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**Assessing the response of vegetation photosynthesis to meteorological drought across northern China**

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Running Head: Cumulative effects of drought on vegetation photosynthesis

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**Abstract:** Satellite-basedsolar-induced chlorophyll fluorescence (SIF) has the potential for an early detection and accurate impact assessment of meteorological drought on vegetation photosynthesis. However, how the response of satellite SIF to meteorological drought varies under different climatic conditions and biome types remains poorly understood. In this study, we determined the drought time-scale at which the vegetation photosynthesis response was highest based on the standardized precipitation evapotranspiration index (SPEI) and satellite SIF, and examined how the sensitivity of SIF signals from different ecosystems to drought varied along an aridity gradient in northern China. The results showed that spatial variability of the annual maximum SIF was constrained by wetness conditions and biome types. Annual maximum SIF was positively correlated with SPEI in 57.9% of vegetated lands (*P* < 0.05). 34.8% of humid ecosystems were characterized by a significant SIF-SPEI correlation (*P* < 0.05). This percentage reached 44%, 71.4% and 86.2% for arid, sub-humid and semi-arid ecosystems, respectively. The variation of SIF-SPEI correlations was a Gaussian function of the aridity index (AI), with the highest SIF-SPEI correlation appearing in the AI bin of 0.4 (0.37-0.46). The drivers for this pattern were vegetation composition and water availability. The variation of SIF time-scales in response to SPEI was a linear function of the AI, but the slope varied among biomes. To summarize with increasing aridity drought-induced declines in vegetation photosynthesis will be quicker and more significant.

**Keywords:** Drylands; Chlorophyll fluorescence; Drought indices; Vegetation vulnerability; Drought time-scales.

1. **Introduction**

Drought triggers plant mortality, suppresses vegetation growth, and weakens the terrestrial carbon uptake (Ciais et al., 2005; Zhao and Running, 2010; Anderegg et al., 2013). Terrestrial ecosystems may lose their ability to reduce anthropogenic carbon emissions and ensure global food security, given that drought is forecast to increase in duration and intensity under climate warming (Friedlingstein et al., 2001; Trenberth et al., 2014; Lesk et al., 2016). Monitoring of drought-induced stress on vegetation health will be of increasing importance in the planning and management of agricultural production, ecological restoration and water resources.

Meteorological drought is defined as a sustained precipitation deficit over a region, and a drought index derived from drought-related meteorological variables (e.g. air temperature and precipitation), shows the regional behavior of drought including duration, intensity and spatial extent (Mishra and Singh, 2010). Satellite-derived visible and infrared images have been used to develop vegetation indices for evaluating drought impacts on vegetation vigor on regional to global scales, as drought causes reduced photosynthetic capacity and variations in absorbed photosynthetically active radiation (AghaKouchak et al., 2015). Reflectance-based vegetation indices serve as an indicator for potential photosynthesis by assessing chlorophyll abundance and light absorption down-regulated by environmental stress (Myneni et al., 1995). The main drawback of reflectance-based vegetation indices is that they do not decline when vegetation remains green but reduces photosynthesis under water deficits (Grace et al., 2007), and suffer from atmospheric and background contamination, causing a misleading signal for the canopy greenness that is not related to vegetation activity changes (Beck et al., 2006). In these cases, the relationships between vegetation and drought indices may fail to indicate the response of photosynthesis capacity to meteorological drought.

Solar-induced chlorophyll fluorescence (SIF) emitted from the cores of the photosynthetic apparatus, allows a more accurate estimation and earlier environmental stress detection on the functional status of actual photosynthesis than traditional vegetation indices do (Guanter et al., 2007; Meroni et al., 2009). Many studies show that SIF responds more strongly and quickly to variations in photosynthetic capacity when vegetation is stressed in contrast to the vegetation indices; for instance, enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) that have been widely used to examine terrestrial photosynthesis dynamics and its response to water stress (Daumard et al., 2010; Lee et al., 2013; Walther et al., 2016; Luus et al., 2017; Liu et al., 2018). Negative anomalies of the satellite-derived SIF observation can reasonably characterize the occurrence and developing processes of drought (Sun et al., 2015; Yoshida et al., 2015; Hu et al., 2019). Though satellite-observed SIF has potential for drought monitoring and impact assessment, it is uncertain to what extent drought stress is responsible for SIF declines. It is suggested that the temporal variation of SIF is mainly driven by fraction of photosynthetically active radiation and is also influenced by environmental stress (e.g. heat and water) that determines photosynthetic light use efficiency (Yang et al., 2015; Madani et al., 2017; Li et al., 2018). Biotic factors, such as plant functional types, affect the capacity to assimilate absorbed photosynthetically active radiation through photochemistry (Verma et al., 2017). To date, how the responses of satellite-based SIF to meteorological drought vary under different climatic conditions and biome types have not been precisely known. This knowledge gap is especially apparent for dryland ecosystems, characterized by frequent drought and high evaporative demand, together with diverse ecosystem types (Smith et al., 2018).

Northern China (73°29′ E–135°04′ E, 31°23′ N–53°34′ N) comprises most of drylands in East Asia, with an area of approximately 5.62 × 106 km2. The natural and artificial vegetation in this region protects against habitat and land degradation, but is vulnerable to climate drying and drought (Xu et al., 2018). The probability of severe drought may increase by 25–33% in the eastern and central parts of northern China based on the RCP4.5 scenario (Chen and Sun, 2017). Evaluating the response of satellite SIF to meteorological drought of different duration and intensity across northern China should enhance the understanding of cumulative effects of drought on vegetation photosynthesis in drylands, and help resource decision-makers to plan adaptation strategies in drought-prone areas.

We hypothesize that the degree to which SIF responds to different time-scales of drought depends on wetness conditions and ecosystem types. To verify this hypothesis, we determined the drought time-scale at which the response of vegetation photosynthesis was highest based on the standardized precipitation evapotranspiration index (SPEI) and satellite-observed SIF, and examined how the sensitivity of SIF signals from different ecosystems to drought varied along an aridity gradient over northern China. The concept of drought time-scale refers to the time lag between the onset of water stress and the identification of its effect (Vicente-Serrano et al., 2013). The objectives of this study are to: (1) confirm whether the spatial pattern of SIF is constrained by water availability; (2) investigate under what wetness conditions SIF shows the highest correlation to SPEI; (3) reveal differences in the drought time-scale across climate zones and land biomes.

1. **Materials and methods**
2. ***Satellite SIF***

The monthly GOSIF (global OCO-2 based SIF) data with a 0.05° spatial resolution from March 2000 to December 2017 were used in this study and were publicly available from the website http://globalecology.unh.edu/data/GOSIF.html. This product was developed by using a data-driven approach, based on discrete SIF observations from the NASA’s Orbiting Carbon Observatory-2 (OCO-2), albedo and land cover datasets from the moderate resolution imaging spectroradiometer (MODIS), along with meteorological reanalysis data from the modern-era retrospective analysis for research and applications (MERRA). Only OCO-2 SIF in the nadir mode was included to avoid directional effects on SIF emission caused by changing viewing geometries. GOSIF correlates well with gross primary productivity from the eddy covariance flux tower across biomes, showing the potential of GOSIF in monitoring photosynthesis (Li and Xiao, 2019). Annual maximum SIF was calculated from the monthly GOSIF based on the maximum value composite approach. The reason why annual maximum SIF was used in this study is that the SIF-GPP correlation generally increases with the increase in daily SIF values due to relatively higher signal-to-noise ratio (Zhang et al., 2016). Furthermore, most areas in northern china show annual maximum SIF during summer, when vegetation photosynthesis is most sensitive to water deficits throughout the year (Hua et al., 2017). The vegetated land was defined as annual maximum SIF > 0 W m-2 μm-1 sr-1 over the period of 2000 to 2017.

1. ***Drought and aridity indices***

The SPEI was used a drought index in this study. The major advantage of SPEI is that it integrates the sensitivity to atmospheric evaporative demand considered in the palmer drought severity index (PDSI) with the multiple time-scale character of the standardized precipitation index (SPI). The calculation of SPEI is based on a climatic balance between precipitation and potential evapotranspiration (PET), using monthly mean temperature and precipitation as the input data. The temperature-based Thornthwaite equation is adopted to estimate monthly PET (Thornthwaite, 1948). Calculation procedures for the SPEI are established at Vicente-Serrano et al. (2010). Different time-scales ranging from 1 to 24 months were used in this study in the light of our previous publication, showing < 24 accumulated months for the cumulative effect of meteorological drought on vegetation greenness in most areas of northern China (Xu et al., 2018).

Monthly mean temperature and precipitation data were collected from 422 meteorological stations in northern China from January 1998 to December 2017 (Fig.1a), and were provided by the China Meteorological Data Service Center (http://data.cma.cn). We adopted thin plate smoothing splines nested in the ANUSPLIN package to process the meteorological data into grid cell with a 0.05° spatial resolution. Thin plate smoothing splines incorporate an elevation dependence of the temperature and precipitation data (Hutchinson, 1995). Fig.S1 provides an example of the spatial interpolation of monthly mean temperature and precipitation in January and July 2017, respectively. Based on the raster layers of temperature and precipitation, and the latitude coordinate of each raster, we computed the SPEI accumulated at the monthly time interval by employing the SPEI calculator program, which is written in the C source code and is downloaded freely at https://digital.csic.es/handle/10261/10002. A negative value of SPEI indicates water deficits and vice versa.

The aridity index (AI) was used as an indicator of the degree of climate dryness, and was calculated from the ratio of mean annual precipitation to mean annual PET over the period of 2000 to 2017. The AI used an aridity category of the United Nations Environmental Program, including arid (AI ≤ 0.2), semi-arid (0.2 < AI ≤ 0.5), sub-humid (0.5 < AI ≤ 0.65) and humid (AI > 0.65) regions.

1. ***Ancillary data***

The land cover type data with a 0.01° spatial resolution in 2000 and 2015 were provided by the Resource and Environment Data Cloud Platform (http://www.resdc.cn/). It was derived from visual interpretations of the Landsat TM and ETM images, with an original 30 m spatial resolution and overall classification accuracy of 94.3% according to a comparison of the land cover map and field survey materials in 2010 (Liu et al., 2014). The land cover classification comprises farmlands, woodlands, grasslands, waters, urban and built-up lands, and no-utilized lands. We reclassified the land cover types into ecosystem types including croplands, forests, grasslands, wetlands, settlements and deserts. Areas with the constant ecosystem type between 2000 and 2015 covered 98.2% of the study area, of which 19.8%, 15%, 31.6%, 1.2% and 21.5% were croplands, forests, grasslands, wetlands and deserts, respectively (Fig.1b). Deserts were composed of sand, Gobi, saline-alkali soil and alpine sparse vegetation. The land cover type data were resampled at a 0.05° spatial resolution by using the majority function nested in the ArcMap Version 10.0 software.

The digital elevation model (DEM) at a spatial resolution of 1 km was available from the NASA Shuttle Rader Topographic Mission (http://www.glcf.umd.edu/). The DEM data were resampled at a 0.05° spatial resolution by using cubic splines nested in the ArcMap, and were then used in the spatial interpolation of temperature and precipitation (Fig.1a).

1. ***Analysis***

Spatial distribution of the annual maximum SIF was compared with that of the AI. The mean and standard deviation of SIF observations in every 0.01 AI bin were calculated. The piecewise linear regression model was used to detect whether there was a divergent trend in annual maximum SIF with increasing AI, with the breakpoint being determined by the least residual error of piecewise linear fits (Xu et al., 2017). The significance level (*P*) of the SIF trend with increasing AI was evaluated by the *F*-test. Additionally, significant differences in annual maximum SIF for various aridity categories and biome types were examined by the Kruskal-Wallis test implemented in the Matlab2014b software. The reason why this test was used was that the compared variables were not always normally distributed and did not have variance homogeneity (Kruskal and Wallis, 1952). In this research, the *P*-value < 0.05 was considered significant.

In view of multi-year distribution of the monthly SIF, we extracted the month in which annual maximum SIF appeared and its spatial distribution. The corresponding monthly SIF from 2000 to 2017 was acquired to form the time series of annual maximum SIF, the value of which in a given year for each pixel was converted to Z-scores. We performed Spearman rank correlation between standardized SIF and SPEI for the time-scale from 1 to 24 months, as the relationship between SIF and SPEI may be nonlinear (Sun et al., 2015). We calculated the maximum correlation coefficient of SIF and SPEI, and the SPEI time-scale at each pixel. The positive SIF-SPEI correlation suggests that meteorological drought reduces vegetation photosynthesis indicated by SIF. The *P*-value was derived from a threshold value table of the Spearman correlation coefficient, and was statistically significant when its value was < 0.05. The mean and standard deviation of the SIF-SPEI correlation and the SPEI time-scale under different biomes were calculated in every 0.01 AI bin to show the variation of the sensitivity of vegetation photosynthesis to meteorological drought along an aridity gradient. Linear and nonlinear curve fits implemented in the Originlab 2019 software were used to simulate the variation of sensitivity, with the model performance evaluated by the R-squared (*R*2).

1. **Results**
   1. ***Spatial distribution of the AI and annual maximum SIF***

We observed an aridity gradient from northwest to southeast across northern China and from basins to mountains, especially in northwestern China (Fig.2a). Percentage of the arid, semi-arid, sub-humid and humid regions was 31.2%, 23.9%, 14.5% and 30.4%, respectively (Fig.2b). Maps of the AI showed that thin plate smoothing splines can capture an elevational gradient of temperature and precipitation.

The intra-annual variation of spatially averaged SIF was close to the normal distribution, with a peak value appearing in July and the growing season lasting from April to October when monthly SIF was > 0 (Fig.2c). Nevertheless, the month in which annual maximum SIF occurred represented a great spatial variability (Fig.2d). Most areas of northern China had a peak value of SIF in July, followed by August and June. The corresponding area percentage was 47%, 43.3% and 8.6%, respectively. A small fraction of northern China (≈ 1%) had SIF maxima in April, May and September. Spatial distribution of the annual maximum SIF was generally in accordance with spatial distribution of the AI (Fig.2e). The highest value of SIF was detected mainly in the Changbai, Greater/Lesser Khingan and Qinling Mountains, with intermediate SIF values in the North China and Northeast Plains, and the lowest SIF value in the central and western portions of the Inner Mongolia, Loess and Qinghai Plateaus. A low SIF value was also found in the inland river basin of northwestern China, such as the Tarim, Junggar and Qaidam Basins.

Spatial distribution of the annual maximum SIF was dependent on climate dryness and biome types (Fig.3a,b). The highest SIF value occurred in humid areas (Mean ± SD, 0.35 ± 0.14 W m-2 μm-1 sr-1), followed by sub-humid (0.26 ± 0.11), semi-arid (0.15 ± 0.11) and arid regions (0.11 ± 0.11). At the biome scale, forests showed a higher value of SIF (0.4 ± 0.11) than croplands (0.3 ± 0.11), wetlands (0.24 ± 0.13), grasslands (0.17 ± 0.13) and deserts did (0.08 ± 0.07). We found a divergent trend in annual maximum SIF along an aridity gradient (Fig.3c). Annual maximum SIF increased with increasing AI when it was ≤ 0.9 (*R*2 = 0.91, *P* < 0.001) and then declined hereafter (*R*2 = 0.84, *P* < 0.001). Regions with a decreasing trend in SIF with increasing AI emerged mostly in the mountain area (Fig.1a). Relatively high SIF values in the arid oasis were induced by irrigation agriculture and afforestation programs to combat desertification (Fig.1b).

Regarding forests, annual maximum SIF followed a logarithmic function of the AI (*R*2 = 0.91, *P* < 0.001), and a saturation effect of SIF with increasing wetness was significant over humid regions (Fig.4a). Annual maximum SIF was a linear function of the AI for croplands (*R*2 = 0.86, *P* < 0.001, Fig.4b) and deserts (*R*2 = 0.22, *P* < 0.001, Fig.4e). A contrasting trend in annual maximum SIF with increasing AI was found in wetlands and grasslands (Fig.4c,d). SIF increased significantly with increasing AI when the AI was ≤ 0.9 in wetlands (*R*2 = 0.69, *P* < 0.001) and grasslands (*R*2 = 0.84, *P* < 0.001), but a reversed SIF trend with increasing AI emerged when the AI was > 0.9, having the *R*2 of 0.19 (*P* = 0.005) and 0.57 (*P* < 0.001) for wetlands and grasslands, respectively. The breakpoint of the SIF trend corresponded to sharp declines in the proportion of forests in relative to the increased proportion of grasslands and deserts (Fig.4f).

* 1. ***Spatial distribution of the SIF-SPEI correlation***

A significant positive SIF-SPEI correlation (*P* < 0.05) appeared in 57.9% of vegetated lands (Fig.5a), of which 4.3%, 43.5%, 25.4% and 26.8% was distributed in arid, semi-arid, sub-humid and humid areas, respectively. Positive correlations between SIF and SPEI were particularly strong on the Inner Mongolia and Loess Plateaus, and in the Tarim and Junggar Basins. Semi-arid ecosystems were found to show the highest correlation between SIF and SPEI, and sub-humid and arid ecosystems took the second and the third places, respectively (Fig.S2a). Though the response of SIF to SPEI was weakest in humid areas, the SIF analysis showed that 34.8% of humid ecosystems were characterized by a significant correlation with SPEI (*P* < 0.05). This percentage reached 44%, 71.4% and 86.2% for arid, sub-humid and semi-arid ecosystems, respectively. At the biome scale, the order of the SIF-SPEI correlation from high to low was grasslands, deserts and croplands, forests and wetlands (Fig.S2b). The corresponding area percentage showing significant SIF-SPEI correlations (*P* < 0.05) within biomes was 70.4%, 59.2%, 56.9%, 41.4% and 35%. Table 1 pointed out that the distribution of areas with significant SIF-SPEI correlations (*P* < 0.05) under different aridity categories was suitable for all biomes. Even in humid areas, 30.9% of forests and 39% of croplands had significant SIF-SPEI correlations (*P* < 0.05). By contrast, this percentage was lower for the cropland in arid areas (32.2%). Moreover, percentage of the area with significant SIF-SPEI correlations (*P* < 0.05) was higher in warm deserts (53.9%) occupied mostly by sand, Gobi and saline-alkali soil, compared to that in cold deserts (28.8%), predominantly alpine sparse vegetation.

The variation of SIF-SPEI correlations was a Gaussian function of the AI for all biomes (*R*2 = 0.93, *P* < 0.001, Fig.6a). The same pattern was found in forests (*R*2 = 0.83, *P* < 0.001, Fig.6b), croplands (*R*2 = 0.80, *P* < 0.001, Fig.6c), as well as grasslands (*R*2 = 0.93, *P* < 0.001, Fig.6e). In general, the SIF-SPEI correlation increased with increasing AI, and reached the highest value when the AI was close to 0.4 but varied from 0.37 to 0.46 for different biomes. The trend of SIF with increasing AI was significant for the wetlands (*R*2 = 0.41, *P* < 0.001) and deserts (*R*2 = 0.76, *P* < 0.001) in arid and semi-arid areas (Fig.6d,f). Furthermore, sharp decreases in SIF-SPEI correlations with increasing AI occurred for all biomes in sub-humid areas, and the SIF-SPEI correlation was similar in humid areas regardless of increasing AI. An exponential function described the relationship between the SIF-SPEI correlation and AI for the wetlands (*R*2 = 0.78, *P* < 0.001) and deserts (*R*2 = 0.50, *P* < 0.001) in sub-humid and humid areas.

* 1. ***Spatial distribution of the drought time-scale***

The spatial variability of drought time-scales was high, and the drought time-scale was divided into 3 categories including short (≤ 6 months), medium (6-12 months) and long (> 12 months) time-scales, which accounted for 29.4%, 29.0% and 41.6% of vegetated lands, respectively (Fig.5b). We identified general patterns that SIF tended to respond to short and medium time-scales in arid, semi-arid and sub-humid areas in relative to long time-scales in humid areas. It was also found that 17.5% of vegetated lands were characterized by drought time-scales ≤ 3 months, especially in the Inner Mongolia Plateau and the arid inland basin of northwestern China. Relatively low SIF-SPEI correlations and long SPEI time-scales were found in the Hetao Plain of Inner Mongolia (a 0.16-0.2 AI bin), where irrigation agriculture and wetlands were extensive.

The dominant drought time-scale was 9.3, 9.5, 12.8 and 15.4 months for arid, semi-arid, sub-humid and humid ecosystems, respectively (Fig.S3a). At the biome scale, the dominant drought time-scale was longest for forests (15.2 months), followed by wetlands and deserts (12.4 months), and croplands (11.3 months), with the lowest value of 11.0 months appearing in grasslands (Fig.S3b). Table 2 further noted that the drought time-scale was shortest for the cropland when compared with other biomes in arid and humid regions, where wetlands and deserts had the longest drought time-scale, respectively. In semi-arid regions, wetlands and deserts represented the shortest and longest drought time-scale, respectively.

We observed a significant increasing trend in the drought time-scale with increasing AI for all biomes (*P* < 0.001), but the increasing rate varied among biomes (Fig.7). The highest value of the increasing rate of drought time-scales with increasing wetness was found to be in wetlands and grasslands, with median values in deserts and forests, and the lowest value in croplands.

1. **Discussion**
   1. ***The ability of GOSIF to indicate vegetation photosynthesis***

Based on the measurements of OCO-2 SIF and gross primary productivity (GPP) from eddy covariance towers, previous studies indicate that the relationship between SIF and GPP is universally linear across a wide variety of biomes (Zhang et al., 2016; Sun et al., 2017; Li et al., 2018). In this research, vegetation photosynthesis is indicated by the GOSIF, which is produced by using a data-driven method based on OCO-2 SIF, MODIS and meteorological reanalysis datasets (Li and Xiao, 2019). We detect a pronounced seasonal cycle of monthly GOSIF (Fig.2), and maps of the annual maximum SIF represent a large spatial variability for various aridity categories and biome types (Fig.3). Biomes with high productivity have high SIF values and vice versa. Moreover, the saturation of annual maximum SIF with increasing AI is only observed in forests, and appears when the AI is above 0.9 (Fig.4). All these results demonstrate the ability of GOSIF to monitor vegetation photosynthesis over diverse biomes. The saturation of forest SIF in humid areas may be caused by nutrient limitation, which can be relieved by fertilization practices in croplands (Mercado et al., 2011; Fisher et al., 2012). The positive SIF-AI relationship is found in most areas of northern China, with an exception of the mountain area, where the SIF-AI correlation is negative due to the fact that vegetation productivity generally decreases with increasing elevation at middle and high altitudes (Gao et al., 2019), and vegetation growth is more limited by heat than water conditions above the treeline (Gottfried et al., 2012). The decreasing SIF trend with increasing AI for the wetland in humid areas may be affected by the increased proportion of water areas that decrease SIF (Petus et al., 2013). Overall, the spatial distribution of SIF is heavily dependent on wetness conditions and biome types.

* 1. ***The degree to which vegetation photosynthesis responds to drought***

We show additional evidence that satellite SIF responds more strongly to meteorological drought than NDVI do, as more areas are characterized by significant SIF-SPEI correlations than that by NDVI-SPEI correlations (Xu et al., 2018), with the area percentage increases by 15% across northern China (Fig.5). It lies in the fact that SIF reflects the functional status of actual photosynthesis and has low sensitivity to clouds and snow cover (Guanter et al., 2007; Frankenberg et al., 2011; Walther et al., 2016). The significant positive SIF-SPEI correlation over most of the drylands also supports previous studies, suggesting that satellite SIF has the potential of assessing drought-induced stress on terrestrial photosynthesis at regional scales (Sun et al., 2015; Yoshida et al., 2015; Hu et al., 2019). The SIF analysis in this study shows that vegetation photosynthesis is responsive to drought over 71.4% and 34.8% of sub-humid and humid ecosystems, respectively, mainly composed of forests and croplands (Table 1). A possible reason is that climate drying and severe drought exacerbate soil moisture and hence reduce their ability to cope with water deficits (Wang et al., 2011; Yu et al., 2014). Besides, afforestation and agricultural practices boost water consumption and aggravate soil drying (Deng et al., 2016; Zhang et al., 2017).

A novel finding of this study is that vegetation photosynthesis in arid ecosystems is less responsive to drought than that in sub-humid ecosystems, as 44% of arid ecosystems showed significant SIF-SPEI correlations (Fig.S2). Arid ecosystems are distributed in northwestern China, where increased precipitation and river runoff may increase soil moisture and shallow groundwater, decreasing the vulnerability of vegetation to drought (Wang et al., 2013). It is noteworthy that the highest sensitivity of vegetation photosynthesis to drought is constrained to semi-arid regions, particularly in agro-pastoral ecotones (Fig.6). This pattern is caused by changes in vegetation composition and water availability. In semi-arid areas, grasslands are the major biome, and its growth highly depends on surface soil moisture that is sensitive to precipitation dynamics because of shallow depths of roots (Kulmatiski and Beard, 2013). In contrast to annual herbs in semi-arid regions, shrubs and perennial herbs are widespread in arid regions, characterized by deeper rooting and higher root biomass that relief the adverse effect of drought on vegetation photosynthesis (Craine et al., 2013). In sub-humid and humid regions, water surplus and a large proportion of forests and croplands decrease the drought sensitivity. The ability of trees to resist drought benefits from deep roots, xylem systems for water storage and a long life span (McDowell et al., 2008). Agricultural practices including crop rotation, irrigation and fertilization, can alter the response of photosynthesis capacity to meteorological drought in croplands (Frankenberg et al., 2011). Even if the biome type is the same, SIF of the semi-arid forest is more responsive to water deficits than that of the moist forest (Table 1). It is very likely because semi-arid forests have low embolism resistance and show anisohydric stomatal behavior that maintains stem water potential by stomatal closure and hence a slowdown in photosynthesis during drought (van der Molen et al., 2011).

The degree to which vegetation photosynthesis responds to drought is similar in humid regions regardless of increasing wetness (Fig.6). This pattern is observed in all biome types. A small fraction of humid areas even have negative SIF-SPEI correlations, which indicates that SIF increases during drought, probably due to changes in leaf phenology and radiation limitation (Xie et al., 2015; Yao et al., 2018; Xu et al., 2019). In addition, annual maximum SIF occurs in summer, and high temperature may decrease the magnitude of SIF responses to meteorological drought, considering that vegetation reduces enzyme-catalyzed reactions and photosynthetic activity under heat stress (Jiao et al., 2019). Our results provide evidence that the sensitivity of satellite SIF to meteorological drought will be much more muted in humid regions. Nevertheless, water stress levels tend to override biome-specific responses to drought if aridity increases. Hence, drought-prone areas are expected to expand over humid regions under a drying climate and severe drought. Moreover, dryland areas are projected to increase by 11% under the RCP4.5 scenario (Huang et al., 2016), and more attention should be paid to evaluate drought impacts on vegetation photosynthesis over semi-arid ecosystems, given its great sensitivity to water stress and dominant role in the trend and variability of the land CO2 sink (Ahlström et al., 2015).

* 1. ***The drought time-scale of vegetation photosynthesis***

A clear picture of how satellite SIF responds to different time-scales of SPEI is provided across a broad range of biome types and environments (Fig.5). Satellite SIF presenting short time-scale responses to SPEI are characterized by lower water availability and vice versa. In addition, SIF of the herbaceous vegetation responds more quickly to meteorological drought than SIF of the woody vegetation (Fig.S3). There is a time lag of soil moisture in response to meteorological drought, and the effect of soil water storage from the wet season and year to alleviate meteorological drought may become stronger with an increase in water availability (Vicente-Serrano et al., 2013). Distinctive functional traits (e.g. root and stem) of the woody vegetation increase drought resistance. However, water availability plays a more important role in driving the spatial variability of drought time-scales than vegetation characteristics do (Table 2). With increasing aridity, vegetation photosynthesis responds more quickly to water stress, and this behavior is more evident for grasslands when compared with that for deserts and forests (Fig.7). Therefore, increases in climate dryness and drought severity may lead to more rapid responses of vegetation photosynthesis but the amplitude varies among biomes.

1. **Conclusions**

The spatial variability of annual maximum SIF and its response to SPEI are dominated by water availability and biome types. The degree to which SIF responds to SPEI is greatest in semi-arid ecosystems, with the strongest SIF-SPEI relationship appearing in agro-pastoral ecotones, characterized by large wet and dry fluctuation. Positive responses of SIF to SPEI are found in 71.4% and 34.8% of sub-humid and humid ecosystems, respectively. It is very likely that drought-induced SIF declines will be more widespread in humid areas, and water stress levels will override biome-specific responses to drought under a drying climate. With increasing aridity SIF responds more quickly to SPEI, and a faster decreasing rate of drought time-scales occurs in herbaceous vegetation compared to that in woody vegetation, having a longer time-scale of the SIF response to SPEI. The spatial variability of the SIF time-scale in response to SPEI is mainly dominated by water availability and is also influenced by biome types. Thus, when drought-induced SIF declines appear they are expected to set in quicker and more significant with increasing dryness.

**Conflict of Interest**

The authors declare that they have no conflict of interest.

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**Table 1** Percentage of the area with significant positive SIF-SPEI correlations (*P* < 0.05) in each aridity category that occupied by different biome types. The value in parentheses shows the area percentage of significant positive SIF-SPEI correlations (*P* < 0.05) within biomes.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Biome type | Arid region | Semi-arid region | Sub-humid region | Humid region |
| Forest | 2.5 (36.3) | 4.6 (86.4) | 19.2 (82.2) | 37.8 (30.9) |
| Cropland | 25.5 (32.2) | 26.6 (79.3) | 41.6 (64.8) | 30.2 (39.0) |
| Wetland | 0.7 (18.4) | 1.1 (69.3) | 1.5 (41.2) | 1.1 (18.2) |
| Grassland | 45.3 (54.0) | 63.4 (90.4) | 36.0 (79.7) | 29.2 (38.4) |
| Desert | 26.0 (53.9) | 4.3 (86.7) | 1.7 (59.8) | 1.7 (28.8) |

**Table 2** The dominant drought time-scales of different biomes in each aridity category. Values are shown in Mean ± SD. The unit is months.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Biome type | Arid region | Semi-arid region | Sub-humid region | Humid region |
| Forest | 9.8 ± 7.0 | 11.7 ± 6.9 | 14.5 ± 6.5 | 16.3 ± 7.2 |
| Cropland | 9.0 ± 7.3 | 9.6 ± 6.6 | 12.5 ± 7.2 | 12.6 ± 7.0 |
| Wetland | 10.0 ± 7.3 | 8.7 ± 6.2 | 13.6 ± 6.7 | 17.5 ± 6.8 |
| Grassland | 9.4 ± 7.1 | 9.0 ± 6.2 | 12.2 ± 6.8 | 16.9 ± 7.4 |
| Desert | 9.2 ± 6.5 | 12.5 ± 7.5 | 12.5 ± 6.2 | 19.0 ± 7.0 |