https://doi.org/10.5194/essd-2025-94
Author's Response

Dear editor and reviewers,

We sincerely appreciate your time and careful review of our work.Please find below the reviewers' comments (in black), followed by our responses (in blue), the contents of the manuscript (in purple), and the revised text (in red) in the manuscript.

In addition, in the revised version, we have adjusted the colour schemes of Figures 5 and 10 to improve accessibility for readers with colour vision deficiencies.

Please let us know if there is any additional information for your evaluation of the manuscript.

Best regards,
Chu Zou
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https://doi.org/10.5194/essd-2025-94
Response to Reviewer 1 Comments:

The authors have addressed nearly all of my major concerns. However, several minor issues remain, which I suggest the authors revise. While the use of pseudo-invariant calibration sites (e.g., deserts) is valuable for evaluating sensor radiometric stability, these regions contain little to no vegetation do not emit meaningful SIF signals. As such, analysis may not convincingly validate the reliability of interannual SIF trends. The dataset has clear value and the revision has improved the manuscript. However, I recommend a minor revision to address the following issue before acceptance.

We sincerely appreciate the reviewer's recognition of our work and the thoughtful suggestions provided. We have carefully addressed each of the comments. In response, we have conducted additional validation of the dataset and refined ambiguous terminology throughout the manuscript. Please find our detailed responses below.

Comment 1: The authors only provide pseudo-invariant calibration site analyses to argue against sensor degradation. Yet, no independent validation is offered to demonstrate whether the strong decline during 1995-2000 reflects real ecosystem dynamics or methodological artifacts. Cross-validation with indepedent datasets (e.g., tree-ring records, AVHRR NDVI, FAPAR, or process-based model simulations) would be necessary to convince readers that these early trends are credible.

Response: We appreciate the reviewer's helpful comment. The cross-sensor harmonization employed in this study can reduce inter-sensor biases but cannot fundamentally correct potential errors in the original GOME retrievals. The early GOME record (1995–2003) may be affected by sensor degradation, coarse spatial resolution (leading to mixed-pixel effects), low signal-to-noise ratio, and increased retrieval uncertainties in low-fluorescence or high-latitude regions (Burrows et al., 1999; Joiner et al., 2013; Köhler et al., 2015). In the revised manuscript, we added comparisons with other SIF products and AVHRR NDVI during this period. While some broad consistencies are observed, notable discrepancies remain, highlighting the need for cautious interpretation of early GOME-based trends. Future work will require dedicated strategies for validation and correction, such as radiometric recalibration using pseudo-invariant sites (Zou et al., 2024) or harmonization approaches based on physical mechanisms. These clarifications are reflected in the revised Section 4.2.

4.2 Limitations and future perspectives

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Although the normalization method was designed to minimize the influence of GOME-related uncertainties on the harmonized dataset, the accuracy of early LHSIF data (1995–2003) still warrants cautious interpretation. Additional analyses were conducted for the GOME observation period. Despite the brief overlap with SCIAMACHY, the two datasets showed broadly consistent seasonal dynamics (Figure 14a). We further compared the temporal trends of LHSIF, LCSIF, and AVHRR NDVI during 1995–2003 (Figure 14b–d). Some regions, such as western Europe, northern Oceania, and the southern parts of both North and South America, showed broadly consistent increasing trends across datasets. Conversely, declines were commonly observed in central Africa, southern Oceania, the Amazon rainforest, and northwestern India. Nevertheless, noticeable discrepancies remain. For instance, LHSIF displayed more extensive declines in high-latitude regions and central North America, which were not consistently captured by either LCSIF or NDVI.

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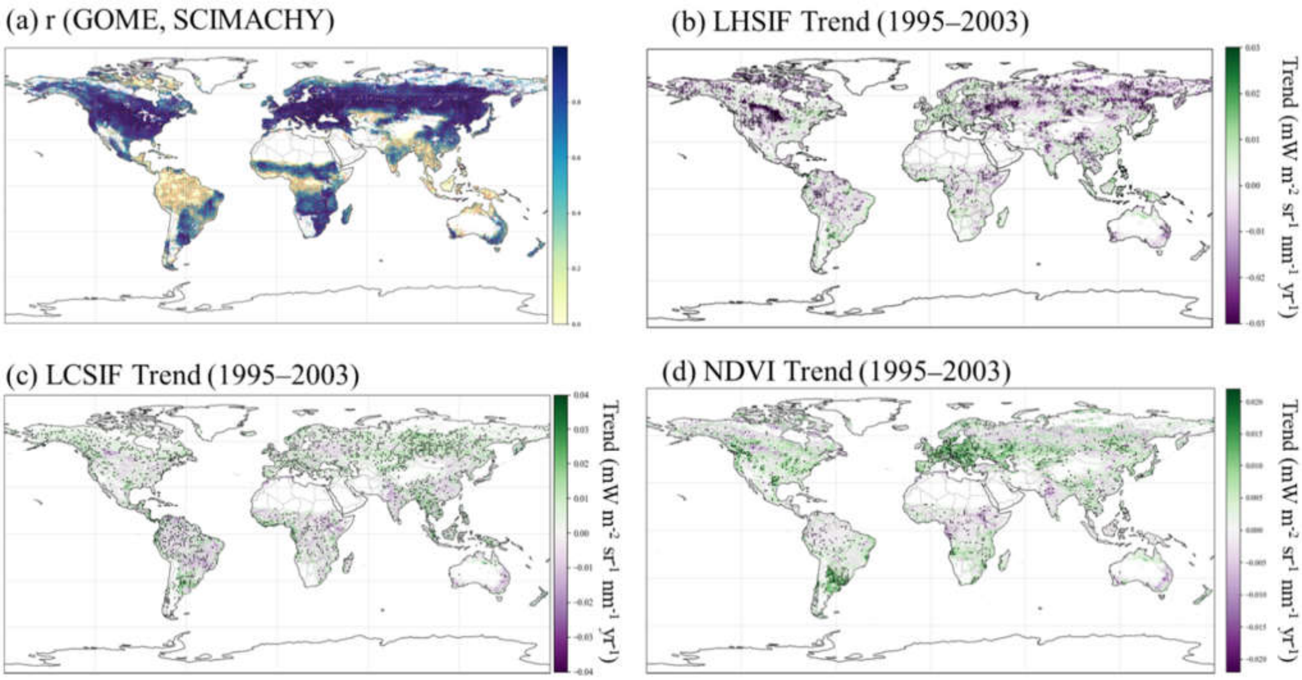

Figure 14 Comparisons of GOME SIF, SCIAMACHY SIF, LHSIF, LCSIF, and AVHRR NDVI during 1995–2003. (a) Correlation coefficient between GOME and SCIAMACHY SIF time series; annual trends of (b) LHSIF, (c) LCSIF, and (d) AVHRR NDVI. The scatter points represent statistical significance($p < 0.05$).

These inconsistencies may reflect several limitations of the early GOME record, including (i) the coarse spatial resolution that amplifies mixed-pixel effects (Joiner et al., 2013), (ii) the relatively low signal-to-noise ratio of the GOME instrument (Burrows et al., 1999), (iii) increased retrieval uncertainties in high-latitude regions with low fluorescence intensity (Köhler et al., 2015), and (iv) potential uncorrected sensor degradation effects. As our harmonization approach primarily reduces inter-sensor biases through normalization, it cannot fundamentally resolve these intrinsic limitations of the original GOME data. In addition, errors may also arise from the propagation and accumulation of uncertainties during the normalization process, since GOME was further adjusted based on the corrected SCIAMACHY product.

Future work will require dedicated strategies to address the intrinsic limitations of early GOME observations. Such strategies may include radiometric recalibration using pseudo-invariant sites (Zou et al., 2024) and also physically-based harmonization approaches to mitigate sensor inconsistencies arising from observation geometry, atmospheric conditions, pixel size, and background signals. Implementing these approaches will enhance the reliability of early trends, providing a more robust foundation for interpreting long-term variations in satellite-observed SIF.

Comment 2: Some terms are over-stated (such as robust, significant (without P value), and substantial) without sufficient quantitative evidence. More cautious and objective wording is recommended. Here are some examples: Line 274: “Our dataset provides a robust estimate…”; Line 512: “…show a significant improvement compared with…”; Line 742: “…a substantial amount of carbon flux variability remains unexplained.”

Response: Thanks for this comment. We noticed that the line numbers provided in the examples may not correspond exactly to the current version of the manuscript. Nevertheless, the entire manuscript was reviewed, and the potentially overstated terms were replaced with more cautious and objective wording. The revisions are as follows:

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Line 77:

Original Sentence: This correction effectively eliminates the influence of sensor degradation over time, providing a robust benchmark for generating long-term harmonized SIF products.

Revision: This correction effectively eliminates the influence of sensor degradation over time, providing a practical reference for generating long-term harmonized SIF products.

Line 302:

Original Sentence: The MSD was significantly reduced after temporal correction, with a notable decrease in the proportion of bias.

Revision: The MSD was reduced after temporal correction, with a decrease in the proportion of bias.

Line 309:

Original Sentence: Significant interannual fluctuations were found for the SIF time series without normalization, with an overall decline (blue line in Fig. 7a).

Revision: Noticeable interannual fluctuations were found for the SIF time series without normalization, with an overall decline (blue line in Fig. 7a).

Line 444:

Original Sentence: The region-based approach allows for a larger sample size within each region, potentially enabling a more robust estimation of the CDF, while the month-specific treatment helps account for seasonal variations in the CDF.

Revision: The region-based approach allows for a larger sample size within each region, potentially enabling an improved estimation of the CDF, while the month-specific treatment helps account for seasonal variations in the CDF.

Line 498:

Original Sentence: Our analysis demonstrated that the harmonized dataset significantly reduced overall errors by more than 49% and exhibited a stable interannual increase ($0.31 \pm 0.07\%$ yr^{-1}).

Revision: Our analysis demonstrated that the harmonized dataset reduced overall errors by more than 49% and exhibited a stable interannual increase ($0.31 \pm 0.07\%$ yr^{-1}).

Comment 3: I recommend you to add all abbreviations for each figure. For example, in Fig. 10, please add the definations or full names for the following abbreviations (including LHSIF (red), LT_SIFc* (green), SIF_005 (purple), and LCSIF (blue)) at the end of the figure caption. In addition, using two stars for significance level is more common (i.e., * for $P<0.05$ and ** for $P<0.01$).

Response: We appreciate this suggestion. To ensure clarity while avoiding redundancy, we have consolidated all dataset definitions into a new summary table (Table 2), which includes descriptions, temporal coverage, sensor sources, and processing methods for each SIF product. This table is referenced in all relevant figure captions (e.g., 'See Table 2 for dataset details'), allowing readers to access complete information without repetitive text in captions.

2.5 Datasets for validation and comparison analysis

Multiple long-term satellite-derived products were utilized for cross-validation in this study. Key characteristics of these benchmark datasets, along with the proposed LHSIF product, are summarized in Table 2.

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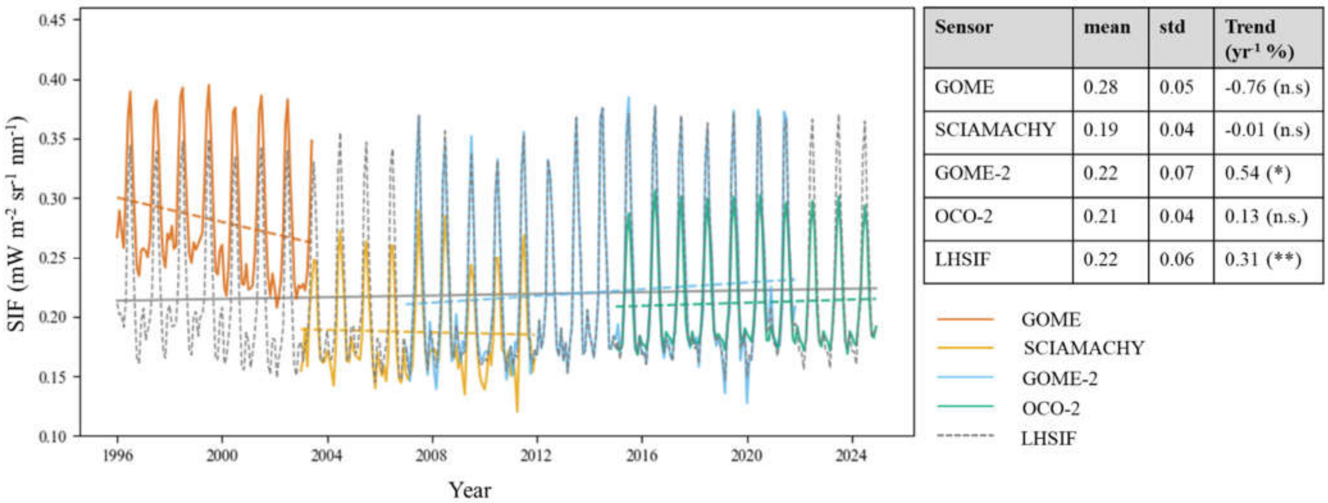
Table 2. The long-term products used in this study and the relevant details about them.

Dataset	Description	Time coverage	Sensors for SIF product	Processing method
LHSIF	Multi-sensor harmonized SIF with extended temporal coverage	1995.07–2024.12	GOME, SCIAMACHY, GOME-2, OCO-2	CDF matching
LT_SIFc*	Multi-sensor harmonized SIF	1995.07–2018.12	GOME, SCIAMACHY, GOME-2	CDF matching
SIF_005	Harmonized SIF	2003.01–2017.12	SCIAMACHY, GOME-2	CDF matching
LCSIF	Spatially continuous reconstructed SIF	1982.01–2023.12	OCO-2	Neural network
BEPS GPP	Simulated GPP using ecological process model	1981.01–2019.12	-	-
AVHRR NDVI	Long term NDVI product addressed for temporal inconsistency	1982.01–2021.12	-	-
AVHRR NIRv	Long term NIRv product addressed for temporal inconsistency	1982.01–2021.12	-	-

Regarding the significance levels, the correlated figures (Figure 5 and Figure 10) were revised as follows:



Sensor	mean	std	Trend (yr^{-1} %)
GOME	0.28	0.05	-0.76 (n.s)
SCIAMACHY	0.19	0.04	-0.01 (n.s)
GOME-2	0.22	0.07	0.54 (*)
OCO-2	0.21	0.04	0.13 (n.s.)
LHSIF	0.22	0.06	0.31 (**)

Figure 5. Global-averaged SIF time series derived from GOME (yellow), SCIAMACHY (blue), GOME-2 (green), and OCO-2 (red), along with the long-term harmonized SIF time series (LHSIF, gray dotted line), which aligns the satellite datasets based on overlapping periods. The table on the right summarizes the statistical characteristics of each sensor, including the mean, standard deviation (std), and the annual trend (Trend) averaged over the respective periods. The statistical significance of the trends is indicated as follows: n.s. for not significant ($p \geq 0.05$), * for significant ($p < 0.05$), and ** for highly significant ($p < 0.01$).

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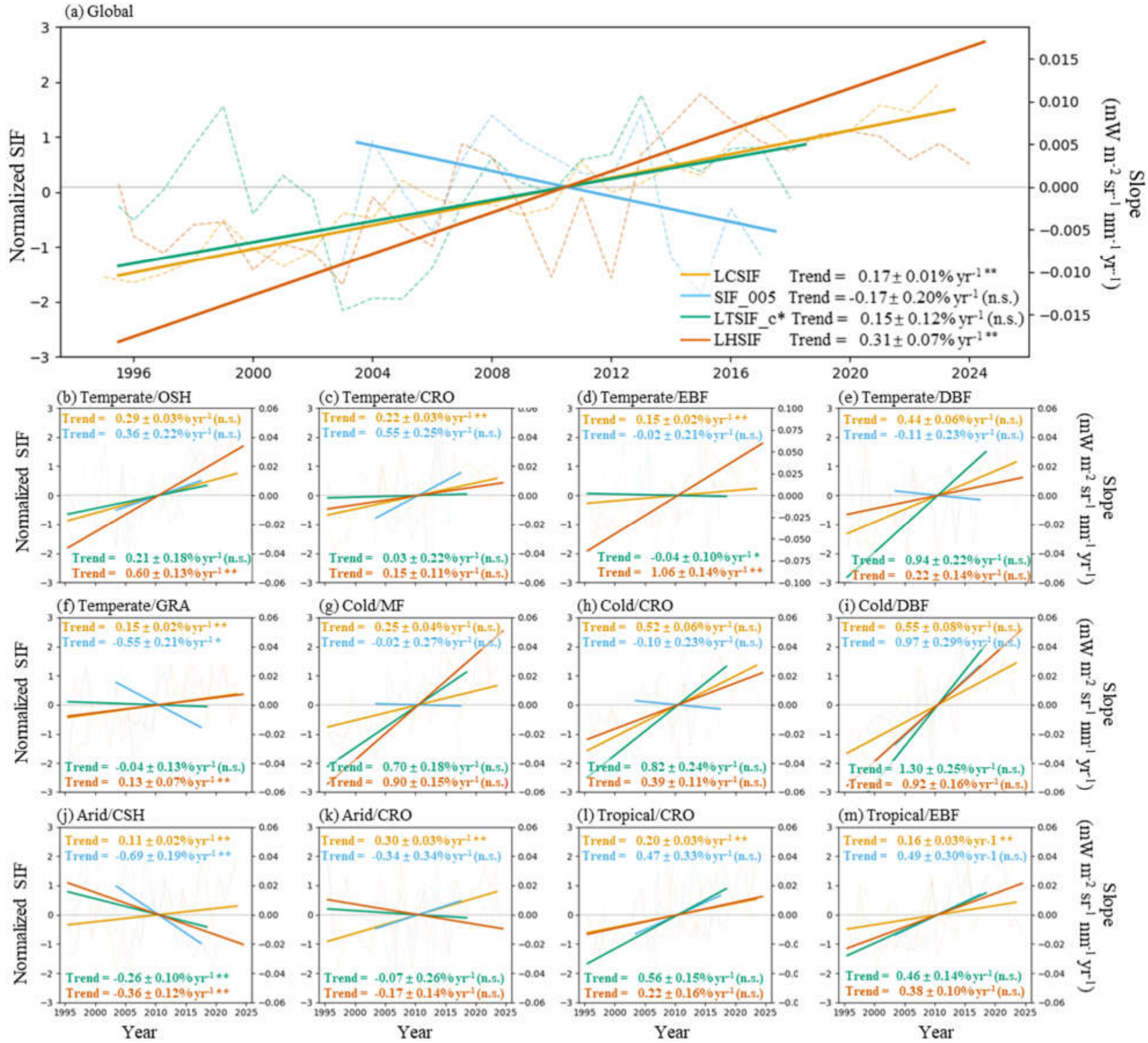

Figure 10. Comparison of interannual variations in long-term SIF products. LHSIF (red), LT_SIFc* (green), SIF_005 (purple), and LCSIF (blue) are compared for (a) the global scale and (b–m) various climatic and vegetation regions. All datasets were normalized using the z-score method. Dashed lines represent yearly maximum values, and solid lines indicate linear trends. To aid visual comparison, trend lines were anchored at the origin (2010, 0). The statistical significance of the trends is indicated as follows: n.s. for not significant ($p \geq 0.05$), * for significant ($p < 0.05$), and ** for highly significant ($p < 0.01$). See Table 2 for dataset details.

Comment 4: Please double check all figures to aviod typo errors.

(1) Fig. 10(d): typo error: ‘Coldl’——>“Cold”;

Response: Thanks for this comment. It has been corrected.

(2) Fig. 10(c), (e): typo error: “Temporate”——>“Temperate”

Response: Thanks for this comment. It has been corrected.

(3) Fig. 10(e), (h): why they are the same name? Maybe the layout could be improved by putting of vegetation in different climate regions in the same row or line.

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Response: Thanks for this comment. The figure has been reorganized, and the labeling inconsistencies have been corrected. The revised figure is as follows:

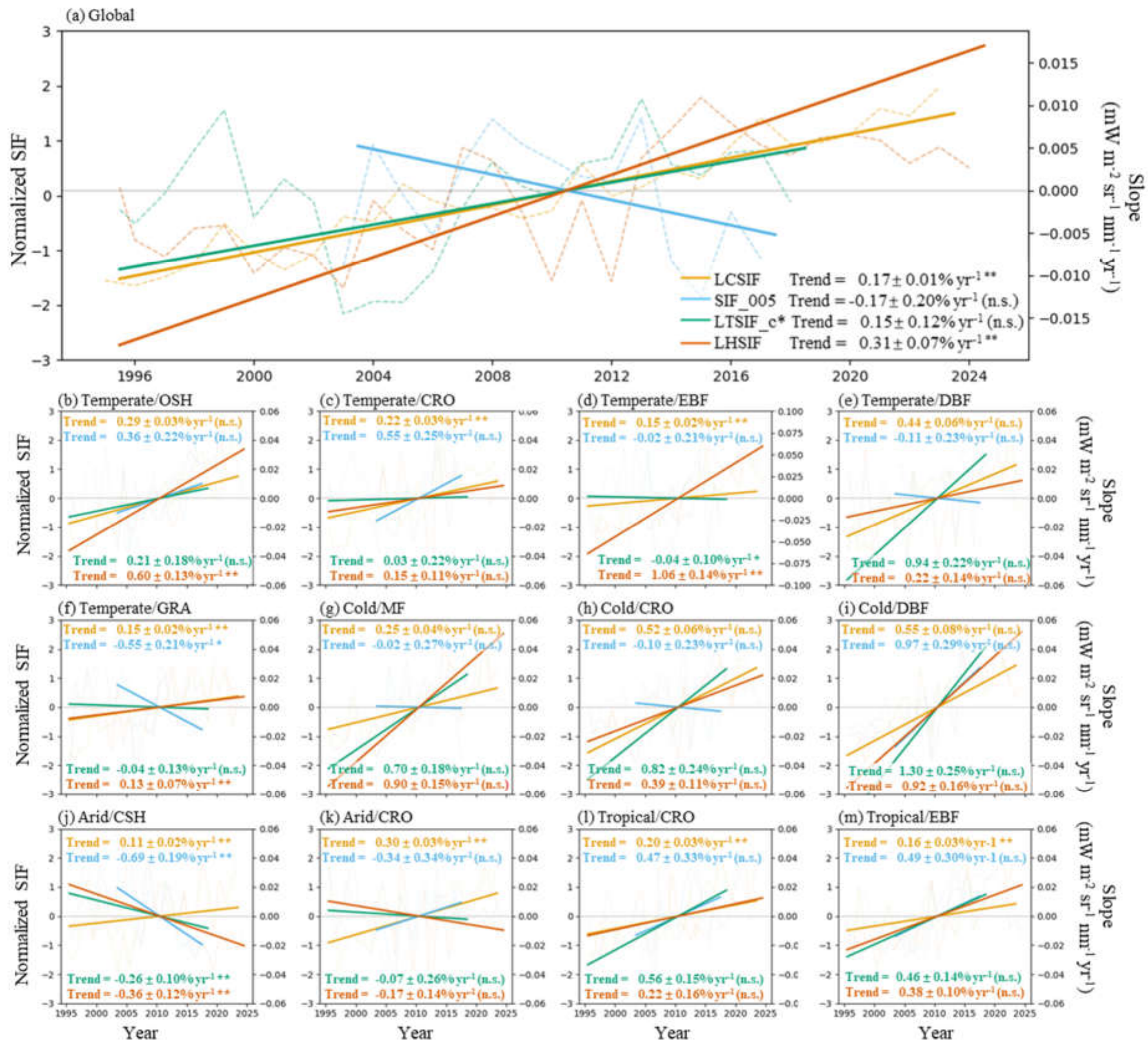

Figure 10. Comparison of interannual variations in long-term SIF products. LHSIF (red), LT_SIFc* (green), SIF_005 (purple), and LCSIF (blue) are compared for (a) the global scale and (b–m) various climatic and vegetation regions. All datasets were normalized using the z-score method. Dashed lines represent yearly maximum values, and solid lines indicate linear trends. To aid visual comparison, trend lines were anchored at the origin (2010, 0). The statistical significance of the trends is indicated as follows: n.s. for not significant ($p \geq 0.05$), * for significant ($p < 0.05$), and ** for highly significant ($p < 0.01$). See Table 2 for dataset details.

Comment 5: Line 22: "…has garnered significant attentions…" (change 'attentions' to 'attention').

Response: Thanks for this comment. It has been corrected.

Comment 6: Line 46-47: "…The Orbiting Carbon Observatory(OCO)-2 satellite…" (Missing space before parentheses).

Response: Thanks for this comment. It has been corrected.

Comment 7: Line 181–185: "…Eq. (1) can be broken down into three terms (Bacour et al., 2019)： " (Replace the full-width colon with a standard English colon).

Response: Thanks for this comment. It has been corrected.

Comment 8: Line 309: Please ensure that the first word in x- and y-axis titles starts with a capital letter for consistency (e.g., Fig. 7a: “Yearly max SIF” instead of “yearly max SIF”). Same as in Fig. 8b.

Response: Thanks for this comment. The figures have been corrected as below:

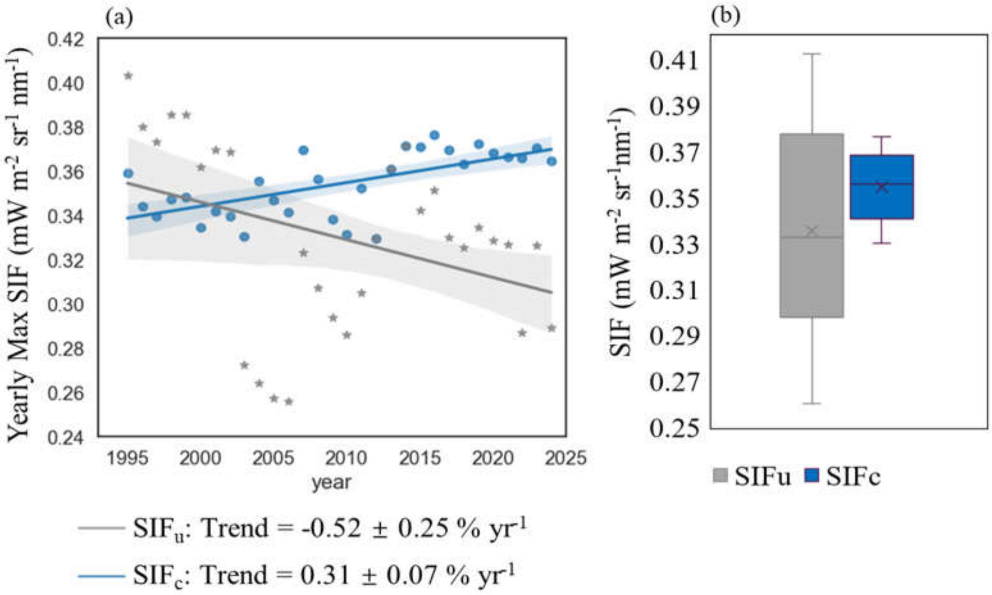

Figure 7. (a) Trend and (b) box plot of the yearly maximum global-averaged SIF of the combined time series before (SIF_u) and after (SIF_c) normalization during 1995–2024.

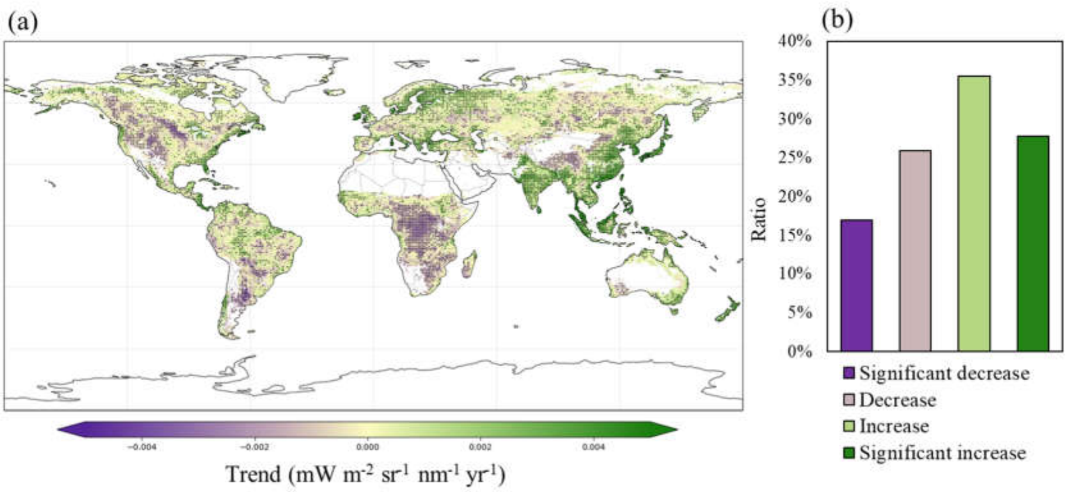

Figure 8. (a) Map of trends in LHSIF for 1996–2024. (b) Percentage of areas in global vegetation covered by four different trend types (significant decrease: negative correlation and $p < 0.05$; decrease: negative correlation and $p \geq 0.05$; increase: positive correlation and $p \geq 0.05$; and significant increase: positive correlation and $p < 0.05$). The black dots in (a) represent statistically significant trends ($p < 0.05$). The statistics begin in 1996 due to incomplete data coverage in 1995, which only includes the second half of the year (July–December).

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Response to Reviewer 2 Comments:

The authors have conducted extensive experimental analyses and made substantial revisions in response to the review comments, which have helped address the main issues.

We sincerely thank the reviewer for the detailed and constructive comments. We have incorporated new validation and discussion based on the reviewer's feedback and corrected a few typing errors. Please see the details below.

Several minor revisions remain as follows:

Comment 1: In response to the previous major comment #1, I appreciate that the novelty of this paper lies in the corrected TCSIF dataset rather than the correction method itself. Still, I was wondering about the following:
(1) Could the authors elaborate a bit more on the reason for changing the matching method? While the advantages of the new method were briefly mentioned, it might be helpful to understand why it wasn't adopted initially.
Response: Thanks for this comment. Regarding the choice of data matching methods, both the moment-matching and CDF-based approaches have their advantages and limitations. The moment-matching method is simple to implement and computationally efficient, and it is relatively robust when the sample size is small. However, it cannot fully account for higher-order distribution characteristics, such as skewness and kurtosis. In contrast, CDF matching can align the entire distribution but requires a sufficiently large sample size. herefore, the choice between these methods depends critically on sample size.
The rationale for the method change is as follows:

(1) Initially, the CDF method was not adopted because in the first version of the manuscript, matching was performed at the pixel level. At this scale, the available data for CDF estimation were limited, so we opted for moment-matching method based on mean and standard deviation to estimate the overall distribution.

(2) In the revised version, we instead applied the CDF matching procedure within different ecological strata. Ecological stratification ensures CDF matching operates within environmentally homogeneous units. Besides, this approach substantially increases the sample size and allows a more reliable estimation of the CDF functions.

In summary, the change in method was made to achieve a more accurate and stable representation of the distribution.
(2) The use of a stratified CDF method based on Köppen climate classification and land cover products, along with accounting for phenological changes, is noted. Given that the LHSIF data cover a relatively long time span, have the authors also considered how long-term land cover changes over the years might affect the results?
Response: Thanks for this comment. To address the potential impact of long-term land cover changes, we accounted for the variability of land cover by using time-dependent land cover products. In the revised manuscript, we have clarified the method as below:
2.3 CDF matching method

The cross-sensor SIF normalization was implemented using a stratified CDF matching approach to account for environmental variability. Specifically, the stratification was done based on a combination of Köppen climate zones (Beck et al., 2023) and the MODIS land cover types product (MCD12C1; Friedl and

Sulla-Menashe, 2022). The land cover map of the central year within the overlapping period was used to construct the CDFs, while the CDFs were applied each year according to the yearly land cover types. For the period before 2001, when MCD12C1 data were unavailable, the land cover map of 2001 was applied. The degradation-corrected GOME-2A dataset was used as the normalization reference for all other satellite-derived SIF datasets, based on their overlapping periods. The normalization of GOME data was based on the SCIAMACHY dataset, which had been previously normalized with GOME-2 data.

This implementation ensured that long-term land cover changes were inherently incorporated into the normalization process. Small fluctuations in land cover or algorithmic uncertainties exert only a minor effect on the fitted distributions, and their impact on the long-term consistency of the harmonized SIF record is expected to be negligible. The limitation is also discussed in the revised manuscript:

4.2 Limitations and future perspectives

Our investigation shows that the CDF normalization approach effectively reduces disparities across sensors, providing a unified reference framework with the longest time series to date. While the normalized dataset exhibits consistent seasonal and interannual patterns across sensors, several methodological considerations warrant discussion. First, as a statistical approach distinct from physical calibration methods (e.g., pseudo-invariant target radiometry), CDF matching may retain minor sensor-specific biases. Second, although we incorporate annual land cover updates using MCD12C1 product to account for vegetation dynamics, inherent classification uncertainties in the reference dataset persist. Nevertheless, the percentile-based CDF matching demonstrates inherent robustness against outliers (Wang et al., 2022), rendering land cover-induced biases negligible in practice.

Comment 2： Regarding previous major comment #3, the authors used overlapping periods between GOME-2, SCIAMACHY, and OCO-2 to illustrate the influence of short overlap periods. The manuscript also appropriately highlights potential uncertainties in the early-stage data. However, I have some additional concerns:

(1) Would it be possible to provide a quantitative estimate or discussion of the accuracy or uncertainty associated with the GOME-phase product? Unlike SCIAMACHY and OCO-2, the GOME data were corrected after SCIAMACHY, which may introduce additional error propagation. The relatively short (six-month) overlap between GOME and SCIAMACHY could further contribute to uncertainty.

Response: Thanks for this helpful comment. We have strengthened the evaluation of the consistency between GOME and SCIAMACHY, and additionally compared LHSIF, LCSIF, and NIRv products during the early period (1995–2003). The early GOME-phase record is subject to relatively high uncertainty, and the cross-sensor normalization cannot fundamentally resolve potential degradation or biases in the original GOME retrievals. These inconsistencies may arise not only from errors inherent to GOME itself, but also from the propagation and accumulation of uncertainties during the normalization process. We have clarified these limitations in the revised Section 4.2 and highlighted potential directions for future improvement.

4.2 Limitations and future perspectives

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Although the normalization method was designed to minimize the influence of GOME-related uncertainties on the harmonized dataset, the accuracy of early LHSIF data (1995–2003) still warrants cautious interpretation. Additional analyses were conducted for the GOME observation period. Despite the brief overlap with SCIAMACHY, the two datasets showed broadly consistent seasonal dynamics (Figure 14a). We further compared the temporal trends of LHSIF, LCSIF, and AVHRR NDVI during 1995–2003 (Figure 14b–d). Some regions, such as western Europe, northern Oceania, and the southern parts of both North and South America, showed broadly consistent increasing trends across datasets. Conversely, declines were commonly

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observed in central Africa, southern Oceania, the Amazon rainforest, and northwestern India. Nevertheless, noticeable discrepancies remain. For instance, LHSIF displayed more extensive declines in high-latitude regions and central North America, which were not consistently captured by either LCSIF or NDVI.

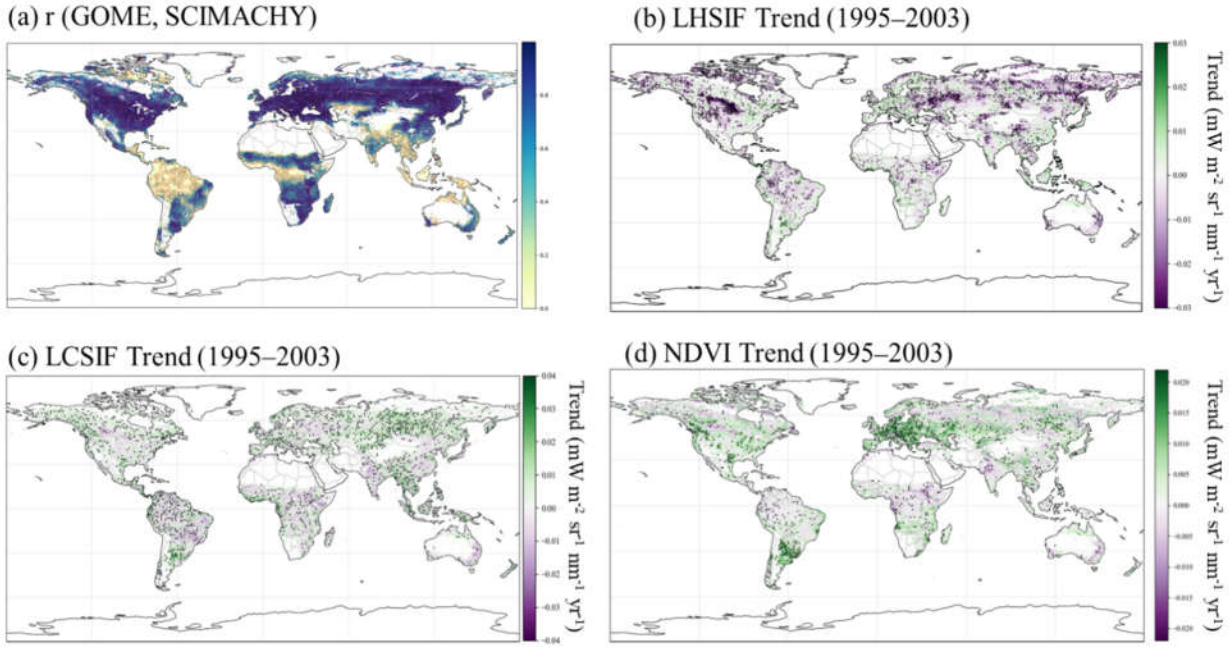

Figure 14 Comparisons of GOME SIF, SCIAMACHY SIF, LHSIF, LCSIF, and AVHRR NDVI during 1995–2003. (a) Correlation coefficient between GOME and SCIAMACHY SIF time series; annual trends of (b) LHSIF, (c) LCSIF, and (d) AVHRR NDVI. The scatter points represent statistical significance($p < 0.05$).

These inconsistencies may reflect several limitations of the early GOME record, including (i) the coarse spatial resolution that amplifies mixed-pixel effects (Joiner et al., 2013), (ii) the relatively low signal-to-noise ratio of the GOME instrument (Burrows et al., 1999), (iii) increased retrieval uncertainties in high-latitude regions with low fluorescence intensity (Köhler et al., 2015), and (iv) potential uncorrected sensor degradation effects. As our harmonization approach primarily reduces inter-sensor biases through normalization, it cannot fundamentally resolve these intrinsic limitations of the original GOME data. In addition, errors may also arise from the propagation and accumulation of uncertainties during the normalization process, since GOME was further adjusted based on the corrected SCIAMACHY product.

Future work will require dedicated strategies to address the intrinsic limitations of early GOME observations. Such strategies may include radiometric recalibration using pseudo-invariant sites (Zou et al., 2024) and also physically-based harmonization approaches to mitigate sensor inconsistencies arising from observation geometry, atmospheric conditions, pixel size, and background signals. Implementing these approaches will enhance the reliability of early trends, providing a more robust foundation for interpreting long-term variations in satellite-observed SIF.

(2) In Figure 10, LHSIF and LCSIF show similar relative magnitudes and variations in the early period, in contrast to LTSIF_c*. This might serve as supporting evidence to strengthen confidence in early-stage SIF data, and could perhaps be discussed in the manuscript. BTW, in 10d (subpanel), there appears to be a typo: “coldl?”. Please correct.

Response: We thank the reviewer for highlighting the potential comparison with early-stage data. The revisions are as below:

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The results show that a six-month overlap leads to a higher standard deviation in SIF time series compared to longer overlaps. As the overlap period was extended from 6 to 12 months, the standard deviations of the normalized SIF series decreased from 0.015 to 0.007 mW m^{-2} sr^{-1} nm^{-1} (SCIAMACHY) and from 0.018 to 0.005 mW m^{-2} sr^{-1} nm^{-1} (OCO-2), representing a reduction of over 53.3%. These results confirm that short overlap periods increase normalization uncertainty and highlight the robustness of our chosen strategy, which avoids using GOME as the baseline. Besides, the early-stage LHSIF exhibits consistency with LCSIF (Fig. 10a), providing additional support for its early-period reliability.

The figure captions have been standardized, the panels have been reordered according to climate zones and land-cover types, and the original typographical errors have been corrected. The revised figure is provided below.

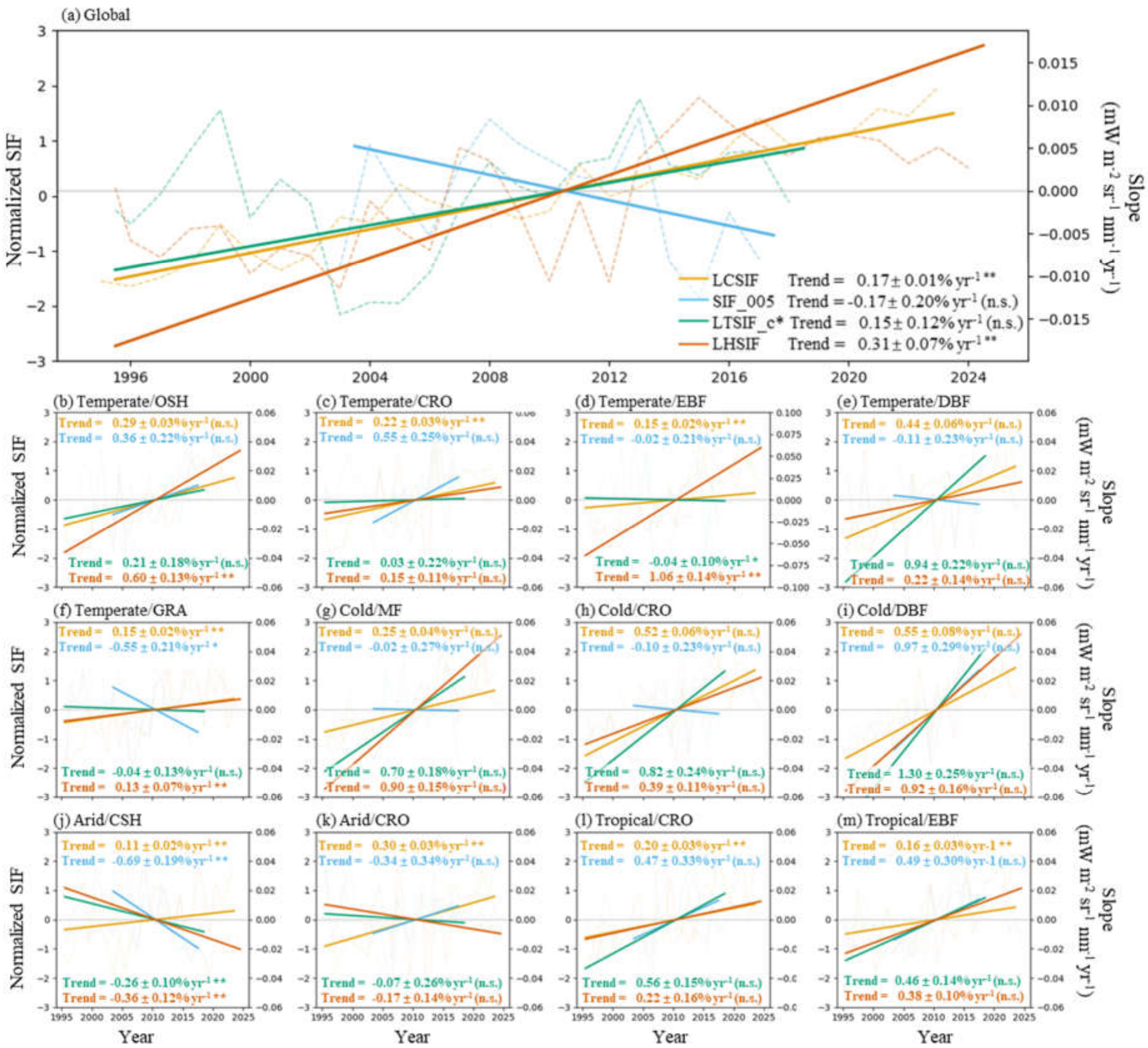

Figure 10. Comparison of interannual variations in long-term SIF products. LHSIF (red), LT_SIFc* (green), SIF_005 (purple), and LCSIF (blue) are compared for (a) the global scale and (b–m) various climatic and vegetation regions. All datasets were normalized using the z-score method. Dashed lines represent yearly maximum values, and solid lines indicate linear trends. To aid visual comparison, trend lines were anchored at the origin (2010, 0). The statistical significance of the trends is indicated as follows: n.s. for not significant (p ≥ 0.05), * for significant (p < 0.05), and ** for highly significant (p < 0.01).

Comment 3: Concerning previous major comment #5, the authors mention that LHSIF can more directly reflect regional responses to environmental variability compared to LCSIF. It would be helpful to include more supporting evidence on this point. For example, in Figure 10a, could the authors highlight specific years where LCSIF and LHSIF differ noticeably, and relate these differences to known climatic events or anomalies? This could help illustrate the advantages of LHSIF more clearly.

Response: We thank the reviewer for this valuable suggestion. Satellite-observed SIF has been shown to capture ecosystem responses to major climatic events, such as the suppression of photosynthesis during the 2015/16 El Niño in the tropics and drought-induced declines in Europe and North America (Shekhar et al., 2020; Sun et al., 2015; Yoshida et al., 2015). Our study builds directly on these observational SIF datasets, thereby retaining their advantages in reflecting environmental variability. Therefore, in principle, LHSIF is expected to capture climate-driven events more effectively than LCSIF, which is based on data-driven method.

While differences between LHSIF and LCSIF may partially related to climate anomalies, this should not be interpreted as definitive evidence. Firstly, interannual fluctuations in SIF products arise from multiple sources, including retrieval uncertainties and residual atmospheric effects. Therefore, annual variations cannot be directly attributed to climatic events. Secondly, extreme climatic events may not be fully represented in the global mean values. Robust attribution would require regionally explicit analyses, which are beyond the scope of this study.

Although Figure 10 does not highlight climate events in specific years, the overall trends reflect the advantages of LHSIF. Consequently, instead of highlighting specific years in Figure 10a, we have expanded the discussion in Section 4.2 to emphasize the benefits of observation-based SIF products and to encourage future studies to examine the relationship between LHSIF and climatic events in a more regionally explicit manner.

4.2 Limitations and future perspectives

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Another type of long-term SIF datasets have been generated by temporally extrapolating SIF observations based on machine-learning methods. These datasets provide more than two decades of high-temporal-resolution data beyond the monthly scale (Zhang et al., 2018b; Li and Xiao, 2019; Fang et al., 2023). However, such datasets predominantly depend on model-driven predictions constrained by satellite observation periods, rather than being based on actual observational data, which is fundamentally different from the approach employed here (Chen et al., 2025; Ma et al., 2022).

Previous findings have demonstrated that satellite-observed SIF is capable of capturing ecosystem responses to major climatic extremes, such as the suppression of photosynthesis during the 2015/16 El Niño event in the tropics and drought-induced declines in Europe and North America (Shekhar et al., 2020; Sun et al., 2015; Yoshida et al., 2015). These findings provide support for the potential advantages of LHSIF in reflecting regional environmental variability. Nevertheless, detailed attribution of interannual differences among products to specific climatic events requires dedicated analyses and applications, which should be pursued in future work. Currently, the temporal resolution of purely observation-based enhanced SIF products that span longer than 20 years remains constrained at the monthly scale, largely due to noise in the satellite SIF products. Overcoming this limitation will require further refinement of existing downscaling models, paving the way for future products to achieve a resolution of 16 days or higher.

Comment 4： In Detailed Comments #14 and #15, the publication year for the reference "Du" is inconsistent. Please verify and correct for consistency.

Response: Thanks for this comment. All citations have now been verified and standardized to "Du et al., 2023".

The references cited in the response are listed below:

https://doi.org/10.5194/essd-2025-94
Burrows, J. P., Weber, M., Buchwitz, M., Rozanov, V., Ladstätter-Weißenmayer, A., Richter, A., DeBeek, R., Hoogen, R., Bramstedt, K., Eichmann, K.-U., Eisinger, M., and Perner, D.: The Global Ozone Monitoring Experiment (GOME): Mission Concept and First Scientific Results, Journal of the atmospheric sciences, 56, 151–175, https://doi.org/10.1175/1520-0469, 1999.

Chen, S., Liu, L., Sui, L., Liu, X., and Ma, Y.: An improved spatially downscaled solar-induced chlorophyll fluorescence dataset from the TROPOMI product, Scientific Data, 12, 135, https://doi.org/10.1038/s41597-024-04325-6, 2025.

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