WEAK RESPONSE OF VEGETATION PHOTOSYNTHESIS TO METEOROLOGICAL DROUGHTS IN SOUTHWEST CHINA: INSIGHTS FROM GOME-2 SOLAR-INDUCED FLUORESCENCE

Yangqian Qi[1], Zhao-Cheng Zeng[2,2], and Yangqian Qi[1]

[1]The University of British Columbia
[2]California Institute of Technology

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Abstract

Drought stress threatens vegetation dynamics across diverse ecosystems. Monitoring how vegetation responds to water stress is vital for ecological conservation. The response of vegetation photosynthesis to water availability variations in Southwest China from 2008 to 2018 is investigated in this study. The solar-induced fluorescence (SIF) derived from GOME-2 is used to characterize photosynthetic changes. We examined the sensitivity of SIF anomaly to standardized precipitation-evapotranspiration index (SPEI) at multiple time scales to evaluate the drought impacts on different ecosystems (i.e. forests, croplands, grasslands, and shrublands). We find that (1) SIF has significant yet weak correlations to SPEI across major ecosystems in Southwest China; (2) Forests are more sensitive to short-term droughts in comparison with other ecosystems. (3) Cropland, grassland, and shrubland are more subjected to long-term droughts compared to forests. Our findings indicate that, in Southwest China, satellite SIF may not be effective in monitoring the impact of drought on vegetation due to its weak response to SPEI. The robustness of using satellite-observed SIF to assess drought's effects still needs to be further tested with high-resolution SIF data.

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Index Terms— Drought monitoring, vegetation photosynthesis, solar-induced fluorescence, GOME-2

1. INTRODUCTION

Vegetation photosynthesis sustains the Earth with oxygen provision and food production. Among all factors that can impede the vegetation photosynthesis, water scarcity has become a concerning issue worldwide recently. China is one of the countries that has been suffering from drought stress for decades [1]. In 2009, an extreme drought hit Southwest China and inflected severe damages on vegetation [2]. Recent studies highlighted that the drought condition in Southwest China is going to become more frequent, intense, and long-lasting in the near future [3]. Monitoring the influence of drought stress on vegetation, therefore, plays a vital role in helping us secure freshwater resources, manage the food production, and mitigate the negative effects of climate warming on diverse ecosystems.

Frequent meteorological droughts, characterized by below-average precipitation and above-average temperature, can disrupt the vegetation photosynthesis with reduced carbon sequestration rates via the stomatal closure [4]. The weakened photosynthesis can thus limit the vegetation productivity over time. How to effectively monitor the response of vegetation photosynthesis to water stress, however, remains a crucial challenge.

The advent of remote sensing technologies has advanced drought monitoring by enabling researchers to track vegetation dynamics with remotely sensed data. In recent years, the use of satellite solar-induced fluorescence (SIF) has gained popularity compared to conventional reflectance-based indices (NDVI, EVI, etc.). Past research shows that SIF can outcompete reflectance-based indices as it is a spectral signal (650 – 800 nm) that directly reflects photosynthetic processes (e.g *in situ* carbon assimilation) [5]. SIF can therefore facilitate the monitoring of photosynthetic changes induced by droughts with increased efficacy [6].

Despite the potential that SIF has in drought monitoring, it has not been widely applied to investigate drought effects yet. Previous studies claim that how SIF responds to drought stress has not been fully understood [7]. To what extent can SIF indicate the drought stress is also poorly explored [7]. To understand the sensitivity of satellite SIF to drought stress, we analyze the relationship between SIF derived from Global Ozone Monitoring Experiment-2 (GOME-2) and water availability changes using standardized precipitation-evapotranspiration index (SPEI). Overall, this study proposes to understand: (1) How sensitive is satellite SIF in response to meteorological droughts in Southwest China? (2) Will the SIF response differ across different ecosystems?

2. METHODS AND DATA

2.1 Study Area

This study focuses on the meteorological drought stress in Southwest China (latitude: 97° – 110° E, longitude: 20° – 34° N; Fig. 1). Covering an area of approximately 1.4 million square kilometers, the study area represents 14% of China's total land territory [4]. The study area is classified as a semi-humid region with uneven distributions of precipitation and temperature due to the joint effects of subtropical monsoon climate, alpine-cold climate, and hilly landforms [4]. The annual precipitation of Southwest China increases from 490 mm in the west to over 2600 mm in the east [4]. The average monthly temperature ranges from -1 °C in the winter to 24 °C in the summer [4]. Major land cover types in the study area include forests (23.5%), grasslands (37.4%), croplands (11.3%), and shrublands (26.9%) based on the MODIS land cover product (MCD12C1 of 2017, Fig.1).

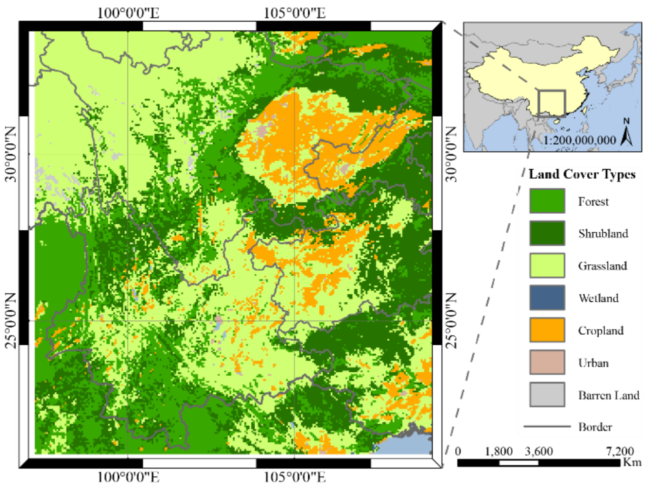

Fig. 1 The land cover types of Southwest China in 2017 from MODIS

2.2 Land Cover Data

In this study, MODIS land cover product (https://e4ftl01.cr.usgs.gov/MOTA/MCD12C1.006/, MCD12C1 version 6 of 2017) was used to categorize the major land cover types in Southwest China. The spatial resolution of this product is 0.05° (5.6 km) in Climate Modelling Grid (CMG). The land cover types in the study area are based on the classification system of the International Geosphere Biosphere Program (IGBP). Four major groups of land cover types were aggregated according to the 17 IGBP biome types: (1) forests (including evergreen needle-leaf/broadleaf forests, deciduous needle-leaf/broadleaf forests, and mixed forests), (2) croplands (including croplands and mosaics of croplands and natural vegetation), (3) grasslands (including grasslands and savannahs), and (4) shrubland (including closed/open shrublands and woody savannahs).

2.3 Solar-Induced Fluorescence Data

Level 3 SIF data (spatial resolution: 0.5°) of GOME-2 were obtained from January 2008 to December 2018 (https://avdc.gsfc.nasa.gov/pub/data/satellite/MetOp/GOME_F/; Fig. 2 (a)). The SIF index was calculated as follows [8]:

$$SIF(\lambda) = PAR \times fPAR \times LUE(\lambda) \times f(\lambda) \qquad (1)$$

$$SIF(PAR) = \frac{SIF(\lambda)}{f(\lambda) \times PAR} \qquad (2)$$

$$LUE(\lambda) = \frac{SIF(\lambda)}{f(\lambda) \times APAR} = \frac{SIF(PAR)}{fPAR} \qquad (3)$$

where λ is the spectral wavelength (e.g. 740 nm) used in the retrieval method, PAR is the photosynthetically active radiation which can affect the SIF signals, APAR is the absorbed PAR photons, fPAR is the fraction of APAR, LUE represents the light-use efficiency (i.e. how much energy is absorbed and re-emitted as SIF signals), and f(λ) quantifies the amount of photons that escape from SIF signals, which might be re-absorbed by other leaves [8].

2.4 Drought Index

Standardised precipitation-evapotranspiration index (SPEI) was used to examine the drought stress in Southwest China. SPEI determines meteorological droughts by considering the historical levels of precipitation as well as the potential evapotranspiration (PET). The involvement of these variables enables SPEI to become an advantageous drought index in recent years compared to previous drought indices, such as the Standardised precipitation index (SPI) and the palmer drought severity index (PDSI) [9]. The monthly SPEI data (spatial resolution = 1°) at time scales from 1 to 12 months were acquired from the SPEI Global Drought Monitor (https://spei.csic.es/map/maps.html). The time scales of SPEI can inform the duration of drought conditions. In general, the time scale of 1 to 4 months implies short-term droughts; the time scale of 5 to 8 months represents medium-term droughts; and the time scale of 9 to 12 months indicates long-term droughts (Fig. 2). This study also classified the dryness/wetness in the study area based on the ranges of SPEI values (Table 1).

Table 1 The dryness/wetness categories for different ranges of SPEI values [9]

Range of SPEI values	Category of dryness/wetness
SPEI ≥ 2.0	Extremely wet
1.5 ≤ SPEI < 2.0	Severely wet
1.0 ≤ SPEI < 1.5	Moderately set
0.0 ≤ SPEI < 0.5	Mildly wet
-1.0 ≤ SPEI < 0.0	Mild drought
-1.5 ≤ SPEI < -1.0	Moderate drought
-2.0 ≤ SPEI < -1.5	Severe drought
SPEI < -2.0	Extreme drought

2.5 Data Processing and Analysis

This study extracted monthly mean SIF and SPEI values for forests, grassland, cropland, and shrubland in Southwest China based on the land cover data. To compare SIF with SPEI, this study calculated the anomaly of SIF as follows [10]:

$$ASIF_{i,j} = \frac{SIF_{i,j} - \overline{SIF}_{i}}{\sigma_{SIF_i}}$$

where $ASIF_{i,j}$ represents the anomaly of SIF for month *i* in year *j*. The average value of SIF for month *i* from 2008 to 2018 is denoted as $\overline{SIF_i}$. The σ_{SIF_i} represents the standard deviation of SIF for month *i* over the 11-year period.

To examine the sensitivity of satellite SIF to SPEI across ecosystems, the correlation and regression analyses were conducted using the Spearman rank correlation coefficients (*R* values) in this research. This study also correlated $ASIF_{i,j}$

with SPEI values from previous months to evaluate whether droughts have lagged effects on vegetation photosynthesis.

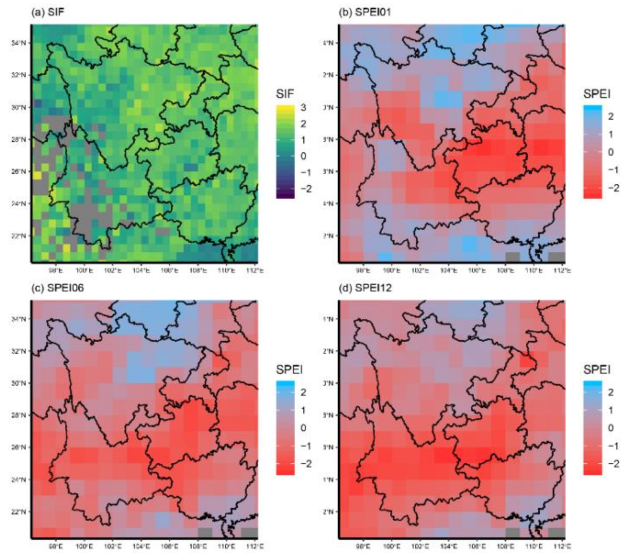

Fig. 2 (a) The spatial distribution of SIF in Southwest China in July 2013 with SPEI values (1-, 6-, 12-month time scale) over the same period showing the (b) short-term, (c) medium-term, and (d) long-term drought conditions

3. RESULTS AND DISCUSSION

3.1 The Correlation of SIF and SPEI at Different Time Scales

Our regression analyses show that SIF has weak correlations to SPEI at different time scales (Fig. 3). In most scenarios, a weakly positive correlation can be found between SIF and SPEI, meaning that SIF slightly increases as SPEI value gets larger. Under certain circumstances (e.g. Fig. 3 (k) and (l)), SIF can also show significant positive relationships with SPEI (*p* value < 0.05). This positive relationship, to some extent, implies that vegetation photosynthesis could become stronger when the water stress alleviates. Yet the improvement of photosynthesis might be hardly noticeable since the strength of the correlation is relatively weak (*R* value < 0.3), suggesting that meteorological droughts in Southwest China may not be a major influencing factor for causing photosynthetic changes.

Multiple studies found that SIF is significantly and positively correlated with SPEI [2][6][10]. Yet correlation does not infer causation. This positive relationship, therefore, cannot indicate that the decreased photosynthesis is caused by the cutback of wetness. Yet the physiological mechanism behind this positive SIF-SPEI relationship does support the idea that the decline of water availability can hold the photosynthesis back. When water scarcity strikes, most vegetation would reduce its water loss through closing stomata, thus slowing down the photosynthetic activities [11]. The decreased photosynthesis is reflected via the changes of SIF signals. If drought prolonged, the plant would lose its leaves to further limit the water loss. The process would therefore continue to decrease SIF signals over time.

SIF, however, could also exhibit a significantly negative correlation to SPEI in some cases (Fig.3 (c)). This negative correlation reflects that when drought condition worsens, the vegetation photosynthesis is not interrupted. Instead, the intensity of photosynthesis becomes slightly greater. This finding is different from previous studies [2][6]. Yet one study also finds similar results [10]. The authors attribute this significantly negative relationship to the self-regulation ability of ecosystems in wet areas. As the authors explained, ecosystems in wet areas are known for high soil moisture content. The high soil moisture can therefore serve as a buffer to regulate the impacts of droughts [11]. The decreasing precipitation and increasing temperature induced by meteorological droughts may not immediately reduce the SIF signals due to the buffering effect of soil moisture. On the contrary, the rising temperature could accelerate their photosynthetic activities on a small scale [11]. The drought threats, thus, may not be captured by SIF retrievals in this case.

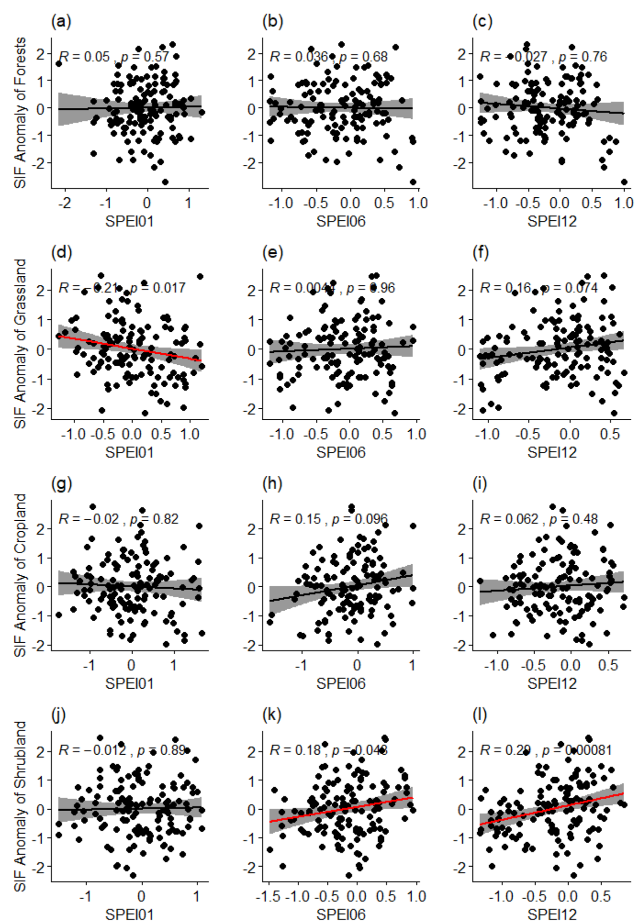

Fig. 3 The relationship between SIF and SPEI (time scale: 1, 6, 12 months) without any time lag (the significant correlations are highlighted using red regression lines)

3.2 The SIF Responses to Meteorological Droughts across Different Ecosystems

Different ecosystems react to meteorological droughts differently in terms of the temporal duration (Fig. 4). We find that forests show significant correlations to SPEI (1-, 2-, 4-, 5-, 6-, 7-, 8-, 9-, and 10-month time scale) when there is a two-month time lag (Table 2). Meanwhile, no SPEI with short-term time scale is found to be significantly correlated with SIF anomalies of grasslands, croplands, and shrublands. Thus, this finding indicates that forests are more easily affected by short-term droughts compared to other ecosystems. Unlike forests, the rest of ecosystem types are more sensitive to medium- to long-term droughts. For example, croplands show high correlations with SPEI 6 to 10 (Fig. 3 (c)) with one-month time lag, indicating that croplands in Southwest China respond to variations of water availability after the drought condition accumulates for 6 to 10 months.

Few studies have also compared the differences of SIF responses to droughts across different ecosystems. One study mentions that drought could stimulate C4 plants to generate certain secondary metabolites (e.g. proline, soluble sugars, etc.) that can promote their drought tolerance levels [12]. Some tree species, however, lack this mechanism, thus being sensitive to droughts in the short term.

Table 2 The SPEI time scale for significant SIF-SPEI correlations considering time lag effects

Ecosystems	Lag	SPEI Time Scale
Forests	2	SPEI 01, 02, 04, 05, 06, 07, 08, 09, 10
Grassland	2	SPEI 08, 09, 10, 11, 12
Cropland	1	SPEI 06, 07, 08, 09, 10
Shrubland	0	SPEI 04, 05, 06, 09, 10, 11, 12

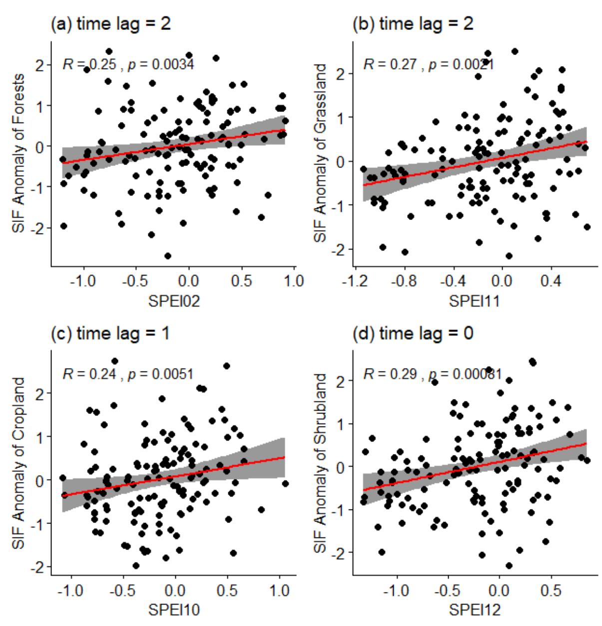

Fig. 4 Examples of significant responses of SIF to SPEI across different ecosystems considering time lag effects

4. CONCLUSIONS

This study examines the sensitivity of satellite SIF to meteorological droughts via correlating SIF anomalies with SPEI at different time scales (1 to 12 months). This study also investigates the drought impacts across major ecosystems in Southwest China. We conclude that (1) SIF has significant yet weak correlations to SPEI across all four types of ecosystems in Southwest China. (2) Forests are less insensitive to short-term droughts compared to other ecosystems. (3) Grassland, cropland, and shrubland can tolerate medium- to long-term droughts better than forests. The findings of this research offer insights in meteorological drought monitoring with remotely sensed data. Satellite-observed SIF may not be an effective indicator for monitoring drought's impact on vegetation in Southwest China due to its weak responses. The robustness and applicability of using satellite-observed SIF to quantify photosynthetic changes caused by droughts need further evaluation with high spatial and temporal resolution observations.

5. ACKNOWLEDGEMENTS

We acknowledge the following datasets for this research: (1) MODIS land cover product, (2) GOME-2 SIF data on board the MetOp-A satellite, and (3) the SPEI data from the SPEI Global Drought Monitor. We also sincerely thank the support of Ms. Sacha Khoury from the University of Cambridge and the Integrated Remote Sensing Studio led by Professor Nicholas Coops from the University of British Columbia.

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1. INTRODUCTION

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2. METHODS AND DATA

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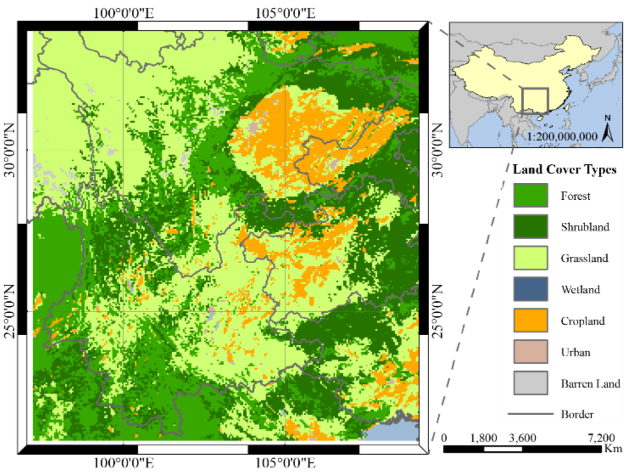

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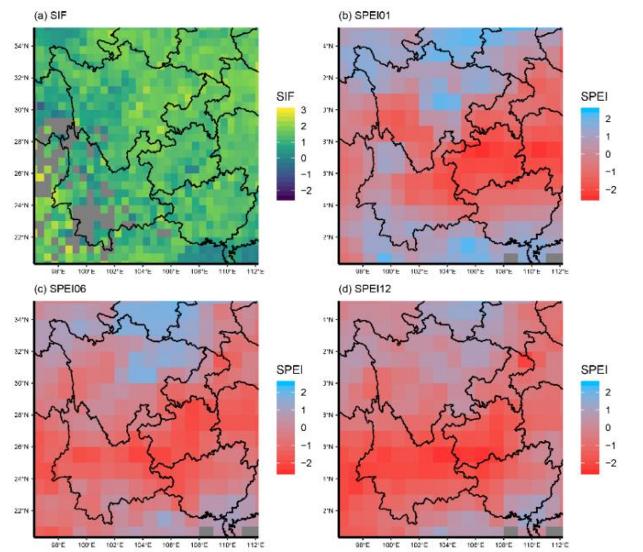

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3. RESULTS AND DISCUSSION

3.1 The Correlation of SIF and SPEI at Different Time Scales

Our regression analyses show that SIF has weak correlations to SPEI at different time scales (Fig. 3). In most scenarios, a weakly positive correlation can be found between SIF and SPEI, meaning that SIF slightly increases as SPEI value gets larger. Under certain circumstances (e.g. Fig. 3 (k) and (l)), SIF can also show significant positive relationships with SPEI (*p* value < 0.05). This positive relationship, to some extent, implies that vegetation photosynthesis could become stronger when the water stress alleviates. Yet the improvement of photosynthesis might be hardly noticeable since the strength of the correlation is relatively weak (*R* value < 0.3), suggesting that meteorological droughts in Southwest China may not be a major influencing factor for causing photosynthetic changes.

Multiple studies also found that SIF is significantly and positively correlated with SPEI [6][11][12]. Compared to our study, few researchers found a much stronger SIF-SPEI correlation (e.g. R > 0.7) than ours [11][12]. The weak and noisy SIF-SPEI relationship in our research implies that some external factors (e.g. irrigation systems, land management strategies, etc.) may have helped vegetation combat droughts. As correlation does not infer causation, the positive SIF-SPEI relationship cannot indicate that the decreased photosynthesis is caused by the cutback of wetness. Yet the physiological mechanism behind this positive relationship does support the idea that the decline of water availability can hold the photosynthesis back. When water scarcity strikes, most vegetation would reduce its water loss through closing stomata, thus slowing down the photosynthetic activities [13]. The decreased photosynthesis is reflected via the changes of SIF signals. If drought prolonged, the plant would lose its leaves to further limit the water loss. The process would, therefore, continue to decrease SIF signals over time.

SIF, however, could also exhibit a significantly negative correlation to SPEI in some cases (Fig.3 (d)). This negative correlation reflects that when drought condition worsens, the vegetation photosynthesis is not interrupted. Instead, the intensity of photosynthesis becomes slightly greater. This finding is different from past studies [6][12]. Yet one study also finds similar results [11]. The authors attribute this significantly negative relationship to the self-regulation ability of ecosystems in wet areas. As the authors explained, ecosystems in wet areas are known for high soil moisture content. The soils with high moisture can, therefore, serve as a buffer to regulate the negative impacts of droughts [13]. The decreasing precipitation and increasing temperature induced by meteorological droughts may not immediately reduce the SIF signals due to the buffering effect of soil moisture. On the contrary, the rising temperature could accelerate their photosynthetic activities on a small scale [13]. The drought threats, thus, may not be captured by SIF retrievals in this case.

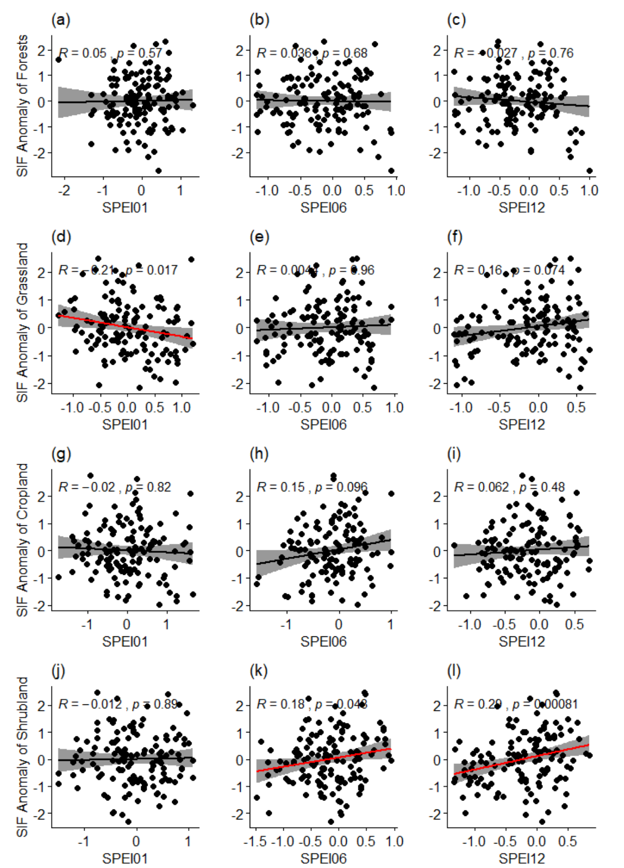

Fig. 3 The relationship between SIF and SPEI (time scale: 1, 6, 12 months) without any time lag (the significant correlations are highlighted using red regression lines)

3.2 The SIF Responses to Meteorological Droughts across Different Ecosystems

Different ecosystems react to meteorological droughts differently in terms of the temporal duration (Fig. 4). We find that forests show significant correlations to SPEI (1-, 2-, 4-, 5-, 6-, 7-, 8-, 9-, and 10-month time scale) when there is a two-month time lag (Table 2). Meanwhile, no SPEI with short-term time scale is found to be significantly correlated with SIF anomalies of grasslands, croplands, and shrublands. Thus, this finding indicates that forests are more easily affected by short-term droughts compared to other ecosystems. Unlike forests, the rest of ecosystem types are more sensitive to medium- to long-term droughts. For example, cropland shows high correlations with SPEI 6 to 10 (Table 2, Fig. 4 (c)) with a one-month time lag, indicating that it responds to variations of water availability after the drought condition accumulates for 6 to 10 months.

Few studies have also compared the differences of SIF responses to droughts across different ecosystems. One study mentions that drought could stimulate C4 plants to generate certain secondary metabolites (e.g. proline, soluble sugars, etc.) that can promote their drought tolerance levels [14]. Some tree species, however, lack this mechanism, thus being sensitive to droughts in the short term.

Table 2 The SPEI time scale for significant SIF-SPEI correlations considering time lag effects

Ecosystems	Lag	SPEI Time Scale
Forests	2	SPEI 01, 02, 04, 05, 06, 07, 08, 09, 10
Grassland	2	SPEI 08, 09, 10, 11, 12
Cropland	1	SPEI 06, 07, 08, 09, 10
Shrubland	0	SPEI 04, 05, 06, 09, 10, 11, 12

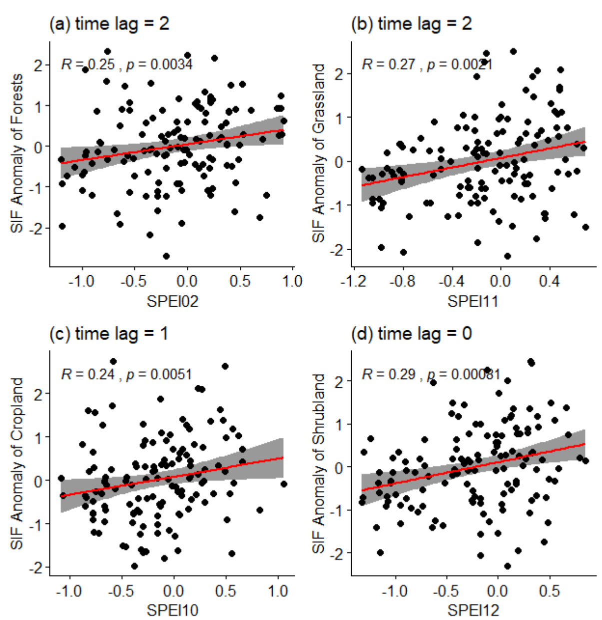

Fig. 4 Examples of significant responses of SIF to SPEI across different ecosystems considering time lag effects

4. CONCLUSIONS

This study examines the sensitivity of satellite SIF to meteorological droughts via correlating SIF anomalies with SPEI at different time scales (1 to 12 months). This study also investigates the drought impacts across major ecosystems in Southwest China. We conclude that (1) SIF has significant yet weak correlations to SPEI across all four types of ecosystems in Southwest China. (2) Forests are less insensitive to short-term droughts compared to other ecosystems. (3) Grassland, cropland, and shrubland can tolerate medium- to long-term droughts better than forests. Our findings shed new light on meteorological drought monitoring with remotely sensed data. Satellite-observed SIF may not be an effective indicator for assessing drought impacts on vegetation in Southwest China due to its weak responses. The robustness and applicability of using satellite-observed SIF to quantify photosynthetic changes caused by meteorological droughts need further evaluation with high spatial and temporal resolution observations.

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