Relationship of surface soil moisture with solar-induced chlorophyll fluorescence and normalized difference vegetation index in different phenological stages: a case study of Northeast China

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Abstract
Solar-induced chlorophyll fluorescence (SIF) is closely related to vegetation photosynthesis, and is considered as a direct and non-invasive indicator of the functional status of photosynthetic machinery; the normalized difference vegetation index (NDVI) can also reflect photosynthetic characteristics. Both are related to surface soil moisture (SSM), which is susceptible to drought, and phenology plays an important role in these vegetation-moisture relationships. Based on a variety of gridded SIF, NDVI, and SSM datasets obtained from satellite sensors, we presented the detailed relationships of SSM with SIF and NDVI in different phenological stages. Results showed that SIF and NDVI were significantly correlated with SSM in different phenological stages, especially during the maturity and senescence stages. For different vegetation types, SIF was more sensitive than NDVI to SSM anomalies in grasslands and forests during the maturity stage and rainfed croplands during the senescence stage. These relationships were regulated by precipitation and mean temperature, and decreased precipitation had the most significant impact when accompanied by increased temperature during the maturity stage or decreased temperature during the senescence stage. Our findings shed light on the role that phenology has in the relationships of SSM with SIF and NDVI on a large scale, which can further improve the understanding of vegetation-moisture relationships.

1. Introduction
Solar-induced chlorophyll fluorescence (SIF) is an electromagnetic signal that is emitted by chlorophyll a molecules in vegetation when the absorbed solar radiation is greater than the energy required for vegetation photosynthesis (Zhao et al. 2018). Because of its close relationship with photosynthesis, SIF often serves as a direct and non-invasive indicator of the functional status of photosynthetic machinery (Rascher et al. 2015). Based on those measurements from tower, aircraft, and satellite platforms, SIF provides a new perspective for observing terrestrial ecosystems at various spatial-temporal scales (Schimel et al. 2015, Li et al. 2018b, Peng et al. 2020). Particularly, global observations of SIF on
satellite platforms are considered as the most directly measurable signal of terrestrial photosynthesis from space (Qiu et al. 2018).

As a probe for photosynthesis, SIF responds rapidly to vegetation function changes induced by environmental stresses, among which drought is the main abiotic stress that limits vegetation growth (Liu et al. 2019, Qian et al. 2019). From a physiological perspective, drought rapidly reduces the expansion of leaves and stomatal conductance until it eventually affects the primary events of the photosynthetic process (Passioura 1994), which is accompanied by a decline in SIF. Decreased stomatal conductance and net photosynthesis rate by closing the stomata distributed on the leaf surface can further halt water loss (Ni et al. 2018, Zhao et al. 2020). Airborne-based and satellite-based SIF have been proven not only to reasonably capture the spatial-temporal dynamics of drought development, but also to evaluate the drought-induced reduction of vegetation productivity at larger spatial scales (Zarco-Tejada et al. 2009, 2013, Joiner et al. 2011, Lee et al. 2013, Chen et al. 2019b, Zhang et al. 2019). Severe drought may cause changes in vegetation greenness and canopy structure, which are reflected by vegetation indices (VIs), including the normalized difference VI (NDVI) and the enhanced VI (EVI) (Zhang et al. 2016). As an indicator of the potential photosynthesis or the photosynthetic capacity, NDVI is often used in conjunction with SIF to observe the effects of drought on vegetation photosynthesis (Liu et al. 2018a). Researchers have found that SIF is more sensitive to short-term meteorological droughts than NDVI, especially during peak growing months (Jiao et al. 2019).

Soil moisture (SM) is considered as the link that connects the soil-vegetation-atmosphere on earth: it enters various physiological processes through the water absorption by root systems, and then enters the atmosphere in the form of water vapor from the stomata of leaves through transpiration. When a drought event occurs, SIF is positively and significantly correlated with root zone SM during the growing season, and shows higher sensitivity than NDVI in a shorter time lag (Liu et al. 2018a). Therefore, it is a better fit for early drought detection, especially over closed canopy. Conversely, greenness-based VIs are often reported to have delayed responses, and NDVI is more useful when the drought spans a long time period (Sun et al. 2015, Liu et al. 2018b). Compared with root zone SM, surface SM (SSM) is mainly from rainfall infiltration, and it is vulnerable to drought. As the key information obtained from remote sensing observations for drought detection (Geruo et al. 2017, Babaiean et al. 2019, Wang et al. 2019), SSM shows strong coupling and similar characteristic time scales with SM at deeper depths under the action of vegetation hydraulic redistribution (Neumann and Cardon 2012). Therefore, the responses of SIF and NDVI to changes in SSM are critical to large-scale drought detection. Liu et al. (2020) has find that SSM is the dominant driver of dryness stress on ecosystem production across more than 70% of vegetated land areas with valid data by combining satellite observations of SIF with estimates of SSM and vapor pressure deficit. However, the response of SIF to drought-induced SM deficits depends on the developmental stages of vegetation in addition to the duration and severity of the drought (Ginestar and Castel 1996, Liu and Zhang 1999, Song et al. 2019). Generally, SM has the greatest impacts on photosynthesis during the vigorous vegetation growth period, and the correlation between SM and photosynthesis rate in the early and late stages of growth is low. Most studies have confirmed that SIF is most sensitive to root zone SM deficits during the vigorous vegetation growth period, and Yoshida et al. (2015) found that photosynthetically active radiation (PAR) normalized SIF (SIF_{PAR, norm}) decreased more rapidly during senescence in autumn than NDVI, while root zone SM showed substantial negative anomalies. However, the relationships of SSM with SIF and VIs remain unclear in different phenological stages (Shen et al. 2020), and their differences in multiple vegetation functional types have not yet been demonstrated.

The researchers have found that photosynthetic rate of typical steppe shows a single peak curve during the growing season: it is at a low level during the early and late period of growth, and increases significantly from July to August and reaches the highest when typical steppe enters the vigorous growth period (Wang et al. 2020b). Photosynthesis of croplands is also most intense during the peak greenness season and the final stage of development for certain species is accompanied by a decline in photosynthetic function when mineral nutrients are translocated to the maturing fruit (or storage organ) (Nooden 1988), whose process needs more SM. Drought that occurs during this process might cause premature leaf senescence and early maturation of crops, which finally results in decreased yields (Guan et al. 2016). Besides, the peak time of vegetation growth during the growing season reflects the time when the photosynthesis intensity of regional forests is the most vigorous (Fan and He 2012). Therefore, based on previous studies and vegetation physiology, we propose the following hypothesis: SIF and NDVI are significantly correlated to SSM changes during the different phenological stages, and their sensitivities to SSM variations can be distinguished within biomes for different vegetation functional types. To validate our hypothesis, we aim to address the following questions: (a) What are the detailed differences in the relationships of SSM with SIF and NDVI in different phenological stages? (b) How do these relationships differ by vegetation types? (c) What are the effects of meteorological factors on these relationships? By examining the responses of SIF and NDVI to SSM in different phenological stages, we can better understand the role.
of water restriction in vegetation photosynthesis. As negative anomalies of SSM can characterize droughts, this study provides new insights into drought detection based on the vegetation–moisture relationships. The relevant results herein have a practical significance for water conservation in agriculture, forestry, and animal husbandry during drought events.

2. Materials and methods

2.1. General description of the study area

As an important production base for commodity grain, forestry, and animal husbandry, Northeast China has suffered from frequent droughts and floods, which seriously affects local economic development (Han and Yang, 2015). The region includes Heilongjiang, Jilin, Liaoning Provinces and four cities of Hulunbuir, Xingan, Tongliao and Chifeng in the Inner Mongolia autonomous region (38°42′N–53°35′N, 115°32′E–135°09′E), covering a total area of 1.24 million km² (An et al., 2017) (figure 1). Northeast China Plain is surrounded by the Changbai Mountains, Greater Hinggan Mountains and Lesser Hinggan Mountains. These mountains are located in the east, west, and north of the region, respectively. The continental monsoon climate, with the feature of ‘warm and rainy in the summer, cold and dry in the winter’, provides favorable conditions for agricultural production. The annual precipitation here is 400–1000 mm and decreases from east to west; the mean temperature can reach 25°C in summer and −20°C in winter. Under the comprehensive control of hydrothermal conditions, the number of vegetation species tends to decrease from southeast to northwest. There are various types of vegetation in this region, including needleleaf forests, broadleaf-conifer mixed forests, meadow steppes and croplands. Soybean, corn, wheat and rice are the main crops grown locally (Liu et al., 2016).

2.2. Data availability

The available data could be categorized into the following seven types: (a) GLDAS-2 SM products, (b) GOME-2 SIF products, (c) MODIS data products, (d) GLASS LAI/fPAR products, (e) CERES PAR data, (f) meteorological data and (g) global irrigated area map (table 1). These data were resampled to 0.5° to ensure the consistency of the spatial resolution of all data.

2.2.1. GLDAS-2 SM products

The Global Land Data Assimilation System (GLDAS) provided monthly SM data of four vertical levels in the Noah model (0–0.1 m, 0.1–0.4 m, 0.4–1.0 m, and 1.0–2.0 m), with a spatial resolution of 0.25° × 0.25°. 1, 1/3, 1/6, and 1/10 were used as correction factors to eliminate the influences of soil thickness, which made SM at different depths comparable (Cheng et al., 2013). SM of the top 0–0.1 m soil layer was regarded as SSM in this paper.

2.2.2. GOME-2 SIF products

The Global Ozone Monitoring Experiment-2 (GOME-2) instrument onboard Eumetsat’s MetOp-A platform provided monthly gridded SIF-740 nm data (Level 3, V28) at a spatial resolution of 0.5° × 0.5° (Joiner et al., 2011, 2013). Some additional preprocessing steps needed to be taken before used. We retained the negative SIF values but removed those values with less than five individual valid observations in a month or a standard deviation (STD) of more than 2 mW m⁻² sr⁻¹ nm⁻¹ (Duveiller and Cescatti, 2016). Further, a local 3 × 3 window (1.5° × 1.5°) smoothing was applied to minimize the noise inherent in the original retrieval (Sun et al., 2015). The cosine of the solar zenith angle (SZA) was used as a proxy for the seasonal cycle of PAR (Joiner et al., 2014), so the SIF_{PAR,norm}, data calculated by the SZA was also used for the study.

2.2.3. MODIS data products

The MCD12Q2 product provided annual global maps of phenometrics since 2001 (Begue et al., 2014). Only two growth cycles at most were recorded in a year and the identification of phenophase transition dates was performed on each of the identified vegetation cycles (Josh et al., 2019). There were seven phenophase transition dates in the product, including green-up, mid-green-up, maturity, peak, senescence, mid-green-down, dormancy (text S1, which is available online at stacks.iop.org/ERL/16/024039/mmedia). Different from the ground phenological observations in point based, remote sensing-based phenological monitoring index was the integrated index by ground observation indexes and corresponding phenological characteristics (Yu et al., 2014). Zhang et al. (2003) believed that the vegetation phenology obtained from remote sensing monitoring was mainly characterized by four key transition dates (the onsets of green-up, maturity, senescence and dormancy), which could be used to determine the key phenological stages of the dynamic changes in vegetation at annual time scales. The datasets of these four key transition dates were extracted, mosaiced and projected. Then, all dates were converted to UNIX epoch time: days since 1 January. The spatial distributions of key transition dates in phenology were shown in figure S1, whose results were consistent with Yu et al. (2014). Finally, four key transition dates formed three phenological stages, namely, the green-up stage, the maturity stage, and the senescence stage, respectively. Figure S2 showed the lengths of different phenological stages. In our study, we converted key transition dates in a specific year to the corresponding month to match the time scales of other data, and determined what phenological stage a pixel was in using the Python programming language based on monthly normalized anomalies of all the variables.

The MCD43C4 Nadir Bidirectional Reflectance Distribution Function (BRDF)-Adjusted Reflectance dataset was a stable and consistent reflectance product
since the view angle effects had been removed from the directional reflectance. The HDF-EOS to GeoTIFF Conversion Tool (HEG) was used for preprocessing on a selectable HDF-EOS object (Taaheri et al 2019), and provided a good platform for VIs calculations (Heck et al 2019). The quality-controlled data was scaled and further used to calculate the daily NDVI (Deering 1978) and Near-infrared Reflectance of Vegetation (NIRϕ) (Badgley et al 2017) (see equations (1) and (2)). EVI and the 2-band EVI (EVI2) were also calculated in our study (text S2). Then, daily VIs were aggregated to monthly VIs through the Maximum Value Composite, which was one of the most commonly used compositing algorithms of VIs (Holben 1986).

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$  \hspace{1cm} (1)

$$\text{NIR}_\phi = \text{NIR} \times \text{NDVI} = \text{NIR} \times \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$  \hspace{1cm} (2)

where NIR and RED were the reflectance of near-infrared band and red band, respectively. From a physical perspective, NIRϕ highlighted the BRDF-corrected NIR reflectance (Huang et al 2019), and represented the proportion of pixel reflectance attributable to the vegetation in the pixel (Badgley et al 2017). It had been found to be well correlated with SIF and could improve gross primary production (GPP) estimates (Wu et al 2020).

The MCD12C1 vegetation product based on the International Geosphere-Biosphere Programme (IGBP) scheme provided the land cover information. These information was used to analyze the potential biome-dependency of the relationships of SSM with SIF and NDVI.

2.2.4. GLASS LAI/fPAR products

The Global Land Surface Satellite (GLASS) products provided global land products of leaf area index (LAI) and fraction of photosynthetically active radiation (fPAR) with long time series, high spatial and temporal resolution and quality (monthly, 0.05°) (Xiao et al 2015). fPAR data was calculated from LAI data based on look-up table to ensure physical consistency of their retrievals. In addition to removing invalid values, the preprocessing steps of LAI and fPAR data included calculating the effective values based on scaling factors of 0.1 and 0.004, respectively (Li et al 2018a).

2.2.5. CERES PAR data

NASA Langley Research Center, Cloud and Earth’s Radiant Energy System (CERES) datasets provided global radiative fluxes with long-term durations to examine the radiation budget at Earth’s surface (Dong et al 2008). PAR data was obtained from the Level 3 Monthly Radiative Fluxes and Clouds (SYN1deg-MonthEd3A) products at a spatial resolution of 1°, and the total surface PAR in all-sky conditions was calculated as the sum of the surface diffuse PAR and direct PAR in all-sky conditions.
2.3. Rationale for SIF dynamics

Similar to GPP model based on the light use efficiency (LUE) logic, the amount of SIF at the top of canopy can be expressed (see equation (3)):

\[ SIF = f\text{PAR} \times \text{PAR} \times \Phi_F \times f_{esc} = \text{APAR} \times \text{SIF}_{\text{yield}} \]

where \( \Phi_F \) refers to the quantum yield for fluorescence, and \( f_{esc} \) accounts for the fraction of SIF photons escaping from the canopy (Zhang et al. 2019). Defined as the product of \( \Phi_F \) and \( f_{esc} \), \( \text{SIF}_{\text{yield}} \) refers to the emitted SIF per photon absorbed, and represents the effective fluorescence yield of the canopy. \( f\text{PAR} \), \( \text{PAR} \), and \( \text{SIF}_{\text{yield}} \) work together to influence actual SIF dynamics. Based on the remotely sensed \( f\text{PAR} \) and \( \text{PAR} \) data, we can calculate \( \text{SIF}_{\text{PAR, norm}} \) and \( \text{SIF}_{\text{yield}} \) (see equations (4) and (5)) to eliminate the effects of \( \text{PAR} \) and \( \text{APAR} \) (vegetation absorbed photosynthetic active radiation) on SIF, respectively, which helps us further understand their individual contributions to SIF (Li et al. 2018b, 2018c, Robinson et al. 2019). SZA is used to replace \( \text{PAR} \) to normalize SIF in some studies (Yoshida et al. 2015).

\[ \text{SIF}_{\text{PAR, norm}} = \frac{\text{SIF}}{\text{PAR}} \approx \frac{\text{SIF}}{\cos(SZA)} \]  

(4)

\[ \text{SIF}_{\text{APAR, norm}} = \frac{\text{SIF}_{\text{yield}}}{\text{APAR}} = \frac{\text{SIF}_{\text{PAR, norm}}}{f\text{PAR}} \approx \frac{\text{SIF}}{\cos(SZA) \times f\text{PAR}} \]

(5)

In most previous studies, \( f_{esc} \) is generally assumed to be fairly constant for a given vegetation type when canopy structure does not change (Guanter et al. 2014). Zeng et al. (2019) has proposed a newly developed algorithm to calculate \( f_{esc} \) from \( \text{NIR}_r \) and \( f\text{PAR} \) (see equation (6)), thus \( \Phi_F \) can also be estimated (see equation (7)).

\[ f_{esc} \approx \frac{\text{NIR}_r}{f\text{PAR}} \]

(6)

\[ \Phi_F \approx \frac{\text{SIF}}{\text{PAR} \times \text{NIR}_r} \]

(7)

The use of \( \text{SIF}_{\text{PAR, norm}}, \text{SIF}_{\text{yield}} \) and \( \Phi_F \) can help us understand the dynamic processes of SIF and the response of SIF to SSM variations during the drought event.

2.4. Data analysis

The following analysis was performed to address the scientific questions raised in the paper. \( \text{SIF}_{\text{PAR, norm}} \)
SIF$_{\text{yield}}$ and $\Phi_F$ were used to understand their contributions to the response of SIF to SSM. First, by using the GLDAS-2 SM, GOME-2 SIF, and MCD43C4 products, we observed the spatiotemporal dynamics of SIF, NDVI and SSM anomalies during the 2014 Northeast China drought. The drought event spanned the spring, summer, and autumn, covering the growing season of most green vegetation, and formed various SSM anomalies, which further affected vegetation growth (Duan et al. 2014, 2015, Wang et al. 2014a, 2014b). Based on those phenophase transition dates from MCD12Q2 product, pixels of vegetation variables and SSM between the onset of greenup and dormancy were retained using the Python programming language. Considering the quantities and distributions of vegetation pixels during the growing season, we only showed the spatiotemporal dynamics of normalized anomalies for these variables from April to September 2014. Besides, the normalized anomalies of precipitation, mean temperature and PAR were used to reflect the environmental conditions during the drought event.

Second, we examined detailed differences in the relationships of SSM with SIF and NDVI in different phenological stages in Northeast China. We determined what phenological stage a pixel was in for the normalized anomalies of monthly SSM, SIF, and NDVI, then calculated the Pearson correlation coefficients between them in the statistical software SPSS 19.0. Different types of vegetation had significant phenological characteristics, and these relationships were distinguished within biomes for different vegetation functional types based on MCD12C1 product. Considering the main vegetation species in Northeast China, we chose grasslands, croplands and forests with larger coverage area as the main vegetation types. Note that a global irrigated area map was used for screening rainfed croplands in order to eliminate the influences of artificial irrigation. Besides, needleleaf forest, broadleaf forest and mixed forest were collectively called forests in this study.

Variability of relationships of SSM with SIF and NDVI in different phenological stages could be driven by several potential factors. Precipitation acted on photosynthesis by infiltrating into the soil and being absorbed by root systems of vegetation, and its deficits would bring negative anomalies of SSM, whose effects were even worse under high temperature. According to the directions of the anomalies, precipitation and mean temperature anomalies could be divided into four types: increased precipitation and temperature, increased precipitation and decreased temperature, decreased precipitation and increased temperature, decreased precipitation and increased temperature, decreased precipitation and temperature. Therefore, we examined the influences of precipitation and temperature on the relationships of SSM with SIF and NDVI in different phenological stages, which were also distinguished within biomes for different vegetation functional types.

In the paper, the normalized anomalies of vegetation variables and SSM were used to analyze the relationships of SSM with SIF and NDVI in different phenological stages. These normalized anomalies were calculated pixel by pixel, whose functional meaning was a departure from the 2007 to 2013 mean and normalized by the STD (see equation (8)) (Li et al. 2018b):

$$\text{Var}_{2014\,\text{anomaly}}(i,j) = \frac{\text{Var}_{2014}(i,j) - \text{Var}_{2007-2013}(i,j)}{\text{std}(\text{Var}_{2007-2013}(i,j))} \quad (8)$$

where $\text{Var}_{2014}(i,j)$ stood for different variables in a pixel $(i,j)$ in 2014 and $\text{Var}_{2007-2013}(i,j)$ and $\text{std}(\text{Var}_{2007-2013}(i,j))$ were the multiyear mean and STD of different variables in a pixel $(i,j)$, respectively.

3. Results

3.1. Spatiotemporal dynamics of SIF and NDVI responses to SSM during the 2014 Northeast China drought

Figure 2 showed the temporal dynamics of vegetation variables and SSM during the growing season in Northeast China from April to September 2014, which provided a comparison with the multiyear mean (2007–2013). SSM was lower than the multiyear mean in April under the combined influences of decreased precipitation and slightly increased mean temperature (figures 2(a) and (b)), but was higher from May to June. It was lower than the multiyear mean again from July to August (figure 2(d)). These environmental condition anomalies resulted in corresponding changes in vegetation. SIF decreased from July to August but did not appear to be lower in April (figure 2(e)). The NDVI was higher than the multiyear mean from April to July, but decreased from August to September (figure 2(f)). The reason for the faster decrease in SIF late in the growing season as compared with NDVI may be that vegetation remained green while its photosynthetic capacity decreased (Yoshida et al. 2015). Thus, SIF exhibited earlier and greater reductions than NDVI at the early stage of the drought during the growing season. Besides, SIF$\text{PAR}_{\text{norm}}$ and SIF$\text{yield}$ presented a similar performance to SIF. Especially, the contrast between the SIF$\text{PAR}_{\text{norm}}$ and SIF$\text{yield}$ curves suggested that PAR could partially offset the negative impacts of drought (Li et al. 2018b) (figures 2(e) and (f)). The reductions in SIF$\text{yield}$ were slightly more significant compared with SIF from July to August, which indicated that the effective fluorescence yield was significantly impacted (figure 2(g)). Meanwhile, the larger anomalies of $\Phi_F$ also reflected the drought-induced changes in vegetation physiology (figure 2(h)). Overall, both SIF-related variables and NDVI could capture the temporal dynamics of vegetation responses to SSM anomalies in the peak growing seasons.
Figure 2. The temporal dynamics of several variables during the growing season in Northeast China from April to September 2014: (a) Prec (precipitation), (b) Tem (mean temperature), (c) PAR (photosynthetically active radiation), (d) SSM (surface soil moisture), (e) SIF (solar-induced chlorophyll fluorescence), (f) SIF\_PAR\_norm (PAR normalized SIF), (g) SIF\_yield (apparent fluorescence yield), (h) Φ\_F (photosystem-scale fluorescence yield) and (i) NDVI (normalized difference vegetation index). The red lines represent the temporal variation of these variables in 2014; the black lines represent the multiyear means of these variables with standard deviation over the period of 2007–2013; the gray lines represent the anomaly of these variables. In addition to Prec, Tem, PAR and SSM, the anomalies of other variables are calculated from by multiplying the values of monthly anomaly by 100, which converts them into percentages (%). Adapted from Shen et al. (2020).

The spatial variations of the normalized anomalies of the above variables in Northeast China from April to September 2014 were shown in figure 3. Precipitation was shown to be much lower in April, July, and August in most areas of the region (figure 3(a)). Conversely, mean temperature and PAR showed significant positive anomalies in April (figures 3(b) and (c)). The spatial variations of SSM anomalies were highly consistent with that of precipitation anomalies during the growing season, whose negative anomalies were shown as mainly distributed in the Liaoning and Jilin provinces and cities of Tongliao and Chifeng in the Inner Mongolia autonomous region from July to August (figure 3(d)). The negative SSM anomalies formed substantial depletion in the surface soil water, and caused the persistence of drought as well as regional anomalies in the SIF and NDVI. SIF showed positive anomalies in most parts of Northeast China from May to June that were consistent with the SSM anomalies. Note that the area with negative SIF anomalies was wider than that with negative SSM anomalies from July to September, especially in August (figure 3(e)), which indicated that photosynthesis was significantly affected during the 2014 Northeast China drought. However, there remained opposite anomalies of SIF and SSM in April, and the same was true for NDVI and SSM (figure 3(f)). The normalized anomalies of other VIs, including NIRv, EVI, and EVI2, showed similar temporal variations and spatial distributions to that of NDVI (figures S3 and S4). Overall, the inconsistency in the spatial distribution of both SIF/VIs and SSM anomalies in April and August indicated that the responses of vegetation variables to SSM may exhibit differences in the early and peak growing months and at the end of growing season. SIF and NDVI could better capture the spatiotemporal dynamics of SSM anomalies during the period of vigorous growth, and SIF was more sensitive to SSM anomalies in terms of magnitude and temporal variations.

Besides, the spatial distributions in the normalized anomalies of SIF\_PAR\_norm and SIF\_yield were consistent with that of SIF during the growing season, while Φ\_F exhibited weaker consistency (figures 3(f)–(h)). Because SIF\_yield was determined by leaf biochemistry and partially by canopy structure, we further observed the spatial distributions in the normalized anomalies of NIR, LAI, fPAR, and f\_esc (figure S5). Among them, NIR was assumed to be correlated to f\_esc (Yang and Van der Tol 2018). Compared with LAI and fPAR, both NIR and f\_esc had more prevalent anomalies that were consistent with the SSM anomalies. The strong absorption characteristics of NIR could sensitively reflect the water state in the leaves. As the trend changes of SM and leaf water content were essentially the same, the VIs calculated by NIR, including NDVI, could also characterize the drought-induced SSM anomalies. Calculated by NIR and fPAR, f\_esc could also reflect the effects of drought to a certain extent. Thus, variations of SIF\_yield as a product of Φ\_F and f\_esc contributed to the observed SIF dynamics during the drought event (Wang et al. 2020a).
Figure 3. The spatial distributions of the normalized anomalies for several variables during the growing season in Northeast China from April to September 2014: (a) Pre (precipitation), (b) Tem (mean temperature), (c) PAR (photosynthetically active radiation), (d) SSM (surface soil moisture), (e) SIF (solar-induced chlorophyll fluorescence) (f) SIF$_{\text{PAR, norm}}$ (PAR normalized SIF), (g) SIF$_{\text{yield}}$ (apparent fluorescence yield), (h) $\Phi_F$ (photosystem-scale fluorescence yield) and (i) NDVI (normalized difference vegetation index). Adapted from Shen et al (2020). CC BY 4.0.

3.2. Relationships of SSM with SIF and NDVI in different phenological stages

Based on the above understanding of the spatiotemporal responses of SIF and NDVI to SSM during the growing season (figures 2 and 3), we further analyzed the relationships of SSM with SIF and NDVI in different phenological stages (figure 4). Our results showed that the monthly SIF and NDVI anomalies were significantly correlated with SSM anomalies in different phenological stages, especially during the maturity and senescence stages, and the correlation between SIF and SSM anomalies was stronger than that between NDVI and SSM anomalies. This suggested that SIF had a higher sensitivity to SSM than NDVI. SIF$_{\text{PAR, norm}}$ anomalies showed stronger correlations than SIF anomalies with SSM anomalies when the effects of PAR on SIF were removed. However, the sensitivities of SIF$_{\text{yield}}$ and $\Phi_F$ to SSM were relatively weaker. Due to the strong coupling of SSM and SM at deeper depths, the relationships of SM at deeper soil layers (10–100 cm) with SIF-related variables and VIs in different phenological stages appeared similar.
phenomenon (table S1). It was worth noting that $f_{ec}$ anomalies were also significantly correlated with SM at different depths anomalies in different phenological stages, especially during the maturity and senescence stages. So, variations of $\Phi_F$ and $f_{ec}$ for SSM anomalies contributed to the response of SIF$_{yield}$ to SSM.

Different types of vegetation had different phenological characteristics. The relationships of SSM with SIF and NDVI for grasslands, rainfed croplands, and forests were further explored in different phenological stages (table 2). SIF and NDVI anomalies showed stronger correlations with SSM anomalies in the grasslands during the maturity and senescence stages; they showed negative correlations with SSM anomalies in the rainfed croplands during the green-up stage, but appeared more sensitive to SSM anomalies during the senescence stage. SIF and NDVI anomalies were shown to be more sensitive to SSM anomalies in the forests during the green-up and maturity stages. Besides, relationships of SSM with SIF$_{PAR_{norm}}$, SIF$_{yield}$, and $\Phi_F$ were similar to that of SSM with SIF for different vegetation types in different phenological stages. The above phenomenon for SIF-related variables and VIs also appeared at deeper depths (10–100 cm) (table S2). In the shallow soil layers (0–40 cm), SIF anomalies tended to be more sensitive to SM anomalies for grasslands and rainfed croplands during the maturity and senescence stages. In the deeper soil layers (40–100 cm), SIF anomalies still had higher sensitivities to SM anomalies for forests. Therefore, effects of SSM anomalies decreased in deeper-rooted vegetation. Thus, forests could usually sustain photosynthesis under lower SSM for longer periods of time, thereby increasing their resistance to drought.

3.3. Climatic controls on the SSM-SIF/NDVI relationships in different phenological stages

Previous research had identified the control effects of precipitation and temperature on SIF and the driving effects on NDVI for different types of vegetation (Merrick et al 2019, Wang et al 2019). We found that SIF-related variables anomalies and VIs anomalies were significantly correlated with precipitation anomalies in different phenological stages, especially during the maturity stage, followed by the senescence stage; they were also correlated with mean temperature anomalies, with smaller correlation coefficients (table S3). This confirmed that meteorological variables (e.g. precipitation and temperature) influenced SIF. In the natural environment, precipitation deficits and rising temperature often occurred simultaneously during the drought event. Thus, SIF-related variables anomalies and VIs anomalies were explained by the combined stress from changes in precipitation and temperature. The controls of precipitation and mean temperature on the relationships of SSM with SIF and NDVI in different phenological stages were observed (table 3). Decreased precipitation and increased temperature had greater effects on the relationships of SSM with SIF-related variables and NDVI during the maturity stage, followed by the senescence stage, while decreased temperature had greater effects during the senescence stage. Therefore, our results suggested that relationships of SSM with SIF and NDVI in different phenological stages were regulated by both precipitation and mean temperature, and decreased precipitation brought greater limitations when accompanied by increased temperature during the maturity stage or decreased temperature during the senescence stage.

Moreover, the climatic controls on the SSM-SIF/NDVI relationships in different phenological stages were different for different types of vegetation (table S4). The sensitivity of SIF/NDVI to SSM for rainfed croplands and forests was higher during the maturity stage under decreased precipitation and increased temperature conditions. Decreased temperature more significantly affected grasslands and rainfed croplands during the senescence stage, especially with decreased precipitation. There was a similar phenomenon observed in the relationships of SIF$_{yield}$ to SM at deeper soil layers (10–40 cm and 40–100 cm) with SIF-related variables and VIs.

4. Discussion

4.1. Influences of phenology on the relationships of SSM with SIF and NDVI

During the 2014 Northeast China drought, both SIF and NDVI could, to a certain extent, capture the spatiotemporal variations of SSM during peak growing months, but the observed anomalies of SIF/NDVI and SSM in April were shown to be the opposite (figures 2(d), (e), (i) and 3(d), (e), (i)). The seasonal characteristics of vegetation in nature were often expressed as phenology, which reflected the response of ecosystems to global environmental changes (Zhu et al 2017). Therefore, the observed phenomenon indicated that the relationships of SSM with SIF and NDVI were affected by vegetation phenology. Our study showed that there were highly significant correlations between SSM and SIF/NDVI anomalies in different phenological stages, especially during the maturity and senescence stages (figure 4). These results were consistent with previous studies (Gonsamo et al 2019). Photosynthesis was most intense during the peak greening season and was weaker during the senescence stage (Wang et al 2016), thus SIF was more sensitive to drought in the peak growing months, whose process was closely related to SM variations. Sun et al (2015) found that SIF—SWC (soil water content) correlations tended to be stronger in summer than in spring and autumn. Therefore, higher sensitivity of SIF/NDVI to SSM during the peak growing season accelerated the rate of fluorescence emission and canopy greenness reduction under drought conditions (Chen 1996, Xu et al 2017).
Figure 4. The correlation coefficients ($R$) between normalized anomalies of monthly SIF (solar-induced chlorophyll fluorescence), SIF$_{\text{PAR\_norm}}$ (PAR normalized SIF), SIF$_{\text{yield}}$ (apparent fluorescence yield), $\Phi_F$ (photosystem-scale fluorescence yield), NDVI (normalized difference vegetation index), and SSM (surface soil moisture) during the growing season in Northeast China (*: Significantly correlated at the 0.05 level (bilateral); **: Significantly correlated at the 0.01 level (bilateral)). Adapted from Shen et al. (2020). CC BY 4.0.

Table 2. The correlation coefficients ($R$) between normalized anomalies of monthly SIF (solar-induced chlorophyll fluorescence), SIF$_{\text{PAR\_norm}}$ (PAR normalized SIF), SIF$_{\text{yield}}$ (apparent fluorescence yield), $\Phi_F$ (photosystem-scale fluorescence yield), NDVI (normalized difference vegetation index), and SSM (surface soil moisture) in different phenological stages in Northeast China in 2014 (*: Significantly correlated at the 0.05 level (bilateral); **: Significantly correlated at the 0.01 level (bilateral)). The high $r$ values for each line are shown in bold. Adapted from Shen et al. (2020). CC BY 4.0.

| Phenological stages | Vegetation type | SIF/VI | Green-up stage | Maturity stage | Senescence stage |
|---------------------|----------------|--------|----------------|----------------|------------------|
|                     | Grasslands     |        |                |                |                  |
|                     | SIF            | 0.017  | 0.544**        | 0.455**        |
|                     | SIF$_{\text{PAR\_norm}}$ | 0.016  | 0.557**        | 0.450**        |
|                     | SIF$_{\text{yield}}$ | -0.037 | 0.443**        | 0.380**        |
|                     | $\Phi_F$       | -0.072 | 0.264**        | 0.151*         |
|                     | NDVI           | -0.257** | 0.530**        | 0.452**        |
|                     | Rainfed croplands |        |                |                |                  |
|                     | SIF            | -0.033 | 0.182          | 0.464**        |
|                     | SIF$_{\text{PAR\_norm}}$ | -0.014 | 0.179          | 0.463**        |
|                     | SIF$_{\text{yield}}$ | -0.010 | 0.153          | 0.375**        |
|                     | $\Phi_F$       | -0.176 | -0.108         | 0.196**        |
|                     | NDVI           | -0.312** | 0.288**        | 0.231**        |
|                     | Forests        |        |                |                |                  |
|                     | SIF            | 0.475** | 0.434**        | 0.308**        |
|                     | SIF$_{\text{PAR\_norm}}$ | 0.470** | 0.443**        | 0.327**        |
|                     | SIF$_{\text{yield}}$ | 0.456** | 0.402**        | 0.264**        |
|                     | $\Phi_F$       | 0.272** | 0.314**        | 0.093          |
|                     | NDVI           | -0.472** | 0.355**        | 0.224**        |

Table 2 presented that the differences in these relationships for different types of vegetation were large. Most grasslands located in Northeast China started to green up in April, and their leaves turned yellow in September (figure S1). When the grasslands NDVI reached its peak at flowering, chlorophyll content of leaves decreased rapidly, which gradually weakened the photosynthesis process. Thus, SIF and NDVI were
more sensitive to drought-induced SSM anomalies for grasslands during the maturity and senescence stages. Compared with grasslands, rainfed croplands usually had a short growing season. From the perspective of vegetation physiology, a large amount of nutrients generated by photosynthesis were used for leaf expansion of crops during the vegetative growth stage. When LAI and NDVI reached their maximum, the distribution of photosynthetic products to the vegetative organs essentially stopped, which signaled that crops entered the reproductive growth stage (Ma and Zhou 2013). During the reproductive growth stage, a large amount of the glucose that was synthesized in the leaves were transferred to the storage organs (Saini and Westgate 2007), whose processes required water support (Oh-e et al. 2011, Cao et al. 2019). Turner et al. (1997) found that moderate SM deficits in the early growing season promoted root systems to expand underground, which may be conducive to crop production; Li et al. (2011, 2012) reported that water deficiency at the rice filling stage brought decreased chlorophyll content and LAI, and accelerated photosynthetic function decline, revealing a greater sensitivity to SM changes during the senescence stage. Jin et al. (2019) found that the reproductive growth stage (grain and pod filling) was the most sensitive to water stress, and the growth of croplands and grassland was suppressed with significant reduction of VIs, SIF and GPP. Therefore, these studies confirmed that rainfed croplands SIF and NDVI were negatively correlated with SSM anomalies during the green-up stage, but were more sensitive to SSM anomalies during the senescence stage. In Northeast China forests, the sensitivity of SIF to SSM during the green-up stage was notable. Most forests grew in those cooler regions in the Greater Hinggan Mountains. The relatively abundant temperature and humidity, and superior upper nutrient and moisture conditions of the soil may promote an earlier green-up, which was reflected in photosynthesis changes, rather than in greenness (Zhang et al. 2018). Besides, table S2 had showed that SM at deeper depths had greater effects to SIF/NDVI of grasslands and rainfed croplands, which had confirmed that deep rooting systems could alleviate the effect of SSM to SIF/NDVI in many forests (Jin et al. 2019). Wholly, the agroecosystems (grasslands and rainfed croplands) in Northeast China were more vulnerable to SSM variations than forests.

In this paper, SIF_{\text{PAR norm}}, SIF_{\text{yield}} and $\Phi_f$ were used to help understand the response of SIF to SSM during the drought event. Similar to SIF, SIF_{\text{PAR norm}}, SIF_{\text{yield}} and $\Phi_f$ were closely correlated with SSM in different phenological stages. From a physiological perspective, $\Phi_f$ reflected the physiology of vegetation that was influenced by more rapidly changing environmental conditions, whereas $f_{\text{esc}}$ may be determined by the canopy structure and leaf optical properties (Wang et al. 2020a). Thus, SIF_{\text{yield}} jointly determined by $\Phi_f$ and $f_{\text{esc}}$ was likely to include both vegetation physiology signals and canopy structure influences. Dechant et al. (2020) demonstrated that canopy structure explained the relationship between photosynthesis and SIF, and varied according to

### Table 3

| Climatic condition | SIF/VI | Phenological stages | SSM values for each line are shown in bold. |
|-------------------|--------|---------------------|--------------------------------------------|
|                   |        | Green-up stage      | Maturity stage | Senescence stage |
| Increased precipitation and temperature | SIF | $-0.018$ | $-0.107$ | $-0.223$ |
|                   | SIF\_PAR norm | $-0.016$ | $-0.126$ | $-0.214$ |
|                   | SIF\_yield | $-0.222$ | $0.032$ | $-0.200$ |
|                   | $\Phi_f$ | $-0.078$ | $0.009$ | $-0.038$ |
|                   | NDVI | $0.033$ | $0.063$ | $-0.325$ ** |
| Increased precipitation and decreased temperature | SIF | $0.091$ | $-0.016$ | $0.198$ ** |
|                   | SIF\_PAR norm | $0.073$ | $-0.027$ | $0.191$ ** |
|                   | SIF\_yield | $0.109$ | $-0.045$ | $0.176$ ** |
|                   | $\Phi_f$ | $0.113$ | $0.002$ | $-0.156$ ** |
|                   | NDVI | $0.050$ | $0.048$ | $0.375$ ** |
| Decreased precipitation and increased temperature | SIF | $-0.045$ | $0.471$ ** | $0.178$ |
|                   | SIF\_PAR norm | $-0.032$ | $0.490$ ** | $0.197$ ** |
|                   | SIF\_yield | $-0.065$ | $0.445$ ** | $0.165$ ** |
|                   | $\Phi_f$ | $-0.233$ ** | $0.195$ ** | $0.015$ |
|                   | NDVI | $-0.296$ ** | $0.472$ ** | $0.067$ |
| Decreased precipitation and temperature | SIF | $0.345$ | $0.124$ | $0.378$ ** |
|                   | SIF\_PAR norm | $0.334$ | $0.134$ | $0.390$ ** |
|                   | SIF\_yield | $0.343$ | $0.276$ * | $0.333$ ** |
|                   | $\Phi_f$ | $0.463$ | $0.120$ | $0.285$ ** |
|                   | NDVI | $0.533$ ** | $0.038$ | $0.092$ |
different SM stresses during different growing stages (Sun et al. 2005). Thus, canopy structure played an important role in the response of SIF to SM, and variations of $SIF_{yield}$ with canopy structure information contributed to the observed SIF dynamics during a drought event. Optical remote sensing indices that characterized canopy structure could, to some extent, reflect SM changes. VIs, including NDVI, NIRv, EVI, and EVI2, were less sensitive to SM anomalies than SIF for different types of vegetation during the maturity and senescence stages. Among them, NDVI characterized vegetation greenness and canopy structure, and responded slowly to environmental stress, which decreased photosynthetic activity (Grace et al. 2007). Yang et al. (2018) found that photosynthesis in the rainforest was suppressed by water stress, while the canopy greenness continued to increase. Therefore, SIF had more advantages than VIs in observing vegetation vitality during a drought event, and it was more sensitive to SM than VIs during the maturity and senescence stage, which resulted from its greater sensitivity to photosynthetic activity (Iteza et al. 2020).

4.2. Precipitation and temperature limitations on the SSM–SIF/NDVI relationships in different phenological stages

Based on different climate conditions, we analyzed the regulation of precipitation and mean temperature on the relationships of SSM with SIF and NDVI in different phenological stages, and observed their biome-dependency (table 3 and table S4). In this paper, precipitation deficits and increased mean temperature had more significant impacts on these relationships during the maturity and senescence stages. These results were consistent with those of previous studies (Madani et al. 2017). Li and Xiao et al. (2020) demonstrated that both SIF and EVI had strong positive correlations with SM in warm, arid or semi-arid areas and were negatively correlated with SM in cold and humid areas. Zhang et al. (2020) found that SSM dominated dryness stress on ecosystem production globally, and more soil water was required to support the increased vegetation activity characterized by SIF when the temperature limitation diminished during the late growing season. In the natural environment, drought stress induced by precipitation deficits and heat stress induced by higher temperatures often occurred concurrently. These interactions resulted in larger effects than that of a single source of stress, and caused SIF to have a higher sensitivity to decreased SSM (Yuan et al. 2016). This phenomenon was supported by field experiments that showed that decreasing SM exerted stronger limits on stomatal conductance and photosynthesis at higher temperatures (Reich et al. 2018), causing greater negative effects (Shah and Paulsen 2003, Mahrookashani et al. 2017). In the future, global warming will bring more extreme weather events with abnormal precipitation and temperature. Frequent droughts and heatwaves will severely threaten terrestrial ecosystems.

4.3. Uncertainties and limitations

Certain crops had short growing seasons that could cause two key transition dates in a month, which may introduce errors in our analysis. The daily-averaged SIF data from Köhler et al. (2015) (ftp://ftp.gfz-potsdam.de/home/mefe/GlobFluo/) had a good correspondence of the absolute values and the spatial patterns from the GOME-2 SIF products, which was confirmed by figures S6 and S7. We intended to use daily SIF data to analyze the relationships of SSM with SIF and NDVI in different phenological stages on a short time scale. The corresponding daily SSM data used was derived from the GLDAS 2.2 products with a spatial resolution of $0.25\degree \times 0.25\degree$ (Rui et al. 2019). Incomplete daily global maps of SIF products were averaged into 8 d intervals to obtain a complete map (Chen et al. 2019a), wherein the day reported in the file corresponded to day five of the 8 d interval. In addition, 16 d averaged SIF data were composited from daily global maps when at least five SIF retrievals were available within each biweekly period (Zhang et al. 2016). The day reported in the file corresponded to day nine of the 16 d interval. However, we did not obtain similar results, although the temporal dynamics and spatial distribution of SIF over the 8 d, 16 d, and monthly scales were similar (figures S8–S10). This phenomenon may result from the significant changes of SSM over a short time period not being adequately reflected in the SIF or NDVI anomalies on a regional scale.

Overall, by examining the relationships of SSM with SIF and NDVI in different phenological stages, we better understand the role of water restrictions in vegetation photosynthesis, which furthered our understanding of moisture effects on vegetation growth. However, this study had some limitations. Reliable fPAR data were the key to accurately estimating the $SIF_{yield}$ and $f_{esc}$, so it was meaningful to compare the $SIF_{yield}$ data calculated by various fPAR products. In addition, SIF as a probe of vegetation photosynthesis had been used to track vegetation phenology (Liu et al. 2018c, Chang et al. 2019, Zhou et al. 2020). Merrick et al. (2019) suggested that satellite-based SIF could distinguish important functioning and phenological differences in vegetation types. Therefore, we could further advance our research to examine the effects of phenology on the response of vegetation photosynthesis to SSM instead of directly using phenological products derived from VIs.

5. Conclusions

By using GLDAS-2 SM, GOME-2 SIF, and MCD43C4 products, we explored the detailed differences in the
relationships of SSM with SIF and NDVI in different phenological stages in Northeast China. Our results showed that both SIF and NDVI were significantly correlated with SSM in different phenological stages, especially during the maturity and senescence stages. The same was true for SIF$_{\text{PAR, norm}}$ and SIF$_{\text{field}}$ that derived from $\Phi_f$ and $f_{\text{esc}}$. These relationships also varied with vegetation types, in which SIF was more sensitive than NDVI to SSM anomalies in grasslands and forests during the maturity stage and rainfed croplands during the senescence stage. Both precipitation and mean temperature played important roles in shaping these relationships, and decreased precipitation had the most significant impacts when accompanied by increased temperature during the maturity stage or decreased temperature during the senescence stage. This study highlighted the influences of vegetation phenology in the relationships of SSM with SIF and NDVI, and further advanced the understanding of the impacts on vegetation-moisture relationships, which provided some helps for using satellite-based SIF to effectively monitor drought in different time periods in the future.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.1088/1748-9326/aab0b1.

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All the data used in this study are publicly available. GLDAS-2 SM products are available at http://disc.sci.gsfc.nasa.gov; GOME-2 SIF products is available at http://avdc.gsfc.nasa.gov, MODIS data products are available at https://lpdaac.usgs.gov. The authors gratefully acknowledge the data sharing platform of Beijing Normal University for GLASS LAI/f-PAR products. The authors also gratefully acknowledge Zhe Fang from School of Remote Sensing and Information Engineering, Wuhan University, China for his assistance in the data processing.

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Author contributions

L Z Liu and Q Shen designed the research. Q Shen processed and analyzed the data. Q Shen wrote the paper. J H Yang, X Y Han, F Tian and J J Wu provided comments and suggestions on the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

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