TCSIF:A temporally consistent global GOME-2A solar-induced chlorophyll fluorescence dataset with correction of sensor degradation

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Abstract. Satellite-based solar-induced chlorophyll fluorescence (SIF) provides a direct way of monitoring the photosynthesis of vegetation globally. Global Ozone Monitoring Experiment-2A (GOME-2A) SIF product has become the most popular SIF dataset given its capacity for global coverage since 2007. However, serious temporal degradation of the GOME-2A instrument is a problem, and no temporally consistent GOME-2A SIF products are yet available. In this paper, the GOME-2A instrument's temporal degradation was first calibrated using a pseudo-invariant method, which revealed 16.21 % degradation of the GOME-2A radiance at the near-infrared (NIR) band from 2007 to 2021. Based on the calibration results, the temporal degradation of the GOME-2A radiance spectra was successfully corrected by using a fitted quadratic polynomial function whose determination coefficient (R^2) is 0.851. Next, a data-driven algorithm was applied for SIF retrieval at the 735–758 nm window. Besides, a photosynthetically active radiation (PAR)-based upscaling model was employed to upscale the instantaneous clear-sky observations to monthly average values to compensate for the changes in weather conditions. Accordingly, a global GOME-2A SIF dataset (TCSIF) with correction of temporal degradation was successfully generated from 2007 to 2021, and the spatiotemporal pattern of global SIF was then investigated. Corresponding trend maps of the global temporally consistent GOME-2A SIF showed that 62.91 % of vegetated regions underwent an increase in SIF, and the global annual averaged SIF exhibited a trend of increasing by 0.70 % yr^{-1} during the 2007–2021 period. The TCSIF dataset is available at https://doi.org/10.5281/zenodo.8242928 (Zou et al., 2023).

Keywords: GOME-2 satellite; temporal degradation; trend analysis; Solar-induced chlorophyll fluorescence

1 Introduction

Solar-induced chlorophyll fluorescence (SIF) retrieved from satellite-based hyperspectral data provides a new way of monitoring the photosynthesis of vegetation globally. Numerous studies have demonstrated that satellite-based SIF observations are able to produce better estimates of gross primary productivity (GPP) than the widely used reflectance-based approaches (Sun et al., 2017; Guanter et al., 2014; Zhang et al., 2014).

Currently, the satellite sensors used for SIF retrieval can be generally divided into two types according to their spectral resolution (Frankenberg et al., 2011; Frankenberg et al., 2014; Guanter et al., 2012; Du et al., 2018). The first type of satellite was originally designed to measure the atmospheric XCO2 concentration using observations with a spectral resolution higher than 0.05 nm; these satellites include GOSAT (Frankenberg et al., 2011; Guanter et al., 2012), OCO-2 (Frankenberg et al., 2014; Sun et al., 2017), TanSat (Du et al., 2018), and OCO-3 (Taylor et al., 2020). The other type of satellite instrument was originally designed for atmospheric chemistry applications and had a spectral resolution of about 0.5 nm. These instruments included the Global Ozone Monitoring Experiment 2 (GOME-2) onboard the MetOp-A/B/C satellites (Joiner et al., 2013;

Joiner et al., 2016; Köhler et al., 2015); the SCanning Imaging Absorption spectroMeter for Atmospheric CHartograhY (SCIAMACHY) onboard the ENVIronmental SATellite (ENVISAT) (Köhler et al., 2015; Joiner et al., 2016); and the TROPO-
40   spheric Monitoring Instrument (TROPOMI) onboard the Sentinel-5P satellite (Köhler et al., 2018).

Given its global coverage capability starts from 2007, the GOME-2 satellite-based SIF dataset has been the most widely used for global monitoring of GPP, crop yield, drought, vegetation phenology, etc. (Sun et al., 2015; Guanter et al., 2014; Yoshida et al., 2015; Lu et al., 2018; Chen et al., 2019). Yet GOME-2 is an optical spectrometer that measures reflected sunlight and is therefore sensitive to instrument degradation, this is likely caused by contamination, mainly that of the scan
45   mirror's surface and the optical elements (Munro et al., 2016). Further, such degradation may affect the solar and Earth radiance measurements in different ways, depending on the optical components involved, and correcting this via the onboard calibration method may be impossible (Munro et al., 2016). Moreover, how degradation impacts the quality of different level-2 products is highly dependent on the individual algorithms used. Generally, there is a strong decreasing trend in the GOME-2A level-2 SIF product as derived from the GOME-2A level-1B radiance product. For example, the GOME-2A SIF generated by Joiner
50   et al. (2016) as well as the Sun-Induced Fluorescence of Terrestrial Ecosystems Retrieval (SIFTER) SIF dataset produced by Sanders et al. (2016) were both found to harbor an artificial trend caused by instrument degradation (Zhang et al., 2018; Koren et al., 2018). For example, Yang et al. (2018) reported the SIF emission of the Amazon Forest decreased during the 2015/2016 El Niño event when analyzed using the GOME-2 SIF data by Joiner et al. (2016), which is in conflict with the increase of the enhanced vegetation index (EVI) and downward solar shortwave radiation. Zhang et al. (2018) argued that the reduced GOME-
55   2A SIF signal in the Amazon Forest observed by Yang et al. (2018) could have been caused by artifacts associated with the temporal degradation of the GOME-2A instrument, instead of an actual decline in photosynthesis. Hence, it is imperative to address the temporal-decreasing artifact of the GOME-2A dataset before its application to any analysis and interpretation of interannual trends.

Researchers have tried to generate consistent long-term SIF datasets. For example, Wang et al. (2022) assembled a long-
60   term consistent global SIF dataset (LT_SIFc*) by combining the global SIF products from GOME, SCIAMACHY, and GOME-2. The temporal degradation problem was corrected based on the satellite SIF measurements over the Sahara Desert between 1995 and 2018. Unfortunately, this attempt is not sufficiently rigorous, in that the degradation of sensors does not transit to SIF in a linear manner due to post-processing processes. Furthermore, the LT_SIFc* is a reprocessed product derived from existing GOME-2 SIF products, which limits its temporal resolution to 1 month and hinders its broader application. Earlier,
65   Schaik et al. (2020) applied a seasonal factor to GOME-2 reflectance and retrieved SIF from that temporally-corrected reflectance data to generate the SIFTER v2 product; however, the function fitted with the season as the smallest unit may entail deviations from the actual reality of sensor degradation. Accordingly, in terms of the processing results, significant interannual variation persists in the SIFTER v2 time series (Wang et al., 2022). Presently, we still lack a robust consistent long-term GOME-2 SIF product that has been generated via rigorous recalibration methods and can yield reasonable, meaningful results.
70   This leaves the long-term observations provided by GOME-2 underutilized scientifically.

The objective of this study was to provide a temporally consistent GOME-2A SIF dataset that overcomes the degradation problem, spanning 2007 to 2021. Temporal degradation of GOME-2A level-1B radiance was first calibrated using the pseudo-invariant method in the Sahara Desert. Then a data-driven approach was applied to retrieve the SIF datasets from the corrected GOME-2A measurements. Finally, a global temporally consistent monthly GOME-2A SIF (TCSIF) dataset for 2007–2021
75   was generated, using the PAR-based temporal upscaling method, from the degradation-corrected GOME-2A instantaneous SIF retrievals. The temporally consistent GOME-2A SIF dataset generated here offers a promising tool for monitoring global vegetation variation from 2007 through 2021 and it will advance our understanding of vegetation's photosynthetic activities at a global scale.

2 Datasets

2.1 Datasets for the generation of TCSIF

GOME-2A (launched on October 19th, 2006) was designed by the European Space Agency to measure atmospheric ozone, trace gases, and ultraviolet radiation. Since 2007, it has been collecting top-of-atmosphere (TOA) radiance data spanning a spectral range of 270 to 790 nm from four channels (Munro et al., 2006). Of these, channel 4 of GOME-2A has a spectral coverage of 593–790 nm wavelengths with a spectral resolution of 0.48 nm, which was successfully used to generate a global SIF dataset (Joiner et al., 2013).

The MODIS Version 6.1 Nadir Bidirectional reflectance distribution Adjusted Reflectance (NBAR) product (MCD43C4) (Schaaf et al., 2002) records the surface reflectance at a nadir viewing angle for each pixel at local solar noon. It has a spatial resolution of 0.05° × 0.05° and a 16-day temporal resolution (Schaaf et al., 2002). The MODIS NBAR product is considered stable over long periods of time and was used here to investigate the homogeneity and stability of the calibration site (see Sect. 3.1).

The EVI product derived from the MODIS Vegetation Indices 16-Day (MOD13C1) Version 6.1 with a spatial resolution of 0.05° was aggregated to 0.5° (Didan, 2021). PAR was obtained from the Merra-2 meteorological assimilation reanalysis data (Gelaro et al., 2017) and this PAR dataset had a spatial resolution of 0.5° × 0.625° (resampled to 0.5° × 0.5°) and a temporal interval of 1 h. The EVI product and Merra-2 PAR dataset were used to upscale the instantaneous SIF to monthly values, as described in Sect. 3.4.

2.2. Datasets for evaluation and comparison

The reliability of this dataset was evaluated using greenness-based vegetation indices and global GPP products, as well as other established long-term SIF products.

Firstly, the NDVI (normalized difference vegetation index) and three global GPP products were utilized for validation purposes. We employed the global NDVI derived from the MOD13C1 product. The MOD17A2H GPP (MODIS GPP) product, with a spatial resolution of 500 m (Running et al., 2021), was mosaicked globally every 8 days during the 2007–2021 period. Global-simulated GPP based on the LUE model (Pmodel GPP) is a daily product from 1982 to 2016, whose spatial resolution is 0.5° (Stocker et al., 2019). The monthly, 0.5° GPP derived from the Dynamic Global Vegetation Model (DGVM) for 2007 to 2021 was also utilized (TRENDY GPP Version 11) (Sitch et al., 2015). The temporal range, temporal resolution, and spatial resolution of these datasets are summarized in Table 1. All these products were resampled at a spatial resolution of 0.5° and a temporal resolution of 1 month to enable their comparison.

Table 1 GPP and NDVI datasets used in this study and their relevant details.

Dataset	Temporal range	Temporal resolution	Spatial resolution
MODIS GPP	2000.2–2023.2	8 days	500 m
Pmodel GPP	1982.1–2016.12	1 day	0.5°
TRENDY GPP	1900.1–2021.12	1 month	0.5°
MODIS NDVI	2000.2–2023.2	16 days	0.05°

Next, we selected four long-term SIF products spanning more than one decade for comparison, including the LT_SIFc*(1995–2018) (Wang et al., 2022), SIFTER v2 (2007–2018) (Schaik et al., 2020), GOSIF (2000–2022) (Li and Xiao, 2019), and GOME-2 SIF products generated by the National Aeronautics and Space Administration (hereon abbreviated as NASA SIF) (2007–2018) (Joiner et al., 2013&2016). The LT_SIFc* is a data fusion product of GOME, SCIAMACHY, and GOME-2, having a spatial resolution of 0.05° and a temporal resolution of 1 month. It dealt with the temporal decay of the instrument based on statistics of SIF signals in the Sahara Desert. The SIFTER v2 product is the point-by-point SIF product

115   retrieved from GOME-2 measurements after applying a time-related correction factor; it was composited to yield a 0.5°, monthly global map in this study. The GOSIF product is the spatiotemporal expansion product based on the global neural network model and OCO-2 SIF V8r product, with a spatial resolution of 0.05° and a temporal resolution of 8 days. Apart from the SIF products spanning decades, the OCO-2 SIF product from 2015 to 2021 is also included here for comparative purposed given its high accuracy and its being less affected by sensor degradation. All SIF products were resampled to a 0.5°, monthly

120   spatiotemporal resolution and were compared with TCSIF to assess long-term trends in this study. Additionally, we used the NASA GOME-2A level2 SIF product, which has not been corrected for temporal decay, to verify the spatial distribution of our product. Key information about these SIF products is presented in Table 2.

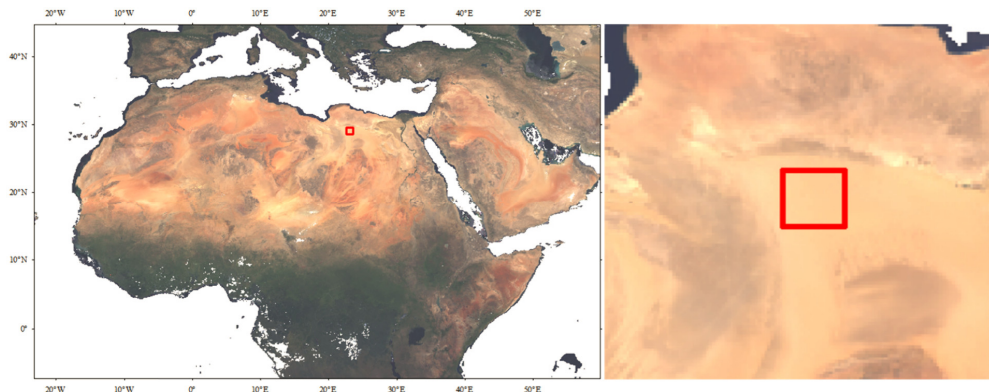
Table 2 SIF products used in this study and their relevant details. This information includes the temporal range of the dataset; whether
125   the dataset initially had a temporal degradation problem, and if so, whether the degraded dataset was corrected. The signal to which the correction factor is directly applied, the temporal unit of the correction factor, and the function describing the temporal correction are provided as well.

Dataset	Temporal range	Temporal degradation problem?	Temporal correction applied?	Signal directly corrected	Temporal unit	Function
TCSIF	2007.1–2021.11	Yes	Yes	Radiance	1 day	Quadratic function
NASASIF	2007.1–2019.3	Yes	No	-	-	-
LT_SIFc*	1995.1–2018.12	Yes	Yes	SIF	1 month	Ensemble Empirical Mode Decomposition approach
SIFTER	2007.1–2018.12	Yes	Yes	Reflectance	3 months	Piecewise function
GOSIF	2000.3–2022.12	No	-	-	-	-
OCO-2 SIF	2014.9–2021.12	No	-	-	-	-

3. Methods

3.1 Pseudo-invariant method for calibrating the GOME-2A degradation

130   A homogeneous square region in the Sahara Desert (22.5°–23.5° E, 28.5°–29.5° N; Figure 1a) was selected as a pseudo-invariant site for calibrating the GOME-2A degradation. Ignoring the spatiotemporal variation in the far-red surface reflectance and atmospheric optical properties over the calibration site during the 2007–2021 period, the temporal trend of TOA GOME-2A reflectance could be deemed equivalent to the amount of temporal degradation in the GOME-2A instrument.

The MCD43C4 product was used here to investigate the homogeneity and stability of this calibration site. Figure 1b
135   depicts the MCD43C4 surface reflectance and its spatiotemporal variance for the calibration site in 2007–2021. These results indicate this site is bright (the near-infrared [NIR] reflectance is high, at 55.3 %–60.6 %), homogeneous (with mean spatial variation = 0.29 %), and stable (with very low temporal variation = 0.81 %). Arguably, this site qualified as an ideal calibration site for implementing the pseudo-invariant method.

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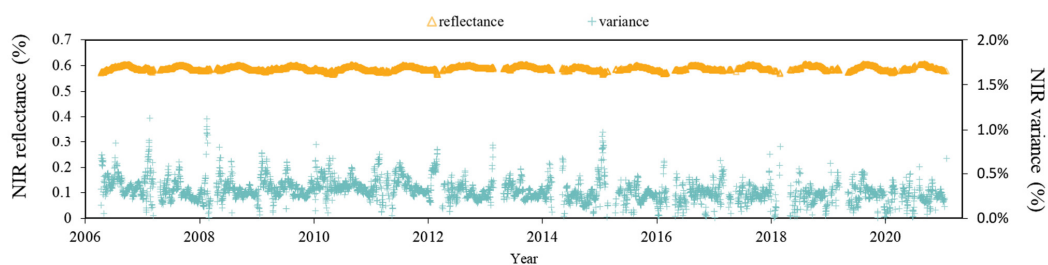
(a) Location of the calibration site in the Sahara Desert

(b) Temporal variation in NIR reflectance at the calibration site

Figure 1. The NIR surface reflectance and its temporal variance at the calibration site (22.5°–23.5° E, 28.5°–29.5° N) during the 2007–2021 period. The NIR reflectance (shown by yellow triangles) and the NIR variance (shown by blue crosses) are respectively the mean and variance of surface reflectance at the near-infrared band.

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The clear-sky GOME-2A level-1B radiance products for the calibration site during 2007–2021 were downloaded to derive the temporal degradation. Two selection criteria for the GOME-2A data were applied: (1) a scanning angle < 20°, and (2) no cloud contamination. This resulted in a total of 6885 GOME-2A level-1B radiance spectra being collected to correct for the GOME-2A degradation.

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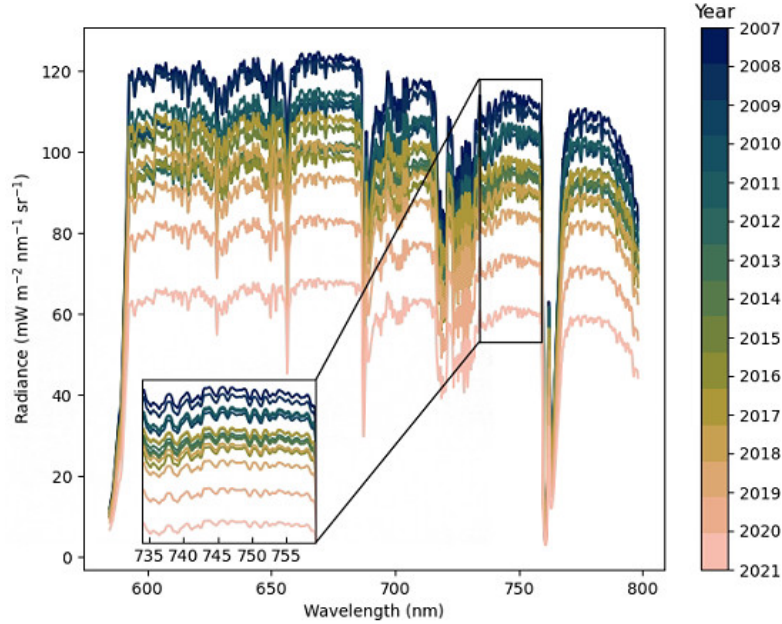
Figure 2. Temporal variation in the GOME-2A level-1B top-of-atmosphere (TOA) radiance spectra at the calibration site (22.5°–23.5° E, 28.5°–29.5° N) for the 2007–2021 period. Different colors represent different years from 2007 to 2021.

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Figure 2 depicts the yearly averaged TOA radiance spectra over the calibration site for each year in 2007–2021. Temporal degradation was determined using GOME-2A level-1B radiance products in the near-infrared (NIR) band between 735 and 758 nm, which served as the fitting window for SIF retrieval. Evidently, there is pronounced temporal degradation in the radiance spectra. Thus, a time-dependent correction factor was calculated as follows:

$$\text{Dfactor} = f(NOD), \tag{1}$$

160 where Dfactor is the normalized correction factor describing the temporal degradation. NOD is the number of elapsed days since January 1st, 1900, starting with 1.

Next, the GOME-2A radiance can be corrected by dividing the measured radiance signal by the Dfactor:

$$Rad_c(\text{NOD}, \lambda) = \frac{Rad_o(\text{NOD}, \lambda)}{\text{Dfactor}(\text{NOD})}, \tag{2}$$

where Rad_c and Rad_o are respectively the corrected radiance and original radiance without correction for the degradation; Dfactor is the normalized correction coefficient in Equation (1), used to compensate for the GOME-2A instrument's

165 degradation since 2007.

3.2 Data-driven based SIF retrieval method

The TCSIF dataset was separated from far-red SIF and corrected radiance spectra in the 735–758 nm range by using an SVD-based data-driven approach, namely that proposed by Guanter et al. (2015).

170 The TOA radiance (L_{TOA}) was modeled this way:

$$L_{TOA} = \left(\sum_{i=0}^{np} a_i \cdot \lambda^i\right) \cdot \left(\sum_{j=1}^{npc} \beta_j \cdot v_j\right) + F_s \cdot h_F \cdot T_\uparrow^e, \tag{3}$$

where L_{TOA} is the TOA radiance at 735–758 nm; λ is the measured wavelength used to represent the low-frequency information in surface reflectance and atmospheric scattering; and v_j is the j-th singular vector derived from non-vegetated

targets (referred to as training datasets) describing the high-frequency information in solar irradiance and atmospheric transmittance. The α_i and β_j are the coefficients of the polynomial and singular vectors, respectively; F_s is the SIF intensity at 740 nm; λ is the wavelength; n_p is the order of the polynomial; and n_{pc} is the number of singular vectors selected. Finally, $T_\uparrow^e$ is the effective upward transmittance estimated as follows (Köhler et al., 2015):

$$T_\uparrow^e = exp\left[ln\left(T_{\downarrow\uparrow}^e \cdot \frac{\sec(\theta_v)}{\sec(\theta_0) + \sec(\theta_v)}\right)\right], \qquad (4)$$

where $T_{\downarrow\uparrow}^e$ is the effective two-way atmospheric transmittance derived by normalizing the TOA reflectance using the low-order polynomial function; θ_0 and θ_v denote the solar zenith angle and viewing zenith angle, respectively.

3.3 Post-processing of SIF retrieval results

The following quality-filtering criteria were applied (Guanter et al., 2012):

(1) Land cover type is set to vegetation;

(2) Range of the mean radiance within the 735–758nm window is between 25 and 200 mW m^{-2} nm^{-1} sr^{-1};

(3) Absolute value of SIF is <5 mW m^{-2} nm^{-1} sr^{-1};

(4) Solar zenith angle is <75°;

(5) χ^2 is <2.

Here, χ^2 is the reduced chi-square value calculated based on the residuals of fitting (Sun et al., 2018), which characterizes the fit between the modeled and measured radiance using the forward model described above, in Equation (3). Its calculation is given by:

$$\chi^2 = \frac{\sum_i^{n_{wi}}(\frac{(Rad_{fit}^i - Rad_{true}^i)^2}{noise})^2}{n_f}, \qquad (5)$$

where Rad_{fit}^i and Rad_{true}^i denote the i-th spectral point of the modeled and measured radiance within the fitting window, respectively; $noise$ denotes the random noise spectra; n_f is the degrees of freedom, and n_{wi} is the number of bands within the fitting window.

Besides, we dealt with the effect of a zero-offset error in the SIF retrievals. The spectrometer radiance signals' nonlinear response and the SVD data-driven algorithm can inevitably introduce systematic biases to SIF retrieval results, especially so in non-vegetated areas. Previous studies have identified systematic biases in SIF retrievals that depend on either the TOA radiance (Frankenberg et al., 2011; Guanter et al., 2012; Sun et al., 2017; Sun et al., 2018) or latitude (Köhler et al., 2015; Joiner et al., 2016; Schaik et al., 2020). Here we corrected the systematic biases (bias) by considering the radiance at the 735–758 nm window (Rad), latitude (lat), and observation zenith angle (θ_0) of each footprint as follows (Joiner et al., 2016):

$$\frac{bias}{\cos(\theta_0)} = A + B \cdot \theta_0 + C \cdot \theta_0^2 + D \cdot \theta_0^3 + E \cdot Rad + F \cdot Rad^2 + G \cdot Rad^3 + H \cdot lat, \qquad (6)$$

where A to H are the correction factors. These factors were firstly determined using the training dataset (where SIF is supposed to be zero and the retrieved SIF can be taken as "bias") which are uniform in latitude dimension by applying the least squares model. Next, the bias was calculated and subtracted from SIF retrievals for each pixel.

3.4 Accuracy evaluation of the product

First, the root mean square of the model residual (RMS_residual) was used to assess the accuracy of the data-driven model to fit the radiance spectra. The model residual (Res) is the difference between the modeled and measured radiance:

$$Res(\lambda) = Rad_{true}(\lambda) - Rad_{fit}(\lambda), \qquad (7)$$

where Rad_{fit}^i and Rad_{true}^i denote the modeled and measured radiance spectra, respectively.

Second, the covariance matrix S_e of the least squares for SIF retrieval was calculated to assess the precision of SIF retrievals:

$$S_e = noise^2 (K^{\mathrm{T}} K)^{-1}, \tag{8}$$

where K is the Jacobian matrix formed by those linear model parameters from Eq. (3), and $noise$ refers to the spectrally uncorrelated noise, which was calculated here based on the radiance and signal-to-noise ratio.

210   The standard error of the weighted mean (σ_{SIF}) within each grid cell was calculated this way (Du et al., 2018):

$$\sigma_{\mathrm{SIF}} = \frac{1}{\sqrt{\sum_1^n (1/\sigma_i^2)}}, \tag{9}$$

where σ_i is the 1–σ error, which is the diagonal element of S_e corresponding to F$_s$, and n is the number of sample points within each grid cell.

3.5 Upscaling the instantaneous SIF to the monthly averaged value

In previous studies, the global satellite-observed SIF was upscaled to a daily scale by using the diurnal cycle of the cosine
215   of the solar zenith angle (cos[SZA]) to correct for day-length effects (Frankenberg et al., 2011; Zhang et al., 2018). These effects can cause large overestimates of SIF on cloudy days because the satellite-observed SIF data are only available on clear-sky days. We relied on the temporal upscaling model of Hu et al. (2018) to upscale the daily observations to monthly values. Using this method, the downwelling PAR rather than cos(SZA) was used to compensate for the significant effects of diurnal weather changes due to cloud and atmospheric scattering. Next, the all-sky monthly averaged SIF (SIF$_{\mathrm{mon}}$) can be determined
220   using the PAR-based upscaling model, as follows:

$$\mathrm{SIF}_{\mathrm{mon}} = \begin{cases} \frac{\sum_{\mathrm{mon}}^M \mathrm{SIF}_{\mathrm{ins}}}{\sum_{\mathrm{mon}}^M \mathrm{PAR}_{\mathrm{ins}} \times \mathrm{EVI}_{\mathrm{ins}}} \times \mathrm{PAR}_{\mathrm{mon}} \times \mathrm{EVI}_{\mathrm{mon}}, & \text{if } \mathrm{EVI}_{\mathrm{mon}} > 0.2 \\ \frac{\sum_{\mathrm{mon}}^M \mathrm{SIF}_{\mathrm{ins}}}{\sum_{\mathrm{mon}}^M \mathrm{PAR}_{\mathrm{ins}}} \times \mathrm{PAR}_{\mathrm{mon}}, & \text{if } \mathrm{EVI}_{\mathrm{mon}} \le 0.2 \end{cases}, \tag{10}$$

where SIF$_{\mathrm{ins}}$ is the GOME-2A level-2 daily instantaneous clear-sky (i.e., <30 % cloud fraction) SIF; the terms PAR$_{\mathrm{mon}}$ and PAR$_{\mathrm{ins}}$ are the corresponding monthly and instantaneous values of PAR; and EVI$_{\mathrm{mon}}$ and EVI$_{\mathrm{ins}}$ are the respective monthly and daily EVI values. M is the number of valid measurements within the 0.5° grid cell during the relevant monthly period. The
225   EVI is negligible if the EVI value for the cell is <0.2.

Based on the PAR-based upscaled model, the instantaneous GOME-2A SIF clear-sky observations with a correction of temporal degradation were upscaled to their monthly average values.

4 Results

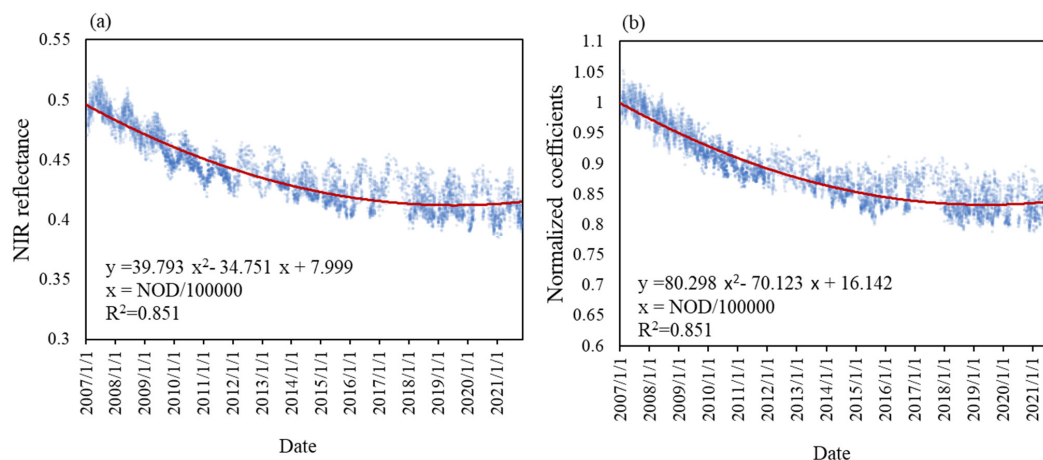
4.1 Correction of GOME-2A sensor degradation

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Figure 3. Temporal variation in the TOA reflectance at 758 nm at the calibration site (left) and the temporal correction coefficients used to compensate for the degradation of GOME-2A since 2007 (right). The blue dots in the two subfigures represent the values of NIR reflectance and normalized coefficients for the calibration sites at different time, respectively. The red curves are the quadratic function fitted based on the blue dots. "NOD" in the degradation correction equation is the GOME-2A acquisition date since 2007, which equals the number of days from 1 January 1900.

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A second-order polynomial was fitted to describe the temporal degradation in the reflectance signal of GOME-2A. Figure 3a illustrates the temporal variation in TOA reflectance at 758 nm at the calibration site. Significant and continuous degradation can be observed; however, this nonlinear trend could be accurately captured by a quadratic polynomial function with a determination coefficient (R^2) of 0.851. These results indicated that, overall, the GOME-2A instrument degraded by 16.21 %

240   from 2007 to 2021. This temporal degradation was considered spectrally constant in the narrow fitting window of SIF retrieval (735–758 nm).

The function derived from TOA reflectance was then normalized, by setting the function value of the start date to 1, as shown in Figure 3b. The normalized Dfactor was used in Eq. (2) to calibrate the instrument's degradation since 2007, as given by

$$\text{Dfactor(NOD)} = 80.298 \times \left(\frac{\text{NOD}}{100000}\right)^2 - 70.123 \times \frac{\text{NOD}}{100000} + 16.142, \ (R^2 = 0.851), \tag{11}$$

245   where Dfactor is the degradation coefficient and "NOD" is the number of days since January 1st, 1900.

4.2 Uncertainty of the data-driven algorithm

The fitting residual and single retrieval error of the TCSIF dataset was analyzed to verify the feasibility of the data-driven retrieval algorithm as well as the quality control process.

250   As Figure 4 shows, the fitted data-driven model described well the measured radiance spectra, with a root mean square (RMS) of the residual that was below 0.30 %. The model considering fluorescence is better capable of reconstructing the radiance spectra than that ignoring fluorescence, with a slightly lower RMS_residual (around 0.02 % on average).
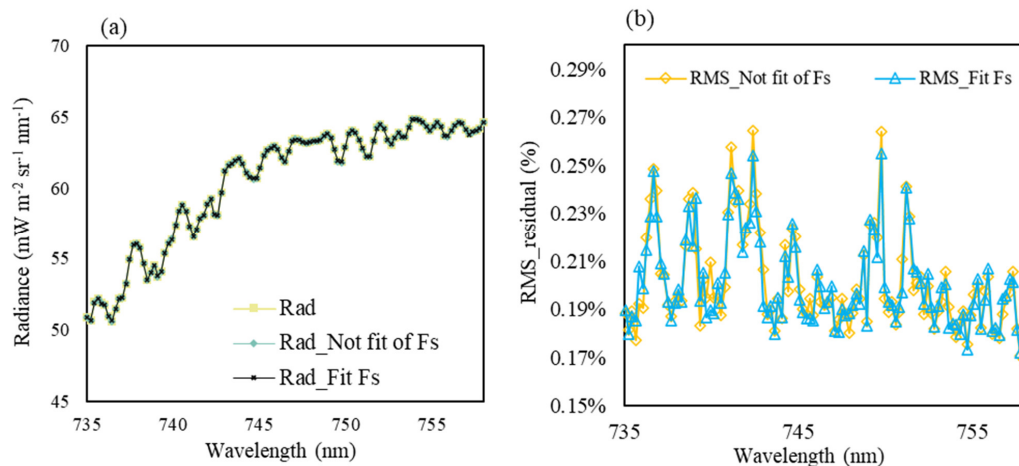
Figure 4. (a) Measured (Rad, represented by square marks) and modeled (with [Rad_Fit Fs, represented by diamond marks] and
without [Rad_Not Fit of Fs, represented by crosses] accounting for SIF) radiance spectra in the 735–758 nm fitting window over
vegetated areas on 15 July 2017. (b) Root mean square (RMS) of the fitting residual with (RMS _Fit Fs, represented by yellow
diamonds) and without (RMS_Not Fit of Fs, represented by blue triangles) accounting for SIF. The spectra are the average of 224
vegetation spectra over pixels with a cloud fraction < 0.1 and SIF intensity > 1.5 mW m^{-2} sr^{-1} nm^{-1}.

4.3 Spatial distribution of the TCSIF dataset

Figure 5 shows the global pattern of monthly TCSIF in the summer and winter of 2008. The monthly GOME-2A SIF dataset captured well the spatial patterning in both seasons, in which Southeast Asia, the North American Corn Belt, and Central Europe in July, and the Amazon Rainforest and most of South America in December, all showed high SIF values. Crucially, the standard error of the weighted mean ($\sigma(F_s)$) is lower than 0.1 mW m^{-2} sr^{-1} nm^{-1} in most regions globally, while the main vegetated areas have $\sigma(F_s)$ of lower than 0.05 mW m^{-2} sr^{-1} nm^{-1} (Figure 6).

We also compared the spatially matched TCSIF and NASASIF pixels in both January and July 2008. The linear relationships between the two SIF products revealed these to be strongly correlated ($R^2 > 0.65$), significant (*p*-value < 0.05), and close to the 1:1 correspondence line (slope > 0.84) for either season (Figure 7a, b). Furthermore, the difference between the two products followed a Gaussian distribution with a mean value close to zero, and the range of our product was slightly lower than that of the NASASIF product (Figure 7c, d).
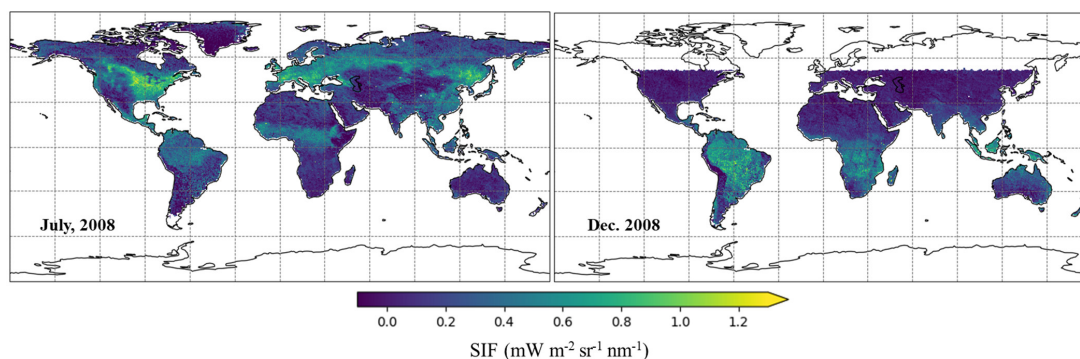
Figure 5. Global patterns in the upscaled monthly TCSIF for July (left) and December (right) in the year 2008.
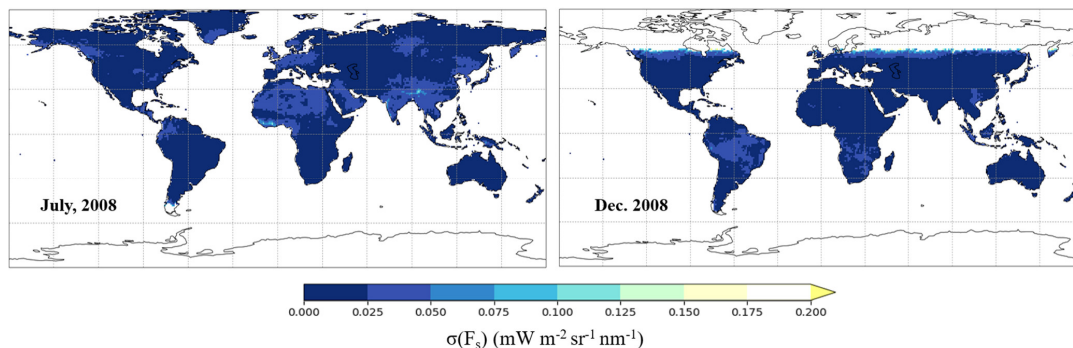
Figure 6. Global standard error of the weighted mean (σ(F$_s$)) in July (left) and December (right) in the year 2008.
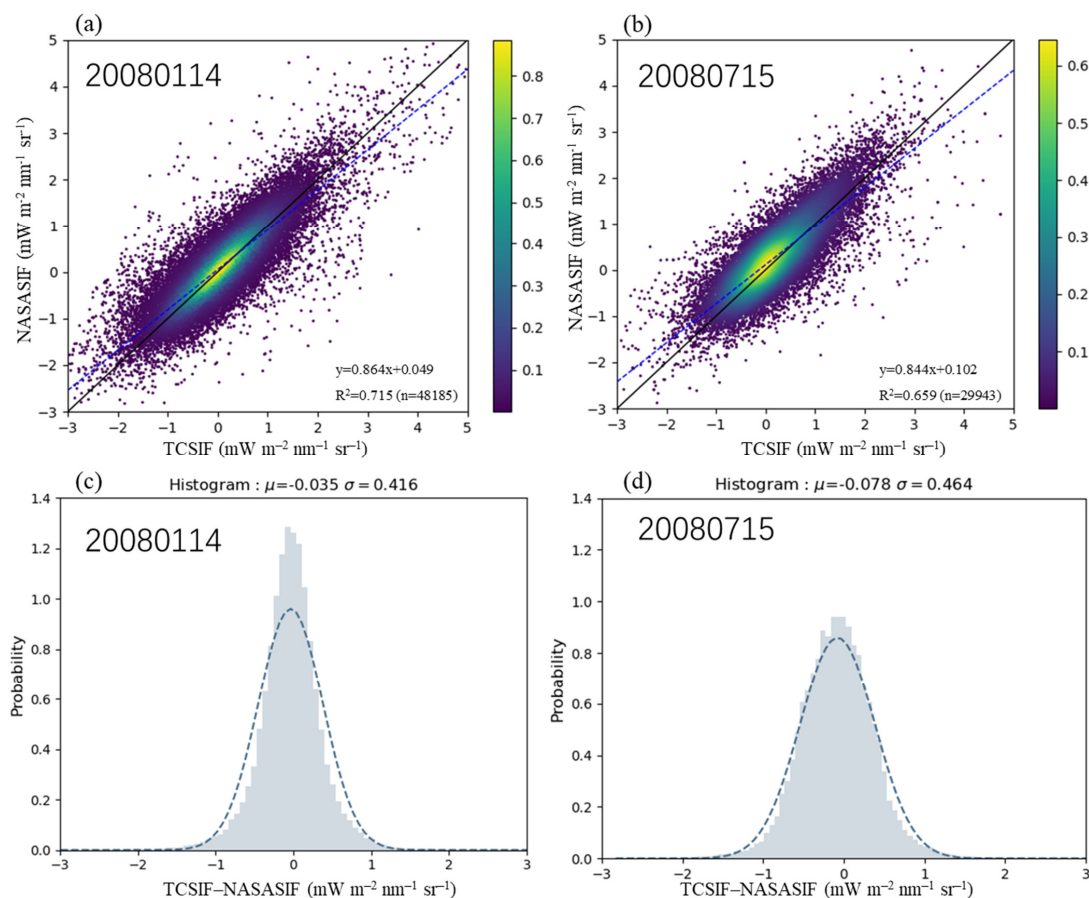
Figure 7. Comparison of TCSIF vs. NASASIF on 14 January (a, c) and 15 July (b, d) in the year 2008. The comparison was made based on the level 2 product. Co-located pixels over land with a cloud fraction < 0.3 have been selected. The color of the scatter points represents the density of the points. The blue dotted line and the black solid line represent the line fitted based on the scatter points and the 1:1 line, respectively.

4.4 Temporal variation in the TCSIF dataset

The global monthly SIF is averaged to demonstrate temporal variation (Figure 8). The autocorrelation coefficient of the time series is calculated for each pixel, and only the vegetation-covered pixels with an autocorrelation coefficient greater than

0.4 are selected to ensure the authenticity of the time series. Compared with the NASASIF products, which gave a downward trend of SIF for 2007–2018, the global monthly mean trend of TCSIF exhibited an upward trend. The monthly trend in global averaged SIF shifted from one of decreasing by 1.15 % yr^{-1} to one of increasing by 0.71 % yr^{-1} after correcting the instrument's

285 degradation. As seen in Figure 9, the trend in SIF's variation in almost all vegetation regions was underestimated before the temporal correction, with the effect of the correction being particularly prominent at low latitudes in the Southern Hemisphere (0°–20° S), as well as at middle and high latitudes in the Northern Hemisphere (30°–70° N).
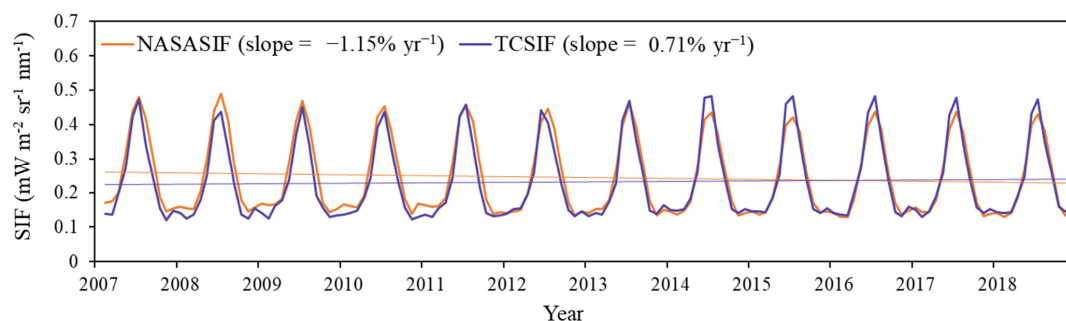
Figure 8. Time series of the monthly averaged global GOME-2A SIF, with (purple line) and without (orange line) the degradation
290 correction, for 2007–2018. The daily level 2 NASASIF product was composited and filtered in the same way as for TCSIF.
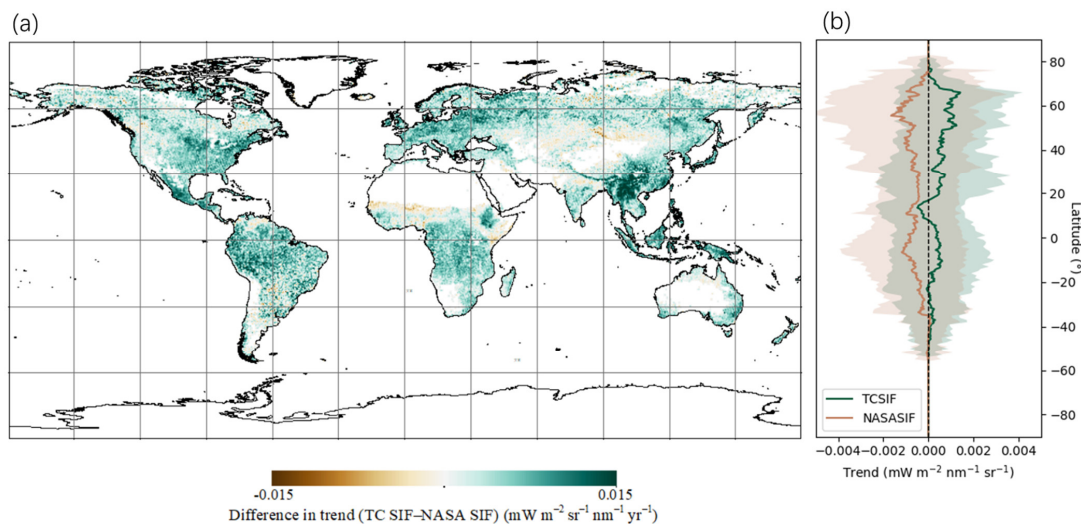
Figure 9. (a) Difference in the temporal trend between SIF products with and without temporal correction, and **(b)** the latitudinal profiles of (a) for 2007–2018. The brown and green shaded areas in (b) represent the standard deviation of the TCSIF and NASASIF trends, respectively.

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The temporally consistent SIF dataset was then applied to reveal spatiotemporal patterns in the photosynthetic activity of global vegetation. Figure 10 shows the global patterns in the trends for the annual average TCSIF in the 2007–2021 period. When tallied, 62.91 % of the vegetation areas overall were distinguished by an upward trend of SIF, whereas 13.86 % corresponded to a significant increase over time ($p < 0.05$). Those regions undergoing a significant increase in SIF were mainly
300 located in Southeast Asia, Eastern China, Western Europe, Central Africa, and South America. Only 4.51 % of the vegetated parts of the Earth's vegetated surface actually experienced a significant decrease in SIF.

Significant increase   Increase   Decrease   Significant decrease
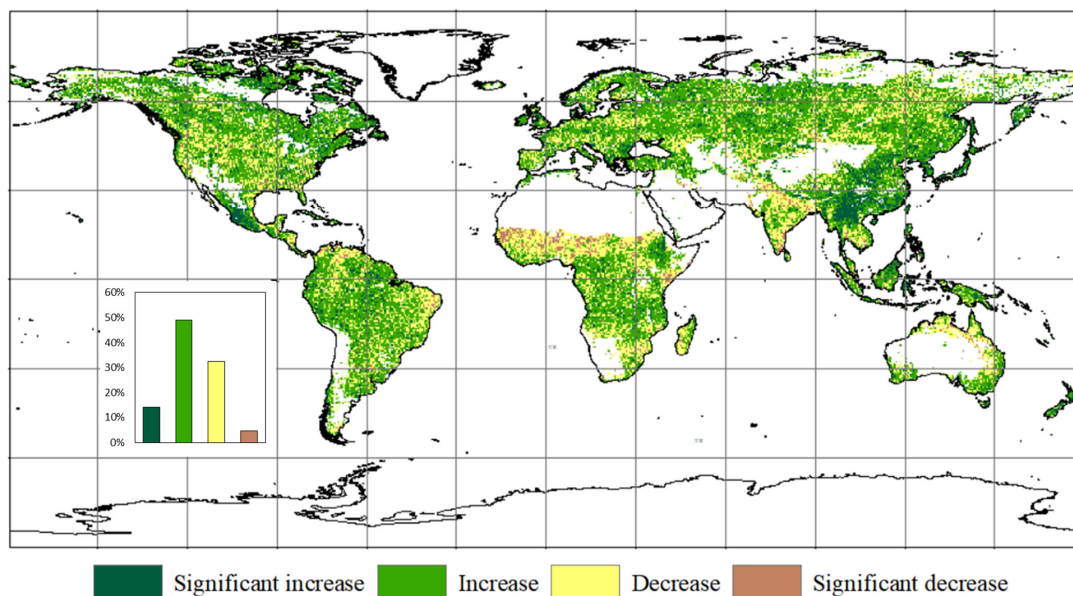
Figure 10. Map of trends in the annual average GOME-2A SIF for 2007–2021. The inset shows the percentage of areas characterized by four types of trends (significant increase: positive correlation with $p < 0.05$; increase: positive correlation with $p \geq$ 0.05; decrease: negative correlation with $p \geq 0.05$; significant decrease: negative correlation with $p < 0.05$).

4.5 Interannual trends for the TCSIF, NDVI, and GPP products

As illustrated in Figure 3, the temporal degradation of GOME-2A level-1B radiance could be accurately quantified by fitting a quadratic polynomial function (with an $R^2 = 0.851$). Furthermore, the TCSIF product's interannual trend could be evaluated by comparing it with NDVI and three GPP datasets.

We first compared the annual maximum of TCSIF with that of GPP and NDVI. As evinced by Figure 11a–e, the global yearly maximum of TCSIF showed a trend of increasing SIF intensity, which was consistent with that of GPP and NDVI. The interannual fluctuation of TCSIF (0.16 %) slightly exceeded that of the GPP and NDVI products (<0.1 % yr^{-1}) during the 2007–2021 period, and likewise for 2007–2016. The interannual trend and associated uncertainty of each product are displayed in Figure 11f. Given that the timespan of Pmodel GPP stops at 2016, we selected the NDVI and TCSIF series from 2007 to 2016 for a fair comparison with Pmodel GPP, this is shown in the bottom half of Figure 11f. Evidently, there are deviations in the interannual growing trend of vegetation when inferred from different GPP products. For example, from 2007 to 2021, the interannual growth trend estimated by MODIS GPP (0.64 %) surpassed that of TRENDY GPP (0.44 %). Meanwhile, the interannual growth rate of TCSIF was close to that of MODIS GPP and Pmodel GPP in 2007–2021 and 2007–2016, respectively. Notably, when compared with the reflectance-based index NDVI, the trend of TCSIF was more similar to that of GPP in both periods examined, indicating that TCSIF was more capable of tracking GPP than NDVI.
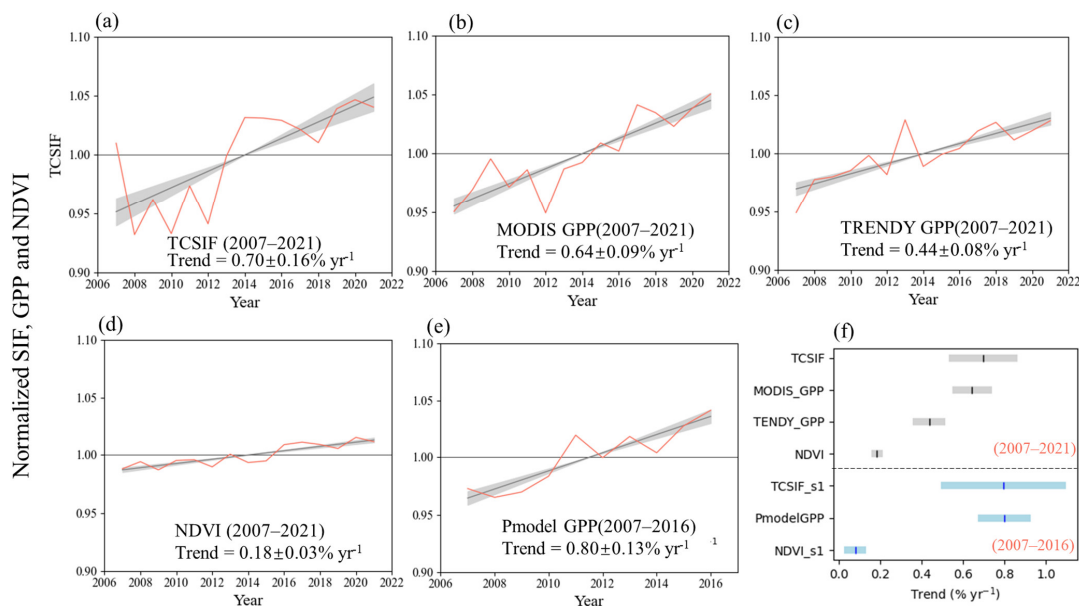
Figure 11. Comparison of temporal trends in the yearly maximum from (a) TCSIF, (b) TRENDY GPP, (c) Pmodel GPP, (d) MODIS GPP, and (e) NDVI. All data shown are normalized to relative values (by dividing the mean). The shaded areas indicate the standard deviations and the gray lines represent the fitted lines which show the general trends. The interannual trends (shown by the gray or blue vertical short lines) of all the products and their uncertainties (shown by the blue or gray horizontal bars) are shown in (f). TCSIF_s1 and NDVI_s1 correspond to the TCSIF and NDVI series for 2007–2016.

The annual maximum values of TCSIF and other long-term SIF products were compared as well (Figure 12). Importantly, all the long-term SIF products were in agreement, featuring an increasing trend of SIF from 2007 to 2018 (Figure 12a–d). Among them, however, TCSIF had a higher rate of increase (0.71 % yr^{-1}) than the other three products (Figure 12a). A slightly increasing trend characterized the SIFTER v2 product (0.04 % yr^{-1}), while the annual fluctuation of SIFTER v2 was clearly greatest among the four products (0.45 % yr^{-1}) (Figure 12b). From Figure 12f, we can see that the interannual fluctuation of LT_SIFc* or GOSIF is smaller than that of TCSIF during 2007–2018, with the GOSIF product having the smallest interannual variation (0.12 % yr^{-1}) (Figure 12d). That of LT_SIFc* (0.17 % yr^{-1}) was close to the increasing trend it provides (0.21 % yr^{-1}) (Figure 12c). The yearly trends according to TCSIF (0.51 % yr^{-1}), GOSIF (0.46 % yr^{-1}), and OCO-2 SIF (0.52 % yr^{-1}) were close to each other in 2015–2021, as shown in the lower part of Figure 12f. There was an even higher consistency of TCSIF with OCO-2 SIF than with GOSIF (which was derived from OCO-2 SIF).
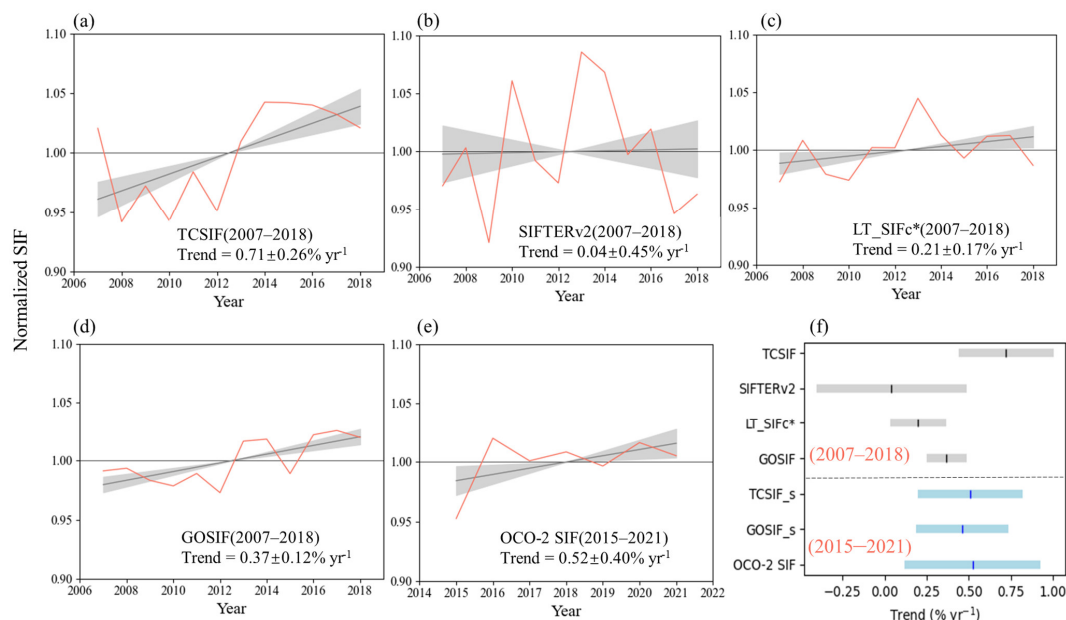
Figure 12. Comparison of temporal trends in the annual SIF maximum from (a) TCSIF, (b) SIFTER v2, (c) LT_SIFc*, (d) GOSIF, and (e) OCO-2 SIF during 2007–2018. All data shown are normalized to relative values (by dividing the mean). The shaded areas indicated the standard deviations. The interannual trends of all SIF products and their uncertainties are shown in (f), in which TCSIF_s and GOSIF_s correspond to the TCSIF and GOSIF series for 2015–2021.

5 Discussion

5.1 Comparison with other long-term SIF products

Although some temporally consistent SIF products have been established in previous research, improvements are still needed to achieve consistent long-term SIF products that are robust.

The large interannual fluctuation of SIFTER may be caused by the fact that its correction factor is seasonally based. No continuous correction functions were applied by SIFTER, which runs counter to the sensor's general pattern of temporal decay. (Lyapustin et al., 2014; Wang et al., 2012). In stark contrast, the least amount of interannual fluctuation was found in the GOSIF product, followed by the LT_SIFc* product. A neural network model was used for the spatiotemporal degradation of the GOSIF product, enabling GOSIF to inherit the time-stable signal from MODIS reflectance. However, this neural network model has been criticized for relying too much on training data such as reflectance data, and overlooking valuable information in the original observations (Ma et al., 2020). The interannual trend of GOSIF is similar to that of OCO-2 SIF during 2014–2016, as shown in the bottom half of Figure 12f. Yet in those years not covered by the original OCO-2 SIF, the spatial distribution of GOSIF depends almost entirely on other input parameters of the data-driven model; hence, it cannot reliably capture the long-term temporal trend of SIF.

The LT_SIFc* product uses weak SIF signals over the Sahara Desert to fit the temporal decay pattern of the sensor, which can quickly generate corrected SIF products based on the monthly global maps provided by NASA SIF. Nevertheless, the method is not rigorous enough, since the sensor's degradation does not alter the SIF retrievals in a linear way. The post-processing steps, such as the zero-offset correction and quality-filtering procedures, will influence the distribution of global-gridded SIF products, leading to uncertainties arising in the correction function. Besides that, a large proportion of noise signals

accompany the weak SIF signals over desert targets, thus restricting the fitting accuracy of the corrective function. Meanwhile, LTSIF_c* is obtained by fusing three SIF products using the cumulative distribution frequency (CDF)-matching approach. Accordingly, the spatiotemporal distribution of the original SIF signal may be forced to change due to adjustments in the distribution frequency of each separate product. In this study, we corrected the degradation in radiance spectra rather than SIF by using pseudo-invariant pixels over the Sahara Desert, which should provide a more reliable method.

To take advantage of SIF's ability to quickly capture changes in GPP, the temporal resolution of long-term SIF products is supposed to be higher than 1 month and even a few days (Zhang et al., 2014; Zhang et al., 2016; Porcar-Castell et al., 2014). However, LT_SIFc* cannot meet those temporal resolution requirements constrained by the original SIF products. By contrast, the shorter, repeating cycle of GOME-2 was fully utilized in this study. Our work provides global daily level-2 SIF products that encompass the world's terrestrial area, which will greatly improve the application ability of global SIF products for monitoring global vegetation dynamics.

5.2 Uncertainty in the temporal correction method

A wide range of radiance is essential for ensuring the representativeness of the temporal correction function, since the signal-to-noise ratio may differ across different radiance levels. Although the pseudo-invariant sampling region selected in this study has a small spatial extent it has a large radiance range (48–284 mW m^{-2} sr^{-1} nm^{-1}), which almost covers that of the main vegetation areas at the near-infrared band (Figure 13); only the lowest value of vegetation radiance (24 mW m^{-2} sr^{-1} nm^{-1}) is not covered. Since the temporal invariance feature is required for the calibration site, it leaves few optional samples to choose from. The representativeness of samples may have an impact on the correction coefficient.

Another limitation is that we only indirectly verify the reliability of the interannual trend of TCSIF when using several long-term remote sensing products, such as GPP, NDVI, and other SIF products. Direct validation data, such as field measurements, were not used to prove the accuracy of our results. In this respect, the huge discrepancy in scale between the satellite SIF products (0.5°) and ground observations (<100 km^2) is one of the major obstacles. In fact, moreover, to our best knowledge, there is no decade-long in-situ SIF validation dataset available that is sufficiently reliable for such a direct validation, and the methodology of directly verifying satellite SIF based on in-situ measurements is still imperfect (Parazoo et al., 2019). The accuracy of TCSIF products needs to be verified via future applications.
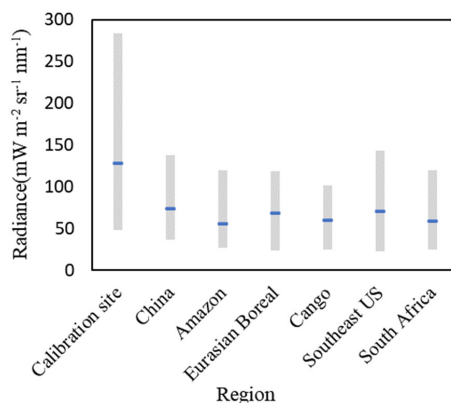
Figure 13. Range of radiance at the near-infrared band at the calibration site and in the six main vegetated areas. The gray bars and blue lines are the range and mean of the datasets, respectively.

6 Conclusion

Degradation of the GOME-2A instrument has been a major barrier to producing consistent SIF products over an extended
time period. By normalizing the instrument's degradation from 2007 to 2021, we were able to develop a temporally consistent
SIF (TCSIF) dataset spanning decades for use in research. The TCSIF is strongly correlated with the NASA SIF products in
terms of its spatial distribution ($R^2 > 0.65$) and has a low retrieval residual (the RMS of residual is under 0.30 %). Our findings
reveal that the TCSIF product yields a more reliable trend in vegetation SIF than does the GOME-2A dataset without a
degradation correction applied. After undergoing the temporal correction, the vegetation SIF increased by 0.70 % per year
during the 2007–2021 period, and 62.91 % of global vegetated regions saw an increase in their SIF, suggesting an overall
increase in vegetation SIF and photosynthesis during the growing season. Compared with NDVI, the results obtained by TCSIF
are closer to the GPP, indicating that the TCSIF product is a reliable proxy of vegetation activity.

We conclude that the TCSIF product developed in this study represents a significant advancement in our ability to
accurately assess long-term changes in the SIF of vegetation on a global scale. This product can thus serve as a valuable
reference for past and future studies of long-term SIF products and may provide important insights into the impact of climate
change on vegetation photosynthesis.

7 Data availability

The global monthly GOME-2A SIF dataset (2007–2021) with correction of temporal degradation is openly available at
https://doi.org/10.5281/zenodo.8242928. The corrected global GOME-2 SIF dataset can be obtained in two forms. The daily
level2 dataset is provided in hdf5 format. The name of these files is given as SIF_daily_YYYYMMDD.h5, in which YYYY,
MM, and DD denote the year, month, and date, respectively. The level 3 datasets, which were aggregated monthly from the
level 2 dataset, have a spatial resolution of 0.5° and are saved in TIFF format in chronological order, from 2007 to 2021. The
name of these files is given as SIFpar_evi_monthly _YYYYMM.tif, in which SIF is the product type, par, and evi represent
upscaled parameters, monthly denotes the temporal scale, and YYYY and MM are the year and month, respectively. The SIF
output is stored in the hdf5 files along with other variables of interest for further processing and visualization. See the Appendix
for the structure of the hdf5 file.

Appendix

The fields of the level 2 products include:

(1) SIF retrievals: including the instance SIF retrieved using the data-driven algorithm (SIF_740), the day-length corrected
SIF (SIF_daily), and the relative error estimations (the 1-σ error (sigma_1), χ^2 and the quality assurance field(QA)).
(2) Geo Locations, fields that describe the location: including the latitude and longitude of the center and the boundary of
each footprint, the solar and viewing angles.
(3) Ancillary data: including the reflectance at red (ps_red) and far-red bands(ps_NIR), cloud fraction, the mean radiance in
the 735–758 nm fitting window (Rad_NIR), and NDVI calculated from GOME-2 reflectance.

Author contribution. LL and XL designed the experiments and CZ carried them out. CZ and SD developed the model code and generated the products. CZ prepared the manuscript with contributions from all co-authors.

Competing interests. The authors declare no conflict of interest.

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