volume, etc.) have significant effects on the ecosystem. Among these, abiotic factors are the determinants of ecosystem productivity on a regional scale [17–20]. Vegetative growth (such as gross primary productivity) is mainly restricted by abiotic factors such as temperature, water and radiation [21,22]. The restrictions of abiotic factors on vegetative productivity vary from region to region under the influence of climate and the geographical environment [22–24]. The influence of water on vegetative growth in different regions is controversial. In the Mediterranean region [21,22], the Alps [25], the Southwestern United States [26,27] and other regions, water is the most important climate factor limiting vegetative growth. The sensitivity of tree growth to water is greater than to temperature and other climate factors. Water deficits caused by drought can have serious negative impacts on crop yield, vegetative productivity and the formation of tree volume [23]. However, vegetative growth is mainly restricted by solar radiation in Western Europe, tropical rain forests and parts of Southern China [19,27–29]. For example, Wang et al. (2017) [19] found that vegetative productivity in Southern China was more sensitive to solar radiation than precipitation, and the decrease in forest primary productivity was mainly due to the reduction in solar radiation (82%) rather than the influence of drought (18%). There is little significance to the study of drought in regions where water is not limited, and it has been ignored in many studies. Therefore, it is necessary to consider the spatial scale of differences in vegetation sensitivity to water when studying the effect of drought.

The influence of water deficit on vegetation growth has a time-lag effect [7,13,30] with lags of one to four years on a global scale [31,32]. For instance, some research that used satellite-derived normalized difference vegetation index (NDVI) data found the response of trees to water is related not only to the current water conditions but also to past precipitation and temperature, which shows a clear time lag [33] and legacy effects [34,35]. The frequency, severity, duration and timing of water deficits have a profound influence on vegetative growth [30,36]. Braswell et al. (1997) [37] investigated the interannual lag of vegetation's response to temperature and found differences in the time-lag effects among different ecosystems. Vegetation growth may not primarily be driven by present water conditions, but earlier water conditions may have the most impact on vegetation growth [38]. There are significant differences in the effects of annual and interannual changes in water deficits on vegetative productivity. Because vegetative productivity and water deficits fluctuate greatly and are complicated by seasonal and monthly differences, it is more typical to analyse the effects of interannual changes in water deficits. Vegetation tends to be more sensitive to long-term drought than to short-term drought [39]. Short-term drought can be understood as a drought in which the water conditions of the previous years are normal, and the water conditions of the current year are in a drought; long-term drought can be understood as a drought in which the water conditions of the previous years and the current year are in a drought. These produce significant differences in the effects of water conditions on vegetative growth [40,41]. Reichmann et al. (2013) [42] and Gao et al. (2020) [43] found that there was a legacy effect in the transition from dry years to wet years (or vice versa). There was a lower aboveground net primary production (ANPP) than predicted if the precipitation of the previous year was lower than the precipitation of the current year (or vice versa), suggesting that the combination of dry and wet in the

previous year and current year is significant to the analysis of the time-lag effect of the previous years' water deficit.

Correlation analysis is used in many studies to determine the optimal time scale using the maximum correlation coefficient between the vegetation index (e.g., normalized difference vegetation index (NDVI), ring-width indices (RWIs) and aboveground net primary production (ANPP)) and the drought index (e.g., standardized precipitation evapotranspiration indices (SPEIs)) at present. In some regions, the time scale of vegetative response to drought is more than 24 months [13,44], whereas other studies that used the same method found that the cumulative lag in vegetative response to drought was five months [45] or even less [38]. Compared with correlation analysis, natural experiments can analyse selectively in detail according to the purpose of the study and can better reflect the response of vegetative growth to drought [30].

Given that GPP is highly uncertain under the influence of drought that may happen in a different time and understanding the role of the previous year's drought is necessary to accurately predict GPP, we aimed to accomplish the following three objectives in this study: (1) identify the water-limited regions where the potential impact of drought should be emphasized in China, (2) apply a machine learning algorithm (i.e., random forest) to evaluate the importance of water conditions at different times on GPP, from which we could quantify the relative importance of the water condition of previous years, and (3) design a series of water deficit scenarios and, accordingly, build a series of regression models to reveal the role of the previous year's water conditions on GPP.

2. Materials and Methods

2.1. The Ecosystem Types and Climate Conditions of China

China is dominated by an Asian monsoon climate where the annual mean temperature (T), photosynthetic active radiation (PAR) and precipitation are 7.82 °C (the standard deviation is 7.98 °C), 60.15 mm/year (the standard deviation is 38.15 mm/year) and 85.36 W/m² (the standard deviation is 15.71 W/m²), respectively (the detailed information of climate data can be found in Section 2.2.2). Under the climate conditions, various ecosystems are widely distributed in China (Figure 1). Additionally, drought is one of the most damaging and disastrous hazards in China [46]. Thus, our research explored the influences of water conditions on vegetation growth (i.e., GPP) and its response in China.

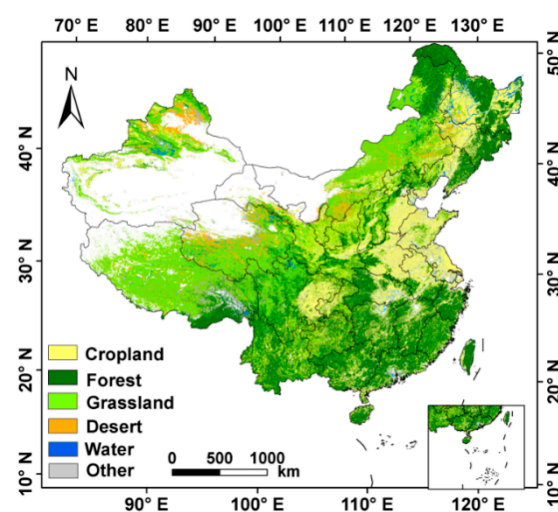


Figure 1. The spatial distribution of ecosystem types in China. The data set of ecosystem types was established by using the fast extraction method of full digital human-computer interaction from Landsat TM digital image, which was obtained from Geographical information Monitoring Cloud Platform (<http://www.dsac.cn>).

2.2. Research Data and Processing

2.2.1. Remote Sensing Data

The scarcity and relatively short duration of field experiments (i.e., the carbon flux data obtained by eddy-covariance flux towers (compiled in FLUXNET)) make it difficult to obtain a full picture of how vegetation responds to climate [47,48], and MODIS-GPP data with high temporal-spatial resolution is always calculated on remote sensing data. Thus, in our research, to characterize the level of vegetative productivity, this study chose MOD17A2H GPP for the period from 2001 to 2016; the product is a cumulative 8-day composite of values with 500 m pixel size based on the radiation use efficiency concept (<http://search.earthdata.nasa.gov/>). Before the analysis of remote sensing data, the original 8-day GPP data were preprocessed by the MODIS Reprojection Tool (MRT), which included image mosaic and projection transformation. After that, we calculated the annual GPP based on these 8-day GPP products. To compare the relative changes in vegetation, we detrended the GPP data by using a linear regression model to eliminate the external factors such as the CO₂ fertilizer effect and the influence of vegetation factors such as forest age. Specifically, we fitted the original GPP data from 2001 to 2016 to get their linear trends and then minus their trends to get GPP data without trends.

2.2.2. Meteorological Data

In this study, we used monthly meteorological data from the Climatic Research Unit (CRU) at the University of East Anglia for the period from 1901 to 2016 (http://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.01/), including temperature (Temp), precipitation and potential evapotranspiration. The version of the dataset was TS 4.01, and the spatial resolution was 0.5°. Monthly photosynthetic active radiation (PAR) was obtained from the Cloud and the Earth's Radiant Energy System (CERES) at NASA's Langley Research Center at a 1° spatial resolution for the period from 2000 to 2019 (https://ceres.larc.nasa.gov/order_data.php). In this dataset, the total photosynthetic active radiation (PAR) was computed from the sum of the surface diffusive and direct PAR in the all-sky conditions [49].

To match these spatial datasets, all spatial data were converted into the WGS84 coordinate system with the spatial resolution uniformly adjusted to 500 m in ArcGIS 10.1 through the nearest neighbour algorithm. At the same time, we detrended the climate factors of temperature, climate water deficit and photosynthetic active radiation by using a linear regression model to eliminate the potential impacts of change trends and to focus on the impacts of interannual variability. Specifically, we fitted the original climate data from 2001 to 2016 to get their linear trends and then minus their trends to get climate data without trends. The anomaly of climate water deficit ($CWD_{anomaly}$), which represents the difference between annual precipitation and annual potential evapotranspiration, was used to reflect the status of water conditions. We first calculated the climate water deficit (CWD) from 2001 to 2016 (Stephenson, 1998) and then defined 7 grades of water deficit (Table 1) based on the standard deviations (SDs) of the anomalies of the CWD series.

Table 1. Seven grades of climate water deficit ($CWD_{anomaly}$).

Water Conditions	$CWD_{anomaly}$
Severely wet	$CWD_{anomaly} > 2 SD$
Moderately wet	$1.5 SD < CWD_{anomaly} < 2 SD$
Mildly wet	$SD < CWD_{anomaly} < 1.5 SD$
Normal	$-SD < CWD_{anomaly} < SD$
Mild drought	$-1.5 SD < CWD_{anomaly} < -SD$
Moderate drought	$-2 SD < CWD_{anomaly} < -1.5 SD$
Severe drought	$CWD_{anomaly} < -2 SD$

SD: the standard deviation of the CWD series.

The dataset of monthly soil moisture for the period from 2000 to 2015 was derived from the Global Land Data Assimilation System (GLDAS) (<http://ldas.gsfc.nasa.gov/gldas>); its spatial resolution was 0.25° , and it included the soil moisture of four layers: 0–10 cm, 10–40 cm, 40–100 cm and 100–200 cm. We computed the annual mean soil moisture in 0–100 cm then resampled this data to 500 m for matching the climate water deficit data.

2.2.3. Identification of Water-Limited Regions

We used the partial correlation method to identify the regions of vegetation that were mainly limited by different climate factors (i.e., Temp, CWD and PAR). Specifically, we first calculated the partial correlation coefficient between the detrended meteorological factors (Temp, CWD and PAR) and GPP at the grid scale, from which we could identify the main limiting climate factors that are potentially related to GPP. Second, we determined the regions that were mainly limited by different climate factors based on the maximum positive partial correlation coefficients between GPP and different climate factors, which reflects the highest positive sensitivity. As a result, the entire study region was divided into two subregions that represented a water-limited region and a water-unlimited region. In other words, water condition was the main impact factor on GPP in the water-limited subregion, whereas temperature and radiation were the main impact factors on GPP in the water-unlimited subregion.

To eliminate the spatial heterogeneity of GPP and focus on revealing the relative changes caused mainly by the various degrees of water stress, we first standardized the detrended GPP (GPP_n) and the corresponding climate factors (Equation (1)) to avoid negative values in the denominator of Equation (2) and then calculated the normalized difference in GPP in drought year i (ΔGPP_i). The calculation of ΔGPP_i is based on the comparison of GPP_n in drought year i ($GPP_{n,i}$) and the corresponding three consecutive normal years when non-drought stress occurred ($GPP_{n,i-1}$, $GPP_{n,i-2}$ and $GPP_{n,i-3}$) (Equation (2)). This method takes the mean value of GPP in a normal year without water stress for three consecutive years as the reference at the pixel scale to compare with the change in GPP value under different drought intensities.

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X is the value of detrended GPP or meteorological data in a certain pixel, and X_{\min} and X_{\max} are the corresponding minimum value and the maximum value.

$$\Delta GPP_i = \frac{GPP_{n,i} - (GPP_{n,i-1} + GPP_{n,i-2} + GPP_{n,i-3})/3}{(GPP_{n,i-1} + GPP_{n,i-2} + GPP_{n,i-3})/3} \quad (2)$$

where $GPP_{n,i}$ is the standardized GPP value (GPP_n) in drought year i , and $GPP_{n,i-1}$, $GPP_{n,i-2}$ and $GPP_{n,i-3}$ are the corresponding GPP_n values in $i - 1$, $i - 2$ and $i - 3$ normal years.

2.3. Constructing the Relationship between Climatic Water Deficit and Soil Moisture

To further understand the mechanism of climatic water deficit (CWD) impacts on vegetation GPP, our research determined the relationship between CWD and soil water. First, we extracted all of the grids' value of the annual mean soil moisture and the annual mean CWD in the water-limited region. Then, we conducted the linear regression relationship between CWD and soil moisture.

2.4. Evaluation of Variable Importance

As the impact of water condition on vegetation exhibits a time-lag effect [31], it is quite important to evaluate the influence of the degree of water deficit at different times (i.e., in the previous or current year). In this study, we took the water-limited region revealed in Section 2.2.3 as the study region and used a machine learning algorithm to further assess the influence of the degree of water deficit in the previous years and current year on GPP. Through the evaluation of importance, we explored the potential impact of early water deficit on GPP. The random forest method was currently widely used in related research, which was considered as a good method to evaluate the importance of variables [50,51]. Thus, the machine learning algorithm (i.e., random forest) was applied in this study. One algorithm has been tested in this machine learning scheme. The random forest model combines the base principles of bagging with random feature selection to add additional diversity to the decision tree models, which means it can improve model performance with meta-learning using an ensemble-based method [52]. The random forest model can calculate the influence of each variable based on the existing data through modelling, that is, the importance. We used the function of randomForest and importance in the package of randomForest in R software in the modelling [53]. During the evaluation of variable importance, we selected all pixels in the water-sensitive region and partitioned them into different groups based on the combinations of water deficit conditions over four years (i.e., the current year and previous three years) (Table S1). For different groups of the water deficit condition, the mean GPP was calculated and regarded as a training set to assess the importance of variables, including the water conditions in the current year (Current), the first previous year (1st), the second previous year (2nd) and the third previous year (3rd). The calculated importance value represents the ability of water conditions in different years to predict GPP and therefore to quantify the degree of influence of water conditions in the previous years and current year. In calculating the importance of the variables, we used the metric of the percentage of Increased Mean Square Error (%IncMSE) and the mean decrease in node impurity (IncNodePurity). The larger the value, the more important the variable.

2.5. The Grades of Water Deficit Conditions

To better quantify the potential impacts of water deficit in the current and previous years, we set three water deficit grades (drought, normal and wet) in the current year and then combined them with the timing of water deficit to obtain the different scenarios, which contained information on both water condition and the timing of water condition (Table 2). To explore the relationships between GPP and water conditions in the previous and current years, we set up linear regression models (i.e., $y = ax + b$) between the GPP in the current year and the water conditions in the current year, first previous year, second previous year and third previous year, respectively. The three water deficit grades included drought ($CWD_{\text{anomaly}} < -1.5SD$), normal ($-1.5SD < CWD_{\text{anomaly}} < 1.5SD$) and wet ($CWD_{\text{anomaly}} > 1.5SD$). The relationship between GPP and water deficit intensity in the previous and current years was established by setting the water conditions in the other years to be normal ($-SD < CWD_{\text{anomaly}} < SD$) (Table 2). Our scenario included a total of 147 water deficit condition combinations. We excluded 14 combinations in which a sample of pixels was empty and/or too small. As a result, there were 133 combinations of effective water deficit (Table S1).

Table 2. Water deficit scenarios based on the current and three previous years' water conditions.

Water Conditions in Different Years				
	3rd	2nd	1st	Current
3rd	Seven water deficit scenarios	Normal	Normal	Seven water deficit scenarios
2nd	Normal	Seven water deficit scenarios	Normal	Seven water deficit scenarios
1st	Normal	Normal	Seven water deficit scenarios	Seven water deficit scenarios
Current	Normal	Normal	Normal	Seven water deficit scenarios

Current represents the water condition in the same year as the GPP value (i.e., the i th year), 1st represents the first previous year (i.e., the $(i - 1)$ th year), 2nd represents the second previous year (i.e., the $(i - 2)$ th year), and 3rd represents the third previous year (i.e., the $(i - 3)$ th year).

3. Results

3.1. Identification of Regions Sensitive to Climate Factors

The sensitivity of GPP to different climate factors has high spatial heterogeneity (Figure 2a). In general, the water-limited region is primarily distributed in Northwestern China and North China. The temperature-limited region, however, is mainly distributed in Western China (e.g., Qinghai Province) and Eastern China. The radiation-limited region is mainly distributed in Southwestern China and Central China. The sensitivity analysis illustrated that GPP was responsive to drought in the water-limited region, and this was therefore a suitable region to further analyse the relationship between water and GPP. For the water-limited region, the results (Figure 2b) indicate that GPP decreased by 42.2% and 72.0% in the mild drought years ($-1.5SD < CWD_{anomaly} < -SD$) and in the severe drought years ($CWD_{anomaly} < -2SD$), respectively, compared with the normal years ($-SD < CWD_{anomaly} < SD$).

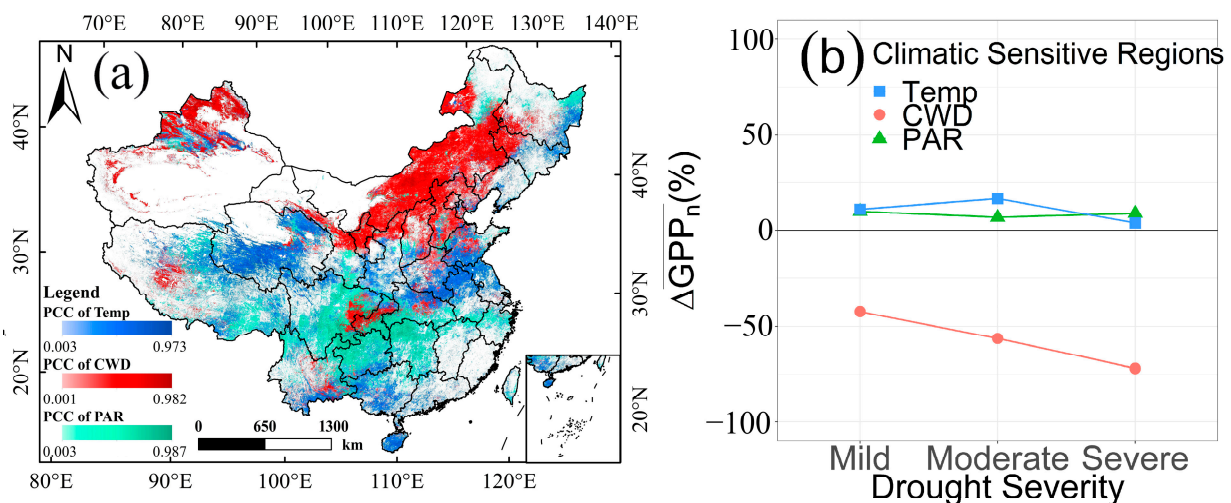


Figure 2. Distribution of main climatic factor-limited regions and the corresponding responses of GPP to drought intensity. (a) Spatial distribution of different limited regions for climatic factors. PCC is the abbreviation for the partial correlation coefficient. (b) Drought responses of different climate-limited regions. Blue, red and green colours represent temperature (Temp), climatic water deficit (CWD) and photosynthetic active radiation (PAR), respectively. The vertical coordinate indicates the percent change in the GPP of vegetation that encountered drought relative to the mean productivity of three consecutive normal years.

3.2. Comparison of Climatic Water Deficit and Soil Moisture

The climatic water deficit (CWD) we used in the study was obtained by subtracting potential evapotranspiration from precipitation. The indicator CWD is biologically meaningful and can be used to characterize site conditions as sensed by plants [54]. Given that soil moisture is another commonly used indicator of water conditions that represents the water held in the soil within reach of the plant roots [55], we compared CWD with soil moisture.

Through the comparison, we found that CWD was well consistent with soil moisture (Figure 3), which suggests that CWD could reflect the soil water well in our study region.

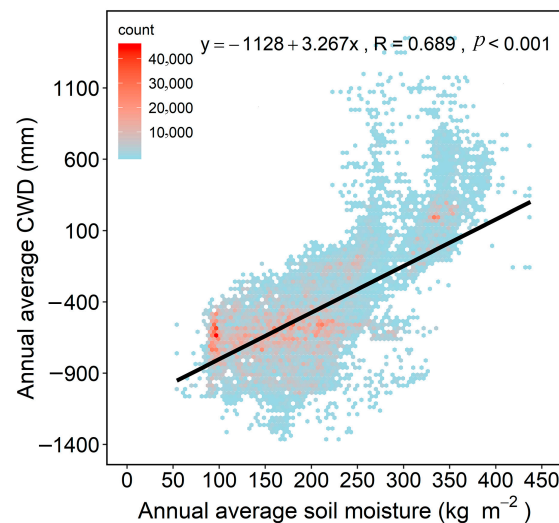


Figure 3. The relationship between the annual average CWD and the annual average soil moisture during 2001 and 2015. The colour of dots represents the number of these spatial pixels, and R is the correlation coefficient.

3.3. Importance Evaluation of Drought in Different Time

We used random forest (rf) to evaluate the impact of water conditions in the previous years and current year on GPP (Figure 4). Specifically, the largest effect of water conditions on GPP was observed in the current year. Random forest highlighted the importance of water conditions in the current year, and the importance value was determined as 52.8% (%IncMSE) and 3.8 (IncNodePurity). However, the variability in importance suggests that water conditions in the previous years, particularly the first year, also have an important effect on GPP, with the importance value of about 20.4% (%IncMSE) and 0.6 (IncNodePurity). The results of the model simulation reveal that although the water conditions in the current year were the most important for vegetative growth, the water conditions in the previous years also need to be considered.

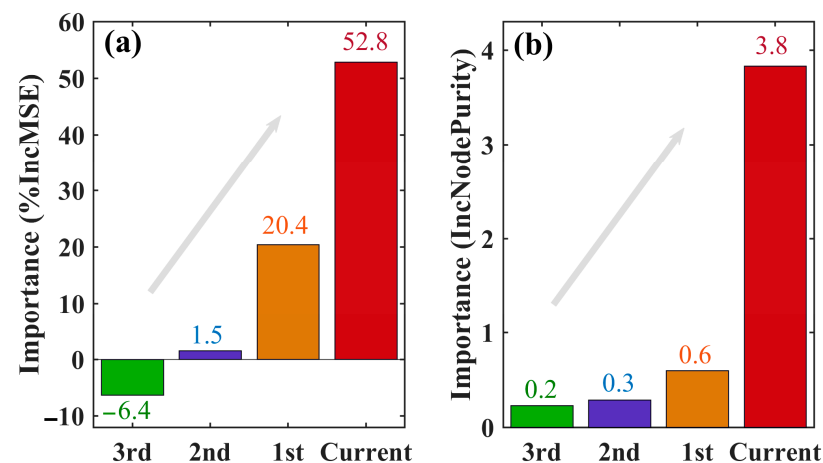


Figure 4. Importance analysis of water conditions in the previous years and the current year using a random forest model: (a) %IncMSE (the percentage of Increased Mean Square Error) and (b) IncNodePurity (the mean decrease in node impurity). 3rd, 2nd, 1st and Current represent the water conditions in the third previous year, the second previous year, the first previous year and the current year, respectively.

3.4. Time-Lag Effect of Water Deficit

Based on the knowledge revealed by the machine learning algorithms in Section 3.3, we further developed the linear regression models between GPP and water deficit conditions in the previous years and current year for the different water deficit scenarios. The results indicate that the water conditions of the current year were positively correlated with GPP (Figure 5), i.e., the better the water conditions, the higher the GPP. When the water conditions in the current year were in a drought condition ($CWD_{anomaly} < -1.5SD$), the water deficit conditions in the previous years had no significant effect on the GPP (Figure 5a,d). However, when the water conditions in the current year were normal ($-1.5SD < CWD_{anomaly} < 1.5SD$) or wet ($CWD_{anomaly} > 1.5SD$), the role of water conditions in the previous year positively impacted the GPP ($p < 0.05$; Figure 5b,c,e,f). The water conditions in the second previous year and third previous year, however, were not significant ($p > 0.05$). The improvement in water conditions in the current year highlights the influence of water conditions in the first previous year on GPP. The effect of water deficit on GPP lagged by approximately one year. This study also found that the GPP was relatively low when the water conditions were in a drought. In contrast, the GPP was relatively high when the water conditions were wet, which suggests that the influence of water conditions in the current year on the GPP was much greater than the effect of water conditions in the previous years, which is consistent with the simulation results of the models in Section 3.3.

The advantage of combining the random forest method and linear regression method is obvious. The random forest could quantify the relative importance of different years' water stress, while the linear regression models that are based on a series of water deficit scenarios could identify the causes of higher or lower importance. Specifically, the random forest revealed that the current year's water condition has the highest importance (52.8% (%IncMSE) and 3.8 (IncNodePurity)), which is consistent with results revealed by linear regression models as they found that impact of the current year's water condition on GPP is stable and unconditional which does not depend on the previous years' water condition. For the role of previous year's water condition, however, the random forest found that it is also important but with relatively lower importance (20.4% (%IncMSE) and 0.6 (IncNodePurity)). The reason revealed by linear regression models is that the water influence of the previous year depends on the water deficit condition of the current year. These results are valuable as they imply that we need to consider two years' water conditions to better predict the interannual variation of GPP.

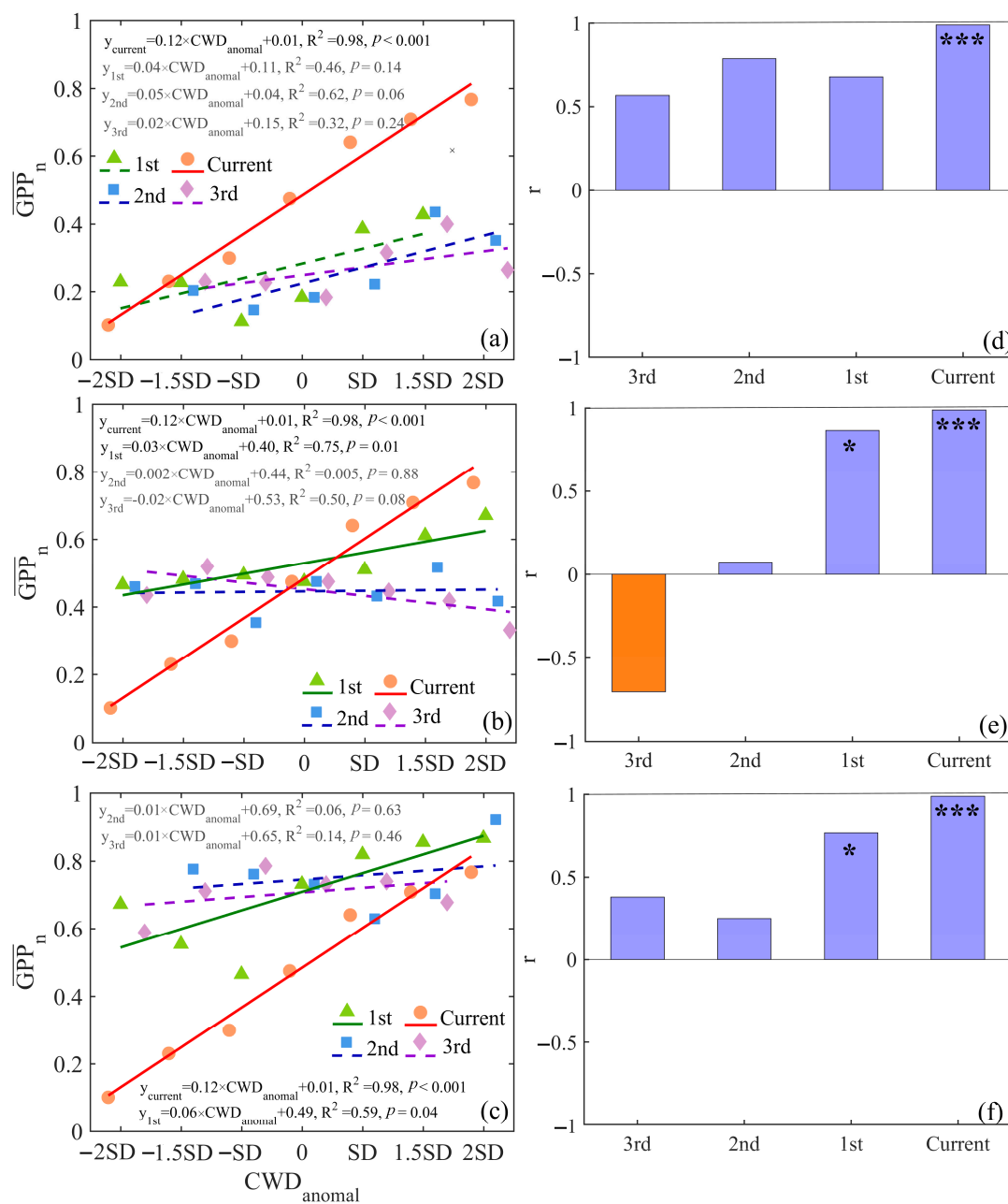


Figure 5. Statistical relationships between GPP in the current year and water conditions in the previous years and their dependence on the current year's water conditions. The water conditions in the current year are (a) drought ($CWD_{anomaly} < -1.5SD$) (Current_drought in the figure), (b) normal ($-1.5SD < CWD_{anomaly} < 1.5SD$) (Current_normal in the figure) and (c) wet ($CWD_{anomaly} > 1.5SD$) (Current_moist in the figure). Purple (cross), red (round), dark green (triangle) and light green (square) colours represent different water conditions in the current year, the first previous year, the second previous year and the third previous year, respectively. The vertical coordinate represents the mean of standardized GPP. A solid line shows that the impact of water deficit in the previous years or current year on the vegetation productivity is significant ($p < 0.05$). A dashed line shows that the impact of water deficit in the previous years or current year on the vegetation productivity is not significant ($p > 0.05$). The second row (d–f) corresponds to the Pearson correlation coefficient between the gross primary productivity of vegetation (current year) and the water conditions in the previous years and current year, respectively. * indicates a significance level of 0.05, and *** indicates a significance level of 0.001.

4. Discussion

4.1. Factors Impacting Vegetative Productivity

The factors that restrict vegetative growth in different regions should exhibit spatial heterogeneity. In this study, we conducted basic sensitivity analysis using the statistical method of partial correlation analysis to reveal the different climate limited regions and then analysed the difference in the response of vegetative productivity to drought intensity in order to explore the time-lag effect of water conditions. We found that the GPP in the water-unlimited region (i.e., the temperature-limited region and radiation-limited region) was less affected by drought intensity, which is similar to the results of previous studies that have found that drought-induced forest deaths tend to occur in water-limited areas [56,57]. Due to the differences among plant functional groups and geographical environments, the sensitivity of global vegetation to climate factors is variable [22]. Most studies have analysed the coupling effect of drought and other extreme weather events [58] and ignored the effect of other climate factors except water when analysing the effect of drought on tree growth; the sensitivity of vegetation to water in the study area is rarely considered. The spatial distribution pattern of vegetation sensitivity to various climate factors and the difference in response to drought intensity shows the importance of regions sensitive to climate factors.

4.2. The Time-Lag Effect of Water Conditions on GPP

Revealing the impact of water stress on GPP is quite important under the background of global climate change. However, due to the time-lag effect [7,13,30,38], the cumulative effect [36] and the legacy effect [42,43], the influence of water stress on vegetation growth is very complicated as the frequency, severity, duration and timing of water deficits have a profound influence on vegetative growth [30]. In this study, we applied a random forest method to quantify the relative importance of current and previous years' water stress. Furthermore, we revealed the role of the previous year's water stress on GPP, especially the importance of the combination of previous and current years' water conditions.

In this study, the relationship between GPP and water deficit intensity in previous years and the current year was established by setting suitable scenarios. Through the relationships identified in the different scenarios, we revealed some rules governing the influence of water conditions in the previous years and the current year on GPP. The results showed that the water conditions of the current year had the greatest impact on GPP. Gao et al. (2018) [30] also found that the water deficit conditions of the current hydrological year had a greater impact on trees than the conditions of the previous hydrological year. The deficit or surplus of water supply in the current year will directly affect the physiological processes of the plant. Plants typically adjust the physiological function of their water conduction system to adapt to water stress [7,59,60]. Water stress limits the photosynthetic rate of plants, thereby reducing vegetative productivity. The aggravation of water stress may also damage the biochemical processes related to respiration and photosynthetic carbon storage, directly forcing plants to engage in adaptive strategies such as defoliation and strengthening of the root distribution [61]. Sufficient water allows an adequate level of photosynthesis for plants and promotes the enhancement of vegetative productivity when water conditions are wet.

Our study also showed that the water conditions in previous years, particularly in the first previous year, are also important for GPP, which shows a clear time-lag effect of water conditions on vegetation and is similar to other studies [13,38,62,63]. The reason may be that water in the previous year tended to permeate through the soil and became soil water which would definitely influence the ecosystem [55]. Luo et al. (2018) [13] found that forests of different stock volume levels were affected differently by the water in the previous years, presumably because of their varying ability to absorb underground water. Therefore, the water conditions in previous years could be better for predicting vegetation GPP and its interannual variation.

Although plants can adapt to water stress through self-regulation, growth is still affected to some extent when plants are subjected to severe water stress. In other words, water stress will have a time-lag effect on vegetative growth after severe drought events [7,41]. We found that the water conditions in the first previous year had a significant impact on GPP when the water conditions in the current year were normal or wetter (i.e., one-year time lag). Tei et al. (2017) [64] found a one-year time lag in the response of tree growth to the climate in the circumboreal region, which probably reflected an adaptation of trees to environments with more severe water stress by carrying over fixed carbon from one year to following years [65]. Wet conditions in two consecutive years can often accelerate the growth of vegetation [66]. However, once a strong drought occurs, there is a strong legacy effect from the first previous year due to the sensitivity of the vegetation to drought [31,36,67]. This shows the resilience of vegetation. However, because the resilience is weak, although the water conditions have improved after the drought, it is difficult for the vegetation to return to the state before the drought. At this point, the water conditions of the previous year control a significant fraction of the GPP in the current year [40,42].

In contrast, the water conditions in the first previous year did not have a significant impact on GPP when the water condition in the current year was in a drought. The impact of the drought in the current year will be greater than the water conditions in the previous year because of the greater sensitivity to drought than wet conditions [67]. Therefore, there is no significant impact of water conditions in the first previous year.

Changes in the temporal pattern of water deficits due to climate change, which are predicted to have great volatility in the 21st century, may have a prolonged impact on the growth of vegetation [68]. The temporal pattern of water deficits is commonly ignored in the assessment of different scenarios of climate change. In this study, we quantitatively assessed the time-lag effect of the water conditions in the previous years and the current year on GPP by considering suitable scenarios. Investigating consecutive interannual changes in water deficit will help us to more deeply understand the mechanism by which drought impacts vegetative productivity and improve the ability of process-based models to predict the carbon storage of terrestrial ecosystems under future climate change.

5. Conclusions

Gross primary productivity (GPP) is related to water conditions and shows high interannual variation. Due to the effect of time lags, not only the current water conditions but also the previous water conditions impact the GPP. In this study, we designed a series of water deficit scenarios under which the role of water deficit during different years was evaluated. We found that the water deficit during different periods had different impacts on GPP. The role of the current year's water on GPP is clear and deterministic. However, the role of water in previous years is multifarious and depends on the water conditions of the current year. The diverse effects of water conditions during previous years on GPP and the time-lag effect revealed in this study imply that not only the current year's water conditions but also its dynamic changes during previous years should be considered when predicting changes in GPP caused by climate change.

Supplementary Materials: The following are available online at <https://www.mdpi.com/2072-4292/13/1/58/s1>, Table S1: The effects of water conditions in the previous years on gross primary productivity of vegetation under different water conditions in the current year.

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