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RESPONSES OF VEGETATION GROWTH TO CLIMATE CHANGE IN CHINA

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ABSTRACT:

Global warming-related climate changes have significantly impacted the growth of terrestrial vegetation. Quantifying the spatiotemporal characteristic of the vegetation's response to climate is crucial for assessing the potential impacts of climate change on vegetation. In this study, we employed the normalized difference vegetation index (NDVI) and the standardized precipitation evapotranspiration index (SPEI) that was calculated for various time scales (1 to 12 months) from monthly records of mean temperature and precipitation totals using 511 meteorological stations in China to study the response of vegetation types to droughts. We separated the NDVI into 12 time series (one per month) and also used the SPEI of 12 droughts time scales to make the correlation. The results showed that the differences exist in various vegetation types. For needle-leaved forest, broadleaf forest and shrubland, they responded to droughts at long time scales (9 to 12 months). For grassland, meadow and cultivated vegetation, they responded to droughts at short time scales (1 to 5months). The positive correlations were mostly found in arid and sub-arid environments where soil water was a primary constraining factor for plant growth, and the negative correlations always existed in humid environments where temperature and radiation played significant roles in vegetation growth. Further spatial analysis indicated that the positive correlations were primarily found in northern China, especially in northwestern China, which is a region that always has water deficit, and the negative correlations were found in southern China, especially in southeastern China, that is a region has water surplus most of the year. The disclosed patterns of spatiotemporal responses to droughts are important for studying the impact of climate change to vegetation growth.

1. INTRODUCTION

Drought is one of the most complex natural hazards, and it has affected economy, agriculture, and society (Beguería et al.2010; Wilhite, 2000). Drought is expected to increase in frequency and severity due to global warming (Dai, 2013; Seneviratne et al., 2012), and it is significant to investigate the response of vegetation growth to drought (Wu et al., 2013; Wagle et al., 2014). Since the 20th century, many efforts have been made to investigate drought by developing many drought indices, and there are three popular drought indices including the Palmer drought severity index (PDSI; Palmer, 1965), the standardized precipitation index (SPI; McKee et al., 1993) and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010). The PDSI is based on the supply and demand concept of the water balance equation, but the main disadvantage is that it has a fixed temporal scale and an autoregressive characteristic (Guttman, 1998). The SPI is based on the cumulative precipitation available and incorporates different time scales (Vicente-Serrano, 2014), but it also includes the precipitation information, and omit other variables such as the temperature and the evapotranspiration that can influence the drought (Vicente-Serrano, 2010). The SPEI is based on the monthly water balance derived from precipitation and potential evapotranspiration (PET) and incorporates the advantages of both the PDSI (sensitivity to the evaporative demand) and the SPI (reflecting multi-scale characteristics) (Vicente-Serrano et al, 2014). This study employed the SPEI as the climatic drought indicator to investigate the climate conditions. As the climatic drought indices were used the meteorological observations and incorporated little vegetation and soil information in determining the vegetation response (Mu et al., 2013). We also used the remote sensing data to reflect the vegetation activity in this study. The normalized difference vegetation index (NDVI; Rouse et al., 1974) is sensitive to vegetation growth and environmental stress, and it is a good indicator for monitoring terrestrial vegetation activities (Zhang et al., 2014). Previous studies have concentrated in the responses of forests to drought (Madrigal-González J et al., 2014; Mendivelso et al., 2014), and few studies have investigated the impact of drought on other vegetation types. This study employed the correlation between the NDVI and the SPEI at various time scales and found the major time scales of SPEI for different vegetation types to investigate the responses of vegetation growth to the climate change.

2. DATA AND METHODS

2.1 Climatic data

This study employed the monthly precipitation and the monthly average temperature data during the period 1960 - 2013 from the National Climate Center of the China Meteorological Administration (CMA). The homogeneity and reliability of the monthly meteorological data have been previously checked and controlled by the CMA (Yu et al., 2014). As there are missing values in the meteorological data, the 5-year running means before and after these missing data were applied to ensure that the time series was continuous. If the meteorological data were missing for more than 12 consecutive months of a specific station, the station was removed out of the analysis. The representative vegetation type for each meteorological station was determined from a 1:1000000 vegetation map of the People's Republic of China (Zhang et al., 2007). 511 meteorological stations covering most regions in China

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involved six major land cover types including needle-leaved forest, broadleaf forest, shrubland, grassland, meadow and cultivated vegetation were picked up for the study (Fig. 1).

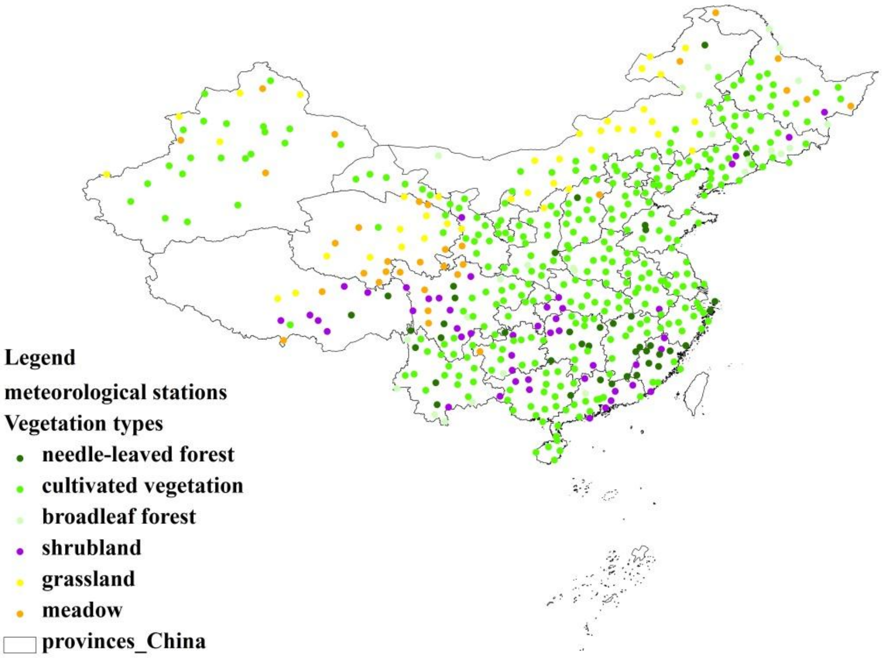

Figure 1**.** Spatial distribution of meteorological stations and the related vegetation types

2.2 Remote sensing data

Remote sensing data has been playing a significant role in monitoring drought-related vegetation condition (Henricksen and Durkin, 1986; Jain et al., 2009). Many vegetation indices have been developed to reflect vegetation characteristics, and the most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979). The NDVI dataset used in this study was obtained from the Global Inventory Modelling and Mapping Studies inventory (Tucker et al., 2005) for the period 1982 - 2011. This dataset has the longest time series and it is appropriate to assess vegetation variability and trends (Beck et al., 2011). The GIMMS NDVI dataset is a bimonthly composite NDVI product at an 8-km spatial resolution (Tucker et al., 2004; Tucker et al., 2005), and it was transformed into a monthly composited dataset based on the maximum value composite to correspond with the resolution of the SPEI.

2.3 Multi-scalar climate drought indicator: SPEI

The Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) was calculated based on the monthly records of mean temperature and precipitation totals at meteorological stations over China for the period 1960 - 2013. The SPEI was used to reflect water conditions at different time scales. Mathematically, the SPEI uses primarily the monthly differences between precipitation and the potential evapotranspiration (PET). There are three major steps to calculate the SPEI at different time scales. The first is to calculate the PET based on the formula of Thornthwaite (1948), and the second is to calculate the accumulated deficit or surplus in the climate water balance at different time scales, and the last is to normalize the water balance into a log-logistic probability distribution to obtain the SPEI index series (Vicente-Serrano, 2010). The SPEI is a standardized value, and it could be compared with other SPEI values over time and space. The various time scales of SPEI is from 1- to 12- months, and these time scales can be grouped into three categories. The short time scales are from 1 to 5 months, and the medium time scales are from 6 to 8 months, and the long time scales are from 9 to 12 months.

2.4 Statistical methods

Twelve GIMMS-NDVI series (i.e., one series per month) were obtained for each meteorological station, and the various time scales (1 to 12 months) were also employed to make the correlation. Pearson correlation analysis between the SPEI at various time scales and the variation of NDVI ($NDVI_{variation}$) that equals to the value of NDVI minus the average value of NDVI for each meteorological station were employed to reflect the responses of vegetation growth to the drought. There were 144 correlation coefficients for each meteorological station (12 monthly NDVI series by 12 SPEI series at different time scales), and the correlation coefficients that satisfy the significance threshold ($\alpha < 0.05$) were selected to reflect the responses of vegetation growth to droughts. The maximum value of the 144 correlation coefficients at each meteorological station was retained to analyse the spatial distribution of China. The SPEI time scales for different vegetation types are summed up to reflect the responses of vegetation growth to the drought, and the maximum correlation coefficient was also kept for further study. All correlation coefficients employed in this study passed the significance test with a significance level of 0.05.

3. RESULTS

3.1 The correlation between the $NDVI_{variation}$ and the SPEI

The correlation analysis between the $NDVI_{variation}$ and the SPEI at different time scales was employed to investigate the responses of vegetation growth to climate change. For the

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needle-leaved forest, the broadleaf forest and the shrubland, the correlation coefficients are mainly negative. These three vegetation types always locate in humid sites, with higher average annual precipitation than average annual potential evapotranspiration (PET). The grassland has higher water deficits, and the correlation coefficients are mainly positive. The meadow has better water conditions than the grassland, so the percentage of positive correlation is lower than the grassland. The cultivated vegetation always located in sub-arid sites, with more positive correlation coefficients than the negative. The meteorological stations for each vegetation type are summed up in Table 1.

Vegetation type	Number of stations	Percentage of correlation coefficients	
		positive	negative
Needle-leaved forest	40	26.17%	73.83%
Broadleaf forest	26	14.61%	85.39%
Shrubland	47	25.73%	74.27%
Grassland	39	78.58%	21.42%
Meadow	32	46.26%	53.74%
Cultivated vegetation	327	62.31%	37.69%

Table 1. The station-based correlations between the NDVIs and the SPEIs

3.2 The different SPEI time scales for vegetation types

Different vegetation types have their own characteristics to reflect their responses to drought at different time scales (Fig. 2). For the needle-leaved forest, the broadleaf forest and the shrubland, they have more percentages of SPEI concentrated in the long time scales. The specific percentages of the needle-leaved forest, the broadleaf forest and the shrubland are about 49.39%, 53.33% and 39.52%. For the grassland, the meadow and the cultivated vegetation, the highest percentages of the SPEI are mainly in the short time scales. For the grassland, the correlation has about 38.10% in the short time scales and 35.70% in the long time scales. For the meadow, the correlation has about 39.73% in the short time scales and 36.03% in the long time scales. For the cultivated vegetation, the correlation has about 36.79% in the short time scales and 35.48% in the long time scales. To sum up, the needle-leaved forest, the broadleaf forest and the shrubland concentrate in the long time scales. For the grassland, the meadow and the cultivated vegetation, they have majored in the short time scales, but they also have some percentages of SPEI in the long time scales that are a little lower than the short time scales.

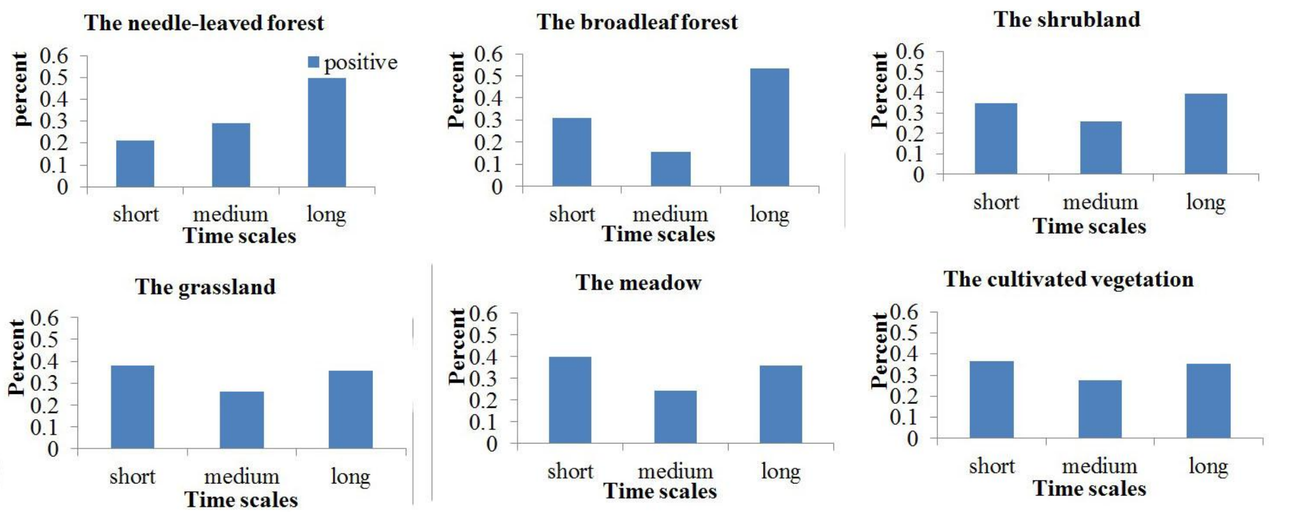

Figure 2. The different time scales for various vegetation types

3.3 The spatial characteristics between the $NDVI_{variation}$ and the SPEI

The maximum correlation coefficient for each meteorological station was employed to reflect the spatial distribution of the relationship between the drought and the climate drought indicator (Fig.3). The meteorological station-based correlation coefficients were interpolated into grids using an ordinary Kriging method with a spatial resolution of 8 km. The negative correlation has majored in the southeast China where also have positive balance in China. There are still some sites that have negative correlation in northeast China, with the major vegetation types are forests. The forests also have positive water balance and they are not too sensitive to the water deficit. Most regions in China has positive correlation coefficients between the $NDVI_{variation}$ and the SPEI, and among all the vegetation types, the sites in the North China especially in the northwest China have the largest positive correlation coefficients.

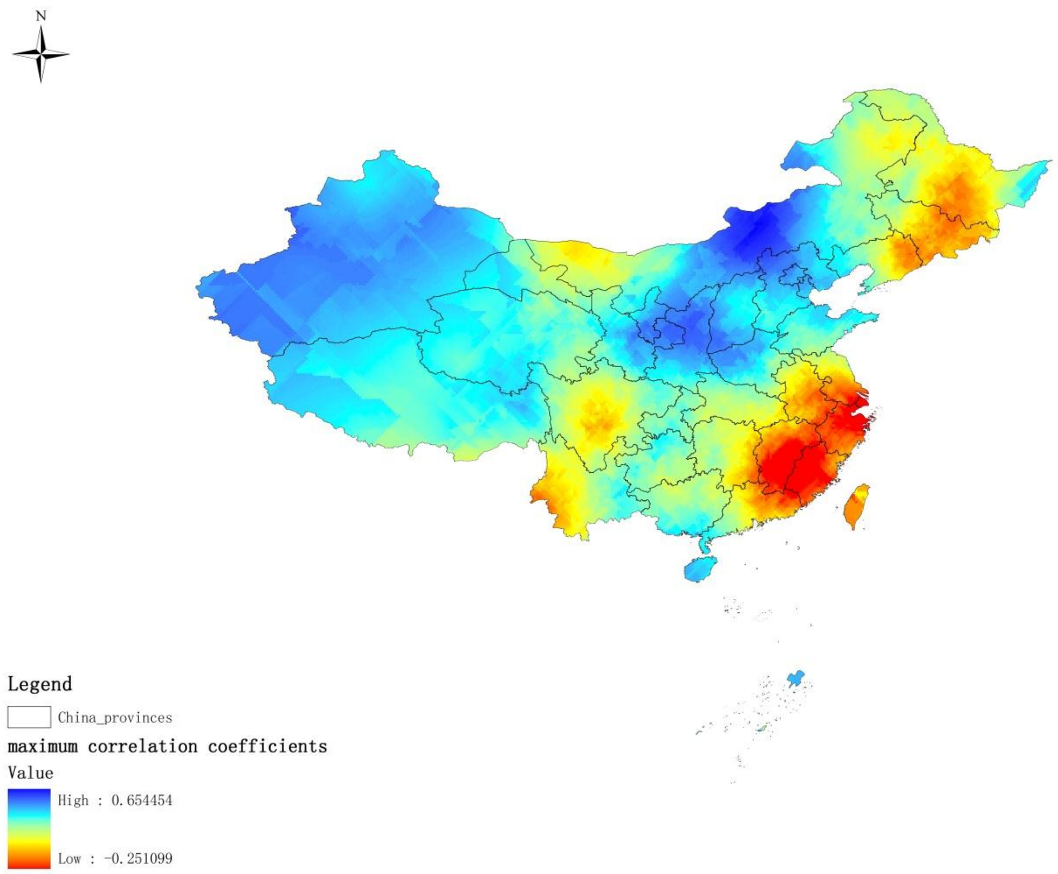

Figure 3. The spatial distribution of the maximum correlation coefficients in China

4. DISCUSSION

The standardized precipitation evapotranspiration index (SPEI) as a site-specific climate drought indicator and the GIMMS NDVI as a vegetation growth indicator were used to reflect the responses of vegetation growth to climate change in China. The correlation analysis was employed between the SPEI at different time scales and the $NDVI_{variation}$ to investigate the impact of climate change on vegetation growth. For the needle-leaved forest, the broadleaf forest and the shrubland, they always have more precipitation and positive water balance (water surplus) compared with the other vegetation types. So they have relatively lower correlation coefficients and even the negative correlations. These vegetation types are not typically affected by water deficits because the growing season temperature is the main constraint on growth (Briffa et al., 1998), and moreover, the radiation can also affect vegetation growth (Vicente-Serrano et al., 2014). The needle-leaved forest, the broadleaf forest and the shrubland are related to the long time scales, mostly because they have deep root systems and they can tolerate the water deficit for the short time scales. For the grassland, the meadow and the cultivated vegetation, they mainly have lower precipitation and more PET and always have water deficit. The positive correlation coefficients of these are higher than the other three vegetation types, and they are more sensitive to the short time scales. But the grassland, the meadow and the cultivated vegetation also have some percentages of SPEI in the long time scales that are a little lower than the short time scales which can be investigated in further study. To investigate the spatial distribution of the correlation coefficients in China, the maximum correlation coefficients are depicted in Fig. 3. Positive correlation coefficients are primarily concentrated in northern China, especially in northwestern China, where the corresponding water balance is primarily negative (water deficit). Negative correlation coefficients are mainly concentrated in southern China, especially in southeastern China, which corresponds to regions with primarily positive water balance (water surplus).

5. CONCLUSIONS

In this study, we investigated the spatiotemporal responses of different vegetation types across China during the period 1982-2011based on the correlations between the $NDVI_{variation}$ and the SPEI with different time scales. The results indicate that the responses in vegetation growth to the SPEI vary for different vegetation types. In general, the needle-leaved forest, the broadleaf forest and the shrubland are mainly concentrated in the long time scales, and the grassland, the meadow and the cultivated vegetation are related to the short time scales. The positive correlations were mostly found in arid and sub-arid environments where soil water was a primary constraining factor for plant growth, and the negative correlations always located in humid environments where temperature and radiation played significant roles in vegetation growth. The spatial analysis indicates that the positive correlations were primarily found in northern China, especially in northwestern China, and the negative correlations were found in southern China, especially in southeastern China. These findings are helpful to adopt the appropriate strategies to mitigate the impact of climate change on vegetation growth.

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