Communication

Comparison of Vegetation Phenology Derived from Solar-Induced Chlorophyll Fluorescence and Enhanced Vegetation Index, and Their Relationship with Climatic Limitations

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Abstract: Satellite-based vegetation datasets enable vegetation phenology detection at large scales, among which Solar-Induced Chlorophyll Fluorescence (SIF) and Enhanced Vegetation Index (EVI) are widely used proxies for detecting phenology from photosynthesis and greenness perspectives, respectively. Recent studies have revealed the divergent performances of SIF and EVI for estimating different phenology metrics, i.e., the start of season (SOS) and the end of season (EOS); however, the underlying mechanisms are unclear. In this study, we compared the SOS and EOS of natural ecosystems derived from SIF and EVI in China and explored the underlying mechanisms by investigating the relationships between the differences of phenology derived from SIF and EVI and climatic limiting factors (i.e., temperature, water and radiation). The results showed that the differences between phenology generated using SIF and EVI were diverse in space, which had a close relationship with climatic limitations. The increasing climatic limitation index could result in larger differences in phenology from SIF and EVI for each dominant climate-limited area. The phenology extracted using SIF was more correlated with climatic limiting factors than that using EVI, especially in water-limited areas, making it the main cause of the difference in phenology from SIF and EVI. These findings highlight the impact of climatic limitation on the differences of phenology from SIF and EVI and improve our understanding of land surface phenology from greenness and photosynthesis perspectives.

Keywords: vegetation phenology; climatic limitation; solar-induced chlorophyll fluorescence; enhanced vegetation index

1. Introduction

Vegetation phenology is the study of the timing of recurring biological events of plants and their interactions among periodic changes in the natural environment [1]. It indicates the response and adaptation of vegetation ecosystems to seasonal and interannual environmental change [2,3]. Since the industrial revolution, climate change (e.g., global warming) induced by human activities has had a profound impact on vegetation phenology; at the same time, changes in vegetation phenology have been regarded as a sensitive indicator of climate change and the carbon cycle [4]. Information on vegetation phenology is playing an increasingly important role in global change monitoring, ecological environment simulation and climate change response [2,4].

Remote sensing provides a useful approach to characterizing seasonal and interannual changes in land surface vegetation from regional to global scales [5–7]. Land surface phenology is mainly extracted based on satellite vegetation datasets using the key phenological metrics, i.e., the start of season (SOS) and the end of season (EOS) [8], to characterize the timing of vegetation dynamics during the growing season. Vegetation indices (VIs), calculated from land surface reflectance, are widely used to extract land surface phenology and analyze its response to climate change in various studies from the leaf and canopy greenness perspective. For example, the global land surface phenology product MCD12Q2 was generated by Zhang et al. [6,8] using the EVI (Enhanced Vegetation Index) time series, which is the only global land surface phenology product available in recent years. However, as VIs are not capable of providing us with a direct proxy of physiological processes, they cannot be perfectly applied to modeling frameworks [9]. In this case, some studies have explored the potential of vegetation phenology extraction from an photosynthetic perspective. Solar-induced chlorophyll fluorescence (SIF), as a new physiological proxy for photosynthesis activity [10], presenting a weak signal emitted by green plants during photosynthesis [11–14]. Compared to traditional VIs, SIF provides a direct indicator for monitoring vegetation physiological functioning [15,16], and has a close relationship with carbon uptake of vegetation. Some studies have indicated that satellite-based SIF observations are highly correlated with in situ Gross Primary Productivity (GPP) over flux towers, and thus have the potential to reveal GPP dynamics under environmental changes over a large scale [15,17].

Some studies have reported that phenology derived from SIF and EVI were different across various vegetation types [18,19], such as coniferous forests, deciduous forests, grasslands and croplands [15–17,20,21]. For example, Wang et al. [14] revealed that EVI-based EOS could be later than SIF-based EOS for more than two weeks in grasslands in Australia, and such differences would be larger when plants are stressed with decreasing soil moisture. Moreover, for different phenological metrics, i.e., SOS and EOS, SIF and EVI also performed differently. For example, Walther et al. [15] indicated that the EVI-based SOS of boreal evergreen coniferous forest was much later (about a month) than the SIF-based SOS, but the EVI-based EOS was slightly advanced (about 1 to 2 weeks) to the SIF-based EOS. Although some studies have revealed differences in phenology derived from SIF and EVI among land cover types, the driving factors and underlying mechanisms are less known.

Except for croplands, which could be largely affected by human activities, the dynamics of land surface phenology are driven by the physical characteristics of the vegetation itself and the external climate environment [22]. The external climate factors that affect vegetation phenology mainly include temperature, precipitation and radiation, which interact to promote or limit natural vegetation growth [23,24]. For example, Ma et al. [25] revealed that 80% of EVI-based phenology dynamics in dryland ecosystems are driven by the variability of annual precipitation. In contrast, recent studies have indicated that SIF has quicker responses to external environmental stress information (e.g., water stress) than EVI did [26,27], as SIF contains additional information on stress conditions that reflects fluorescence efficiency [11]. However, climate controls on EVI-based phenology (greenness) and SIF-based phenology (photosynthesis) have not been compared, and a comprehensive analysis across different climatic conditions is still scarce.

In this study, we defined the climatic limiting controls on vegetation growth as climatic limitations, which include temperature-limiting, water-limiting, and radiation-limiting factors. We focus on naturally vegetated areas in China and divide them into climate-limited areas (i.e., temperature, water, and radiation limitations). We then employed SIF and EVI to extract phenology from photosynthesis and greenness perspectives, respectively, and compared their characteristics across climate-limited areas. We further explored the underlying mechanisms by investigating the relationships between the differences in phenology derived from SIF and EVI and climatic limiting factors. This work can provide insights into the mechanistic differences between SIF and EVI in characterizing land surface

phenology to improve our understanding of vegetation dynamics from greenness and photosynthesis perspectives and their interactions with climate conditions.

2. Materials and Methods

2.1. Data Sources and Reprocessing

2.1.1. SIF Datasets

The GOSIF (Global OCO-2 SIF) is a reconstructed SIF product based on Orbiting Carbon Observatory-2 (OCO-2) observations, Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation data, and meteorological reanalysis data. The GOSIF datasets from 2003 to 2016 were downloaded from http://globalecology.unh.edu/ (accessed on 10 February 2021), which were globally spatio-temporal continuous at 0.05° and 8-day resolution derived with a machine learning algorithm trained with OCO-2 SIF [28]. The datasets had a good performance validated by original SIF observations (RMSE = 0.07 W m^{-2} µm^{-1} sr^{-1}) and also showed a good correlation with the in-situ GPP over flux sites (R^2 = 0.73, $p < 0.001$) [28].

2.1.2. EVI Datasets

The MODIS Terra/Aqua Vegetation Indices (MOD13C1/MYD13C1, V006) were combined to generate EVI time series from 2003 to 2016 at 8-day interval and 0.05° spatial resolution, which were available at https://ladsweb.modaps.eosdis.nasa.gov/ (accessed on 15 March 2021). Global MOD13C1 and MYD13C1 are cloud-free spatial composites of MOD13A2 and MYD13A2 at 16-day intervals and 1 km spatial resolutions, respectively.

2.1.3. Land Cover Map

We utilized the global land cover product (GLC), freely available at http://data.ess.tsinghua.edu.cn/index.html (accessed on 22 September 2021) to map the natural vegetated areas and mask croplands that are vulnerable to human interference [29]. This product consists of 17 land cover types, among which the developed land types and non-vegetated land types were masked to generate natural vegetated areas. The accuracy for 2010, 2015 and 2020 are 86.39% ± 9.05%, 86.44% ± 8.99% and 84.83% ± 10.19%, respectively [29]. We aggregated the original land cover dataset from 2015 to 0.05° to match the spatial resolution of the SIF and EVI datasets in this study.

2.1.4. Meteorological Datasets

The reanalysis meteorological datasets from 2003 to 2016 were obtained from the ERA-Interim global reanalysis data (https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/, accessed on 13 December 2020). Here, we selected 2 m temperature, total precipitation and photosynthetically active radiation (PAR) from ERA-5. All of these variables were obtained from the surface-level fields of this reanalysis at 0.125° for a daily interval. The potential evapotranspiration (PET) was downloaded from the gridded Climatic Research Unit (CRU) datasets (https://catalogue.ceda.ac.uk/uuid/10d3e3640f004c578403419aac167d82, accessed on 27 January 2021). The original climate datasets from 2003 to 2016 were aggregated to a monthly time scale at a 0.05° spatial resolution to calculate climatic limitation indices.

2.2. Methods

2.2.1. Phenology Extraction

Due to cloud, atmosphere and snow contamination, we used Savitzky–Golay filtering to smooth the time series of GOSIF and MODIS EVI. Then, a double logistic function was fitted based on the smoothed time series to generate continuous curves. The double logistic is a flexible model for monitoring seasonal and inter-annual land surface dynamics based on satellite data, which has been widely used for various vegetation types at global or regional scales [30,31]. The double logistic function can be written as follows:

$$V(t) = V_{\min} + (V_{\max} - V_{\min}) \times \left(\frac{1}{1 + e^{-mS \times (t-S)}} + \frac{1}{1 + e^{mA \times (t-A)}} - 1 \right) \tag{1}$$

where $V(t)$ is the value of vegetation proxies (i.e., GOSIF or MODIS EVI) at day of the year (DOY) t, $V_{\max}$ is the maximum vegetation proxies in the year, $V_{\min}$ is the minimum vegetation proxies in the year, mS and mA are the maximum slope of the curve in green up and in senescence, respectively, S and A are their corresponding DOYs. Finally, the SOS and EOS were estimated as follows [32]:

$$SOS = \frac{2\ln(\sqrt{3} - \sqrt{2})}{mS} + S \tag{2}$$

$$EOS = \frac{2\ln(\sqrt{3} - \sqrt{2})}{mA} + A \tag{3}$$

2.2.2. Determination of Climate-Limited Area

We used long-term monthly average climate data to develop scaling factors (0–1) (refer to the climatic limitation index) [24]. The temperature limitation index, radiation limitation index and water limitation index were calculated using the criteria proposed by Nemani et al. [24] as follows:

$$iT = \begin{cases} 1 - \frac{T_{\min} - TM_{\min}}{TM_{\max} - TM_{\min}}, TM_{\min} < T_{\min} < TM_{\max} \\ 1, T_{\min} < TM_{\min} \\ 0, T_{\min} > TM_{\max} \end{cases} \tag{4}$$

where iT is the temperature limitation index, $T_{\min}$ is the daily minimum temperature, $TM_{\min}$ and $TM_{\max}$ are the thresholds of the daily minimum temperature, which were set as $-5\,^{\circ}\text{C}$ and $5\,^{\circ}\text{C}$ in this study, respectively.

$$iR = \begin{cases} 1 - \frac{R_{mean} - RM_{\min}}{RM_{\max} - RM_{\min}}, RM_{\min} < R_{mean} < RM_{\max} \\ 1, R_{mean} < RM_{\min} \\ 0, R_{mean} > RM_{\max} \end{cases} \tag{5}$$

where iR is the radiation limitation index, R_{mean} is the daily mean PAR, $RM_{\min}$ and $RM_{\max}$ are the thresholds of the daily mean PAR, which were set as 75 W and 150 W, respectively. In addition, we used the ratio of precipitation to potential evapotranspiration (P/PET) as an indicator of water-limited conditions, as below:

$$iW = \begin{cases} 1 - \frac{P}{0.75*PET}, \frac{P}{PET} < 0.75 \\ 0, \frac{P}{PET} \geq 0.75 \end{cases} \tag{6}$$

The spatial patterns of the three climatic limitation indices are shown in Figure 1a. For classification, we define the pixels as the dominant temperature-limited area if: (1) iT is higher than iR and iW, and (2) iT is larger than 0.25. Radiation-limited areas and water-limited areas were determined by the same criteria. We determined the pixels as having no climatic limitation where iT, iR and iW are all lower than 0.25 (Figure 1b).

Figure 1. Spatial pattern of climatic limitations in China (**a**) and dominant climatic limitations (**b**).

2.2.3. Relationship of Phenology Derived from SIF and EVI and Climatic Limitations

We randomly sampled 5000 pixels for each climate-limited area and adopted linear correlation regression analysis to explore the relationship between phenology generated using SIF and EVI and the dominant climatic limiting factors. Furthermore, we adopted the *C*-index proposed by Garonna et al. [33] to quantify the relative contributions of phenology derived from SIF and EVI to their differences with climatic limitation indices [34], which were calculated as follows:

$$C = \frac{|S_{\text{SIF}}| - |S_{\text{EVI}}|}{|S_{\text{SIF}}| + |S_{\text{EVI}}|} \tag{7}$$

where S_{SIF} or S_{EVI} is the gradient (i.e., slope) of linear regression relationships between SOS/EOS generated using SIF or EVI and climatic limitation indices. As the *C*-index is unitless, ranging from −1 to 1, the contribution ratio based on the *C*-index (*Cr*) can be calculated as Equation (8). If the *Cr* of phenology from SIF or EVI is larger than 50%, this means that this factor is mostly attributable to the difference of phenology between SIF and EVI under climatic limitations.

$$C_r = \frac{1 + C}{2} \times 100\% \tag{8}$$

3. Results

In general, the multi-year average phenology of natural vegetation from SIF and EVI has consistent spatial patterns in China, with a delaying pattern in SOS and an advanced pattern in EOS from southeast to northwest (Figure 2a–d), which is consistent with previous studies reported by Wang et al. [35]. Furthermore, we found substantial differences between the SIF and the EVI in the derived phenological metrics (Figure 2e,f). Specifically, the SOS derived from SIF is generally later than that from EVI, which accounts for 70% of the total natural vegetated area, except for those areas of evergreen forest in the south. The EOS from SIF is generally earlier than that from EVI, accounting for 87% of the total natural vegetated area.

Then, the differences in phenology derived from SIF and EVI were presented statistically across different climate-limited areas (Figure 3). We found that the differences in SOS generated using SIF and EVI (here denoted as ΔSOS) mainly ranged from 0 to 20 days (Figure 3a), while the differences in EOS generated using SIF and EVI (here denoted asΔEOS) mainly distributed between −30 and −10 days (Figure 3b). This indicates that the difference in EOS generated using SIF and EVI is generally larger than that generated using SOS. For both SOS and EOS, the largest difference of phenology from SIF and EVI (i.e., ΔSOS > 30 days or ΔEOS < −30 days) occurred in temperature-limited areas and water-limited areas, while the difference of phenology from SIF and EVI at no climatic limitations was the smallest.

Figure 2. The spatial pattern of multi-year average phenology of natural vegetation from SIF (**a**,**c**) and EVI (**b**,**d**) and their differences, i.e., SOS/EOS derived from SIF subtracted by that derived from EVI (**e**,**f**).

Figure 3. The differences in SOS (**a**) or EOS (**b**) derived from SIF and EVI among different climatic limitation areas.

As shown in Figure 4, we found that increasing the climatic limitation index could result in larger differences in SOS and EOS from SIF and EVI for each dominant climatic

limitation area. This finding could explain why the difference in phenology derived from SIF and EVI with no climatic limitations is the smallest in Figure 3. In terms of different climatic limitations, we found that the slope of linear regression of ΔSOS or ΔEOS to water-limitation index was the highest, followed by temperature-limitation index, and then radiation-limitation index, which might be a consequence of divergent responses of SIF and EVI to different climatic or environmental constraints. In addition, the climatic limitation indices were more correlated with ΔSOS than with ΔEOS. A likely cause is that autumn phenology is more complex than spring phenology, as it may be affected by multiple climatic factors, thus weakening the relationship between one dominant climatic limitation index and ΔEOS.

Figure 4. Scatterplot of differences of SOS (**first row**) and EOS (**second row**) derived from SIF and EVI versus climatic limitation index at temperature-dominant area (**a**,**d**), water-dominant area (**b**,**e**) and radiation-dominant area (**c**,**f**). The black line shows the linear regression between phenology from SIF or EVI and climatic limitation indices; r is the correlation coefficient of the linear regression.

Table 1 quantified the relative contributions of phenology from SIF and EVI to ΔSOS and ΔEOS under the dominant climatic limitation areas. We found that the phenology extracted using SIF was more correlated with temperature, water and radiation limiting factors than that using EVI, making it the main cause of the difference of phenology from SIF and EVI. Especially in water-limited areas, the contributions of phenology from SIF to ΔSOS or ΔEOS is much larger than those from EVI (SOS: 90.00% vs. 10.00%, EOS: 80.00% vs. 20.00%), as phenology derived from EVI had a low correlation with the water limitation index. These different responses of SIF and EVI to the water limitation index attributed to the differences in phenology from SIF and EVI in the water-limited area, which was also shown in Figure 4.

Table 1. The relationships between phenology from SIF or EVI and climatic limitation indices. s: slope of the linear regression between phenology from SIF or EVI and climatic limitation indices. r: correlation coefficient of the linear regression. Cr: contribution ratio of phenology from SIF or EVI to the difference of phenology derived from SIF and EVI under climatic limitations.

| | SOS | | | | | | EOS | | | | | |
| | SIF | | | EVI | | | SIF | | | EVI | | |
Parameters	s	r	Cr	s	r	Cr	s	r	Cr	s	r	Cr
Temperature-limitation	150.23	0.73	62.00%	92.55	0.62	38.00%	−67.31	−0.57	68.50%	−31.07	−0.26	31.50%
Water-limitation	97.10	0.55	90.00%	10.62	0.07	10.00%	−70.82	−0.54	80.00%	−17.52	0.14	20.00%
Radiation-limitation	197.98	0.87	53.65%	166.89	0.80	46.35%	−183.13	−0.90	49.35%	−191.74	−0.88	50.65%

4. Discussion

In this study, we analyzed the characteristics of phenology derived from SIF and EVI for natural vegetated areas in China and found substantial differences between SOS/EOS generated using SIF and EVI. Specifically, the SOS derived from SIF was generally later than that derived from EVI, which was the case in 70% of the total natural vegetated area in China. We found this occurred in climatic limiting areas, where deciduous forests, mixed forests and grasslands were mainly distributed. Those vegetation types initiate photosynthesis after green leaves emerge in spring [17,20]; thus, photosynthesis phenology tends to be later than greenness phenology for SOS, which explains our results. In those areas covered by evergreen forests in the south with no distinct climatic limitations, the SOS derived from SIF was slightly earlier than that from EVI. A higher PAR supply in humid areas would stimulate photosynthesis more quickly, leading to photosynthesis starting earlier than greenness in spring for evergreen forests [15,19,36]. The EOS from SIF was generally earlier than that from EVI, which is consistent with previous studies [15,17,19], implying seasonal hysteresis of EVI in response to photoperiod changes in the period of senescence [15,17].

Furthermore, we revealed that the differences between phenology generated using SIF and EVI were diverse in SOS and EOS. We found that the difference in EOS generated using SIF and EVI was generally larger than that generated using SOS. Possible reasons include the following: (a) The autumn phenology extracted from satellite VIs had higher uncertainty (and perhaps bias) relative to spring phenology [37]. For example, Lu et al. [20] presented that EVI could hardly predict the autumn phenology of deciduous forests accurately with an overall R^2 less than 0.3, while the R^2 of spring phenology was generally higher than 0.7. (b) Seasonal decoupling of physiological status and greenness information occurred in autumn. Specifically, SOS derived from SIF and EVI occur relatively synchronously, but they become increasingly asynchronous as the growing season progresses [38], leading to larger differences in EOS generated using SIF and EVI than that in SOS.

We further inferred that the differences between SIF-based phenology and EVI-based phenology in space have a close relationship with their different responses to climatic limitations. In contrast to information about green biomass proxied by EVI, SIF contains information on the absorbed photosynthetically active radiation by vegetation (APAR) and environmental stresses (especially water stress) related to photosynthetic light-use efficiency (LUE) [10]. Therefore, SIF is more sensitive to climate variability than EVI [39,40]. This is consistent with our finding that phenology from SIF was more correlated with climatic limitations than that from EVI, making it the main cause of the difference between phenology generated using SIF and EVI. Under these divergent responses to climatic limitations, the differences in SOS and EOS from SIF and EVI become larger, along with a higher climatic limitation index. However, in the radiation-limited area, a higher radiation limitation index did not contribute to a larger difference in EOS derived from SIF and EVI. This happened as EOS derived from SIF and EVI had similar regression slopes with the radiation limitation index, suggesting that autumn phenology is more radiation-limited than spring phenology from both greenness and photosynthesis perspectives [41]. In

addition, the radiation-limiting area in this study was distributed in northern China, where snow cover existed in autumn and winter, which may introduce the undesired errors of EOS extracting from reflectance-based EVI [42].

Although the GOSIF product was generated using remote sensing data from the MODIS and meteorological reanalysis data as inputs to the predictive SIF model, which may increase the correlation of SIF and climatic factors in a time series, this correlation from data sources will be offset in the spatial statistics adopted in this study. In addition, we employed SIF and EVI to extract phenology from photosynthesis and greenness perspectives, respectively. Other proxies, such as Chlorophyll/Carotenoid Index [43], Normalized Difference Vegetation Index, can be further analyzed in future studies to investigate the unique characteristics of each proxy on remote sensing derived phenology. The relationship between vegetation phenology and multiple climatic factors instead of one dominant climatic limitation index needs to be analyzed further to explore whether and how the impacts of climatic interactions on vegetation dynamics. Moreover, we focused on natural vegetated areas in China as a target, as it provides a natural laboratory with a wide variation of ecosystems and climate types. Further research could be expanded to the hemisphere or global scale to evaluate our findings.

5. Conclusions

This study revealed a substantial difference between phenology extracted using satellite-derived SIF and EVI data across areas limited by different climatic factors (temperature, radiance, water). We inferred that the differences between SIF-based phenology and EVI-based phenology have a close relationship with their different responses to climate limitations. The higher climatic limitation index could result in larger differences in phenology derived from SIF and EVI for each dominant climatic limitation area. The phenology extracted using SIF was more correlated with climatic limitations than that using EVI, especially in water-limited areas, making it the main cause of the difference between phenology extracted using SIF and EVI. These findings improved our understanding of land surface phenology from greenness and photosynthesis perspectives and provided insight into the mechanistic differences between SIF and EVI in characterizing land surface phenology.

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