Dear Reviewer,

We sincerely thank you for your thorough review of our manuscript and for your valuable comments and suggestions. Your insights have been instrumental in improving the clarity, depth, and overall quality of our work. Below, we address each of your comments in detail.

Major Comments:

(1) Threshold Values for Ecoregion Grouping:

Comment: The authors grouped the 11 ecoregions into three categories based on their precipitation regimes, using various thresholds such as high monthly variability (standard deviation ≥ 120 mm), relatively high mean annual rainfall (> 2400 mm), low monthly variability (standard deviation ≤ 100 mm), and relatively lower mean annual rainfall (< 2200 mm). However, the selection of these threshold values appears arbitrary, with no references provided to justify their choice.

Response:

We understand your concern about the selection of thresholds appearing arbitrary. However, considerable thought and analysis went into determining these groupings. Our classification was based on a combination of geographical location, environmental thresholds, and the observed characteristics of the seasonality in the spaceborne vegetation indices (VIs) and solar-induced chlorophyll fluorescence (SIF) data.

To address your comment and enhance clarity, we have moved and expanded upon our rationale, which was at the beginning of the results section, to the end of the methods in Section 2.8.:

2.8 West African and Central African Tropical Forests

We noticed that the wettest ecoregions also had the highest variability in monthly total rainfall, and that there was a dissimilarity in our results among the wettest ecoregions with high variability in monthly precipitation and the drier ecoregions with low variability. Thus, we classified the 11 ecoregions into three groups according to their precipitation regime, monthly variability, and mean annual rainfall (Table S1). Four ecoregions in West Africa were characterized by seasonalities that had distinctive single wet and dry periods each year, high monthly variability (standard deviation ≥ 120 mm), and relatively high mean annual rainfall (> 2400 mm). We classified these ecoregions as West African moist tropical forests, which included the Cameroonian Highlands, Cross-Sanaga-Bioko Coastal Forest, Nigerian Lowlands and Niger Delta, and Western Guinean Lowlands. The six Central African ecoregions were characterized by seasonalities that typically had a double-peak pattern, low monthly variability (standard deviation ≤ 100 mm), and relatively lower mean annual rainfall (< 2200 mm). We classified these forests as Central African tropical forests. The precipitation regime of the Eastern Guinean ecoregion in West Africa had mean annual rainfall (1544 mm) and monthly rainfall variability (81 mm) that was more similar to the Central African ecoregions.

Additionally, we have included a new figure (Figure S1; below) in the supplementary materials. This figure plots the mean annual total precipitation and the standard deviation of monthly total precipitation for the 11 African tropical evergreen broadleaf ecoregions, color-coded according to the forest groups used in our study. This visual representation demonstrates the natural clustering of ecoregions based on their precipitation characteristics and supports our grouping methodology.

Our primary goal in grouping the ecoregions was to facilitate a meaningful discussion of regions with similar environmental conditions and observed seasonal patterns in SIF and VI data. The thresholds we selected emerged from our analysis of the data and were instrumental in highlighting the distinctions and similarities among the ecoregions. While these specific thresholds may not have been previously cited in the literature, they are grounded in the observed data and are appropriate for the context of our study.

Grouping ecoregions in this manner is a common practice when analyzing ecological data, as it allows for more nuanced interpretations and discussions of regional patterns and processes. Our approach does not necessitate prior usage in other research but is justified by the logical grouping based on observed environmental and phenological characteristics relevant to our study objectives.

We hope this explanation clarifies our rationale and assures you of the thoroughness of our methodology. Thank you again for your valuable feedback, which has helped us improve the clarity of our manuscript.

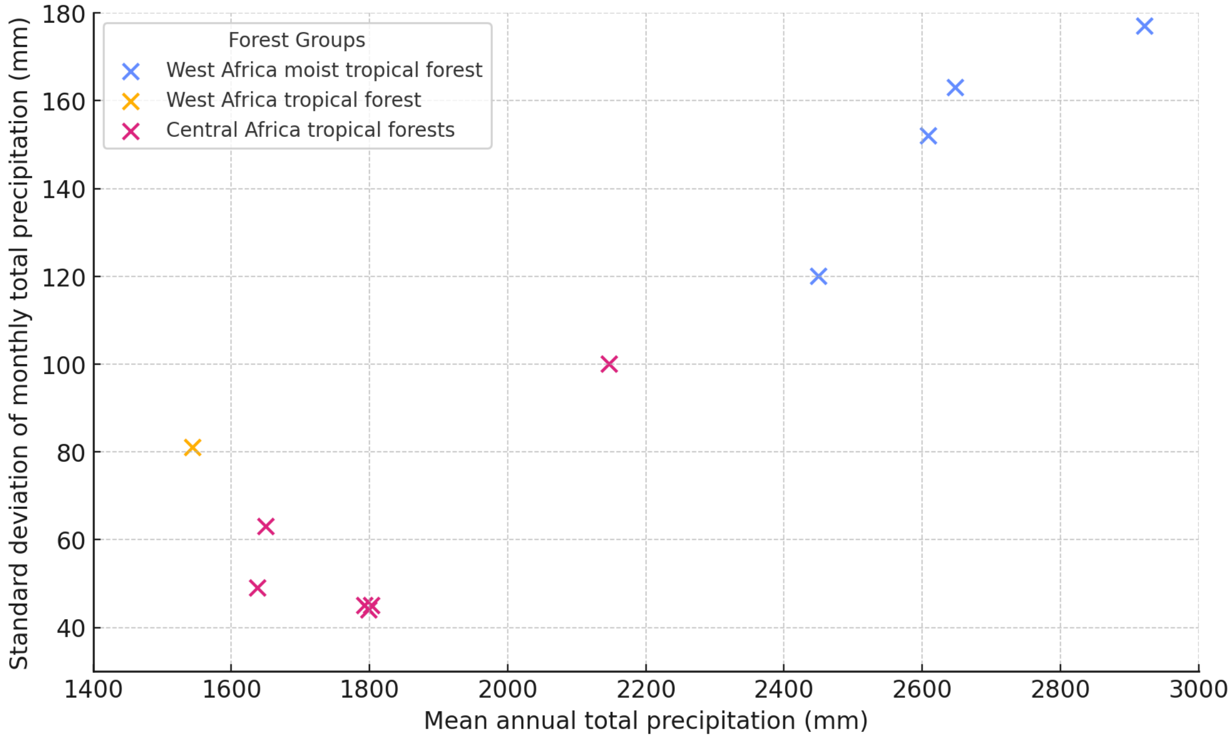

Figure S1. Mean annual total precipitation and standard deviation of monthly total precipitation in 2019-2021 for 11 African tropical evergreen broadleaf ecoregions, color coded according to the forest groups we used in our study.

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(2) Addressing the Second Hypothesis and Physiological Mechanisms:

Comment: For the second hypothesis, the authors sought to test whether SIF would be more strongly linked to precipitation in less moist African forests and whether SIF and VPD would be positively correlated in moist forests. However, this hypothesis was not addressed in the Results and Discussion. There is a lack of explanation from the perspective of plant physiology regarding how these two distinct mechanisms—soil moisture deficit and atmospheric dryness—operate in African forests.

Response: We appreciate your pointing out that our second hypothesis was not adequately addressed. We have re-written section 3.2.2, now labeled section 3.3, to more clearly address our hypothesis and provide a deeper understanding as requested in major comment number 5. Here is the text of the new session.

Section 3.3

Our second hypothesis posited that solar-induced fluorescence (SIF) would be more strongly coupled with precipitation in less moist African forests and that SIF and vapor pressure deficit (VPD) would be positively correlated in moist forests. Our analysis supports the first part of this hypothesis but contradicts the second.

In less moist forests (mean annual precipitation < 2000 mm), we found that SIF was significantly positively correlated with precipitation and significantly negatively correlated with VPD (Figs. S1 and S2). This suggests that soil moisture availability is a key driver of photosynthesis in these regions; limited precipitation leads to soil moisture deficits that constrain plant physiological processes.

Examining relationships across all ecoregions, we observed that as mean annual precipitation and the variability of monthly total precipitation increased, the correlation between SIF and precipitation weakened, while the correlation between SIF and VPD strengthened (became more negative) (Fig. 4). This indicates that in moist forests (mean annual precipitation > 2000 mm), SIF was more strongly related to VPD than to precipitation.

Contrary to the second part of our hypothesis, we found that SIF and VPD were negatively correlated in moist forests rather than positively correlated. This suggests that in these high-rainfall ecosystems, high atmospheric dryness (high VPD) inhibits photosynthesis, leading to decreased SIF.

We also examined the relationships between vegetation indices (VIs) and environmental factors. Across all sites—except for the Atlantic Equatorial Coastal Forest where relationships were not significant—the Enhanced Vegetation Index (EVI), Near-Infrared Reflectance of vegetation (NIRv), and Normalized Difference Vegetation Index (NDVI) were negatively related to VPD and positively associated with precipitation. The correlations between these VIs and temperature and photosynthetically active radiation (PAR) were generally negative or insignificant.

Assessing whether SIF and the VIs were more strongly correlated with VPD or precipitation at each site, we found that conclusions could depend on the correlation method used. For instance, in the Nigerian Lowland and Niger Delta Forest, Spearman's correlation coefficient between SIF and VPD was –0.73, and between SIF and precipitation was 0.57. However, using Pearson's correlation, the coefficients were –0.65 and 0.66, respectively. Thus, Spearman's correlation suggests that SIF is more strongly correlated with VPD, while Pearson's indicates negligible differences between the correlations. To address this discrepancy, we reported correlation matrices for both methods (Figs. S1 and S2).

To determine how relationships between SIF, EVI, and NDVI with VPD and precipitation changed with increasing mean annual precipitation and variability in monthly precipitation, we compared correlation coefficients across all ecoregions. Regardless of the correlation method used, the correlation between SIF and VPD strengthened (became more negative), while the correlation between SIF and precipitation weakened with increasing mean annual precipitation and greater variability in monthly precipitation (Fig. 4). This indicates that in forests with higher annual rainfall and more variable monthly precipitation, SIF becomes increasingly related to VPD and less related to precipitation.

Conversely, NDVI showed a stronger correlation with precipitation and a weaker correlation with VPD in these wetter forests. However, this relationship is likely influenced by NDVI's saturation in dense canopies, causing it to mirror the seasonality of precipitation without capturing changes in photosynthetic activity. No significant correlation was found for EVI in these forests.

When assessing the relationships between SIF, environmental factors, and VIs, we observed differing patterns in their responses to precipitation and VPD across the ecoregions (Fig. 4). Specifically, while SIF showed a weakening correlation with precipitation and a strengthening negative correlation with VPD as mean annual precipitation increased, EVI and NIRv did not exhibit significant changes in their correlations with these environmental factors. NDVI displayed an opposite trend to SIF, showing an increasing correlation with precipitation and a decreasing correlation with VPD in wetter forests.

These differing patterns suggest a potential decoupling between photosynthesis (as indicated by SIF) and canopy structure (as indicated by VIs like EVI and NIRv) in African tropical forests. In moist forests with high mean annual precipitation and variability, the canopy structure remains relatively constant throughout the year due to the evergreen nature of the forests. This results in stable EVI and NIRv values that are less sensitive to short-term environmental fluctuations. In contrast, photosynthetic activity, as indicated by SIF, can vary significantly in response to atmospheric conditions such as VPD.

One possible explanation for this decoupling is that SIF is more directly linked to the physiological status of leaves, capturing changes in photosynthetic efficiency and electron transport rates not necessarily reflected in canopy structural metrics. High VPD in moist forests can lead to stomatal closure to prevent excessive water loss, reducing CO_2 uptake and photosynthesis without significantly altering canopy structure or leaf area index (LAI). As a result, SIF decreases while EVI and NIRv remain relatively unchanged.

In less moist forests, where soil moisture deficits are more common, both photosynthesis and canopy structure can be affected by changes in precipitation. Limited water availability can lead to reduced leaf area through leaf shedding or inhibited growth, which is reflected in decreases in both SIF and VIs. This explains the stronger coupling between SIF and VIs in response to precipitation in these regions.

(3) Enhancing the Introduction with African Forest Background:

Comment: The Introduction should be reworked to emphasize the importance and current understanding of African forests. Now there is little description of the background of African forests. I would like to see (i) what is the climate background, (ii) what are the dominant vegetation species, and (iii) what is the current understanding of trends, inter-annual variations, and seasonality (most important since this is the topic of the study).

Response: Great suggestion! We have added two paragraphs to the introduction that follow the first. Here they are:

Rainfall seasonality in the tropical regions of West and Central Africa are primarily driven by the monsoon and the Intertropical Convergence Zone (ITCZ) (Longandjo and Rouault 2024). These two large-scale atmospheric processes create seasonal variations that bring distinct wet and dry seasons. Most areas near the equator including parts of Coastal West Africa and Central Africa experience two distinct passes of the ITCZ each year, resulting in a bimodal rainy season (Nicholson and Grist 2023). Byrne et al. (2018) reported a narrowing and strengthening of rainfall in the ITCZ over recent decades, based on satellite observations and simulation studies. However, their study found no evidence of a shift in the ITCZ's location.

The floristic composition and distribution of the tropical forests in the Guineo-Congolian region of West and Central Africa remain poorly sampled and understood (Sosef et al., 2017). Despite this, there is a general consensus that rainfall significantly influences floristic patterns across the region (Fayolle, 2014). Various authors have classified African tropical forests in different ways over time, including White (1979). However, a recent study by Fayolle et al. (2014) categorizes these forests into four groups: Wet-moist West Africa, Dry West Africa, Wet Central Africa, and Moist Central Africa. Using the RAINBIO database of tropical African vascular plant species, Sosef et al. (2017) reported a total of 22,577 species in the region. However, the authors emphasized that tropical forest biodiversity is still inadequately sampled.

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(4) Introducing Satellite Vegetation Indices Earlier:

Comment: In the Introduction, the author mentions the use of satellite SIF to explore the relationship between photosynthesis and environmental factors. However, since satellite vegetation indices are also used later in the study, it would be beneficial to introduce these indices earlier and provide justification for the use of multiple satellite vegetation indicators.

Response: We agree with this suggestion, and Reviewer 1 had a similar comment. We now introduce VIs in the title and abstract. We also further elaborate on our focus of EVI over NDVI. Please see our responses to Reviewer 1.

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(5) Exploring Differing Patterns of SIF and Vegetation Indices:

Comment: The differing patterns of SIF in comparison to EVI and NIRv in response to precipitation in Fig. 4 are interesting. I would expect the authors to explore this more thoroughly, providing a deeper explanation rather than only describing the empirical relationship. Does this suggest a decoupling between photosynthesis and canopy structure? Additionally, I would suggest the authors test whether the sampling times for SIF and MODIS vegetation indices are approximately the same. The authors mention that SIF retrieval is less sensitive to cloud cover, whereas MODIS vegetation indices are more affected by clouds.

Response: We have rewritten section 3.2.2 (now 3.3) to provide a deeper explanation; please see our response to major comment number 2 above.

It is not immediately clear what the implications would be for the differences in overpass time for MODIS and the satellites from which SIF is retrieved, as the reviewer seems to have something in mind here. SIF values are aggregated to daily values to account for differences in sampling time, as discussed in the methods section and the papers for the SIF datasets. Also, vegetation indices (or vegetation greenness) do not have diurnal patterns that would have affected comparisons. One of the reasons we chose a monthly time step at the ecoregion scale was to marginalize potential biases that might arise due to variances and differences in data acquisition from the different sensors.

We have added a section to the discussion that discusses the potential limitations of our study, which includes sensor characteristics and cloud cover. Please see our response below and Section 4.4.

Minor Comments:

Abstract:

Line 16: *The authors did not investigate actual photosynthesis; instead, they investigate SIF, which is an indicator of photosynthesis.*

Response: We agree! We have revised it as, "...to investigate the seasonality and synchrony of photosynthesis…".

Line 17: *Maybe delete the Amazon here since the aim of the study is not to compare African tropical forest and Amazon.*

Response: Thank you for this suggestion, but we see it important to compare and contrast our findings with what is known from field and spaceborne observations of the Amazon. Please see our response to Reviewer 1 on this point:

Our primary aim is to enhance the understanding of the seasonality of photosynthesis in African tropical forests and its synchrony with environmental factors. We chose to compare our findings with those from the Amazon for several important reasons:

Benchmarking Against Well-Studied Systems: The Amazon rainforest has been extensively studied, particularly regarding the seasonality of photosynthesis and its environmental drivers. By comparing African tropical forests to the Amazon, we can contextualize our results within a broader framework of tropical forest ecology. This comparison allows us to identify unique patterns and commonalities, thereby enriching the global understanding of tropical forest dynamics.

Highlighting Regional Differences and Similarities: Our comparison reveals both parallels and contrasts in the seasonality of photosynthesis between the two regions. For instance, while both regions exhibit increases in SIF during the dry season, the underlying environmental drivers and physiological responses differ. Discussing these differences enhances the scientific value of our work by highlighting how regional climatic conditions influence tropical forest productivity.

Addressing Knowledge Gaps: Given that African tropical forests are less studied compared to the Amazon, drawing parallels helps to fill knowledge gaps. It allows us to leverage the extensive body of research from the Amazon to interpret our findings and propose hypotheses about the mechanisms driving photosynthesis seasonality in Africa.

Advancing Ecological Theory: Comparing these two major tropical forest systems contributes to the development of general ecological theories about tropical forest functioning. It helps determine whether observed patterns are consistent across different continents or are region-specific due to unique environmental conditions.

Informing Global Climate Models: Understanding similarities and differences in photosynthetic responses is crucial for improving the accuracy of global carbon cycle models. By incorporating data from both African and Amazonian forests, we can better predict how tropical forests might respond to climate change on a global scale.

In light of these points, we believe that the comparison with the Amazon significantly enhances the interpretation and relevance of our findings. It not only aligns with the manuscript's aim but also provides a comprehensive perspective that benefits the broader scientific community.

Once again, we appreciate your feedback and hope this explanation clarifies the importance of including the comparison in our discussion.

Introduction:

Line 25: *"Carbon store" -> "carbon storage"?*

Response: Reviewer 1 suggested we change ‘carbon store’ to ‘carbon stock’, so we did so accordingly.

Line 31-33: *Add references.*

Response: We have added references.

Line 35: *What is the meaning of "carbon gains"? Carbon fluxes or storage?*

Response: We have reworded this to specify we are discussing carbon sink, “...assess gains and losses in the net carbon stock…”.

Paragraph Line 41: *Please rephrase this paragraph. The first sentence mentions little work has been done to study the seasonality of West African tropical forests. However, the other part does not mention anything related to the seasonality. It seems the authors tried to introduce several knowledge gaps but without very clear and organized presentation.*

Response: Thank you, the paragraph now reads:

Satellite remote sensing studies have identified a double peak in the seasonality of leaf area and greenness in the Congolian tropical forests, which aligns with precipitation patterns. However, little research has been published on the seasonal dynamics of West African tropical forests, highlighting a significant knowledge gap. Understanding these seasonal patterns is crucial, especially amid debates over long-term vegetation changes in African tropical forests. While some studies have suggested a significant long-term browning trend in the Congolian forests, potentially linked to large-scale drying events (Zhou et al., 2014; Asefi-Najafabady and Saatchi, 2013; Jiang et al., 2019; Malhi and Wright, 2004), the most recent research found no widespread long-term decline in leaf area or greenness (Sun et al., 2022). This finding aligns with field observations showing no significant trend in the net carbon sink, suggesting that African tropical forests may be relatively resilient to climate variability. Addressing the lack of knowledge on the seasonality of West African tropical forests is therefore essential to fully understand the ecological dynamics and climate resilience of these ecosystems.

Line 65: *Maybe add Wang et al. (2023) in the introduction, which explores how different climate factors influence tropical forests using SIF.*

Response: Thank you for the suggestion, we have added Wang et al. (2023).

Line 67-68: *Not a complete sentence.*

Response: This sentence is a list that uses semicolons to separate the elements:

The studies that have utilized spaceborne SIF to investigate tropical Africa have found that (1) temperature and vapor pressure deficit (VPD)—which are interlinked because higher temperatures increase VPD by raising the air's capacity to hold moisture— control the productivity of African tropical forests (Madani et al., 2017; Umuhoza et al., 2023); (2) SIF tracks well the seasonality of photosynthesis, or gross primary productivity (GPP), over Africa (Mengistu et al., 2021); and (3) SIF has weak to insignificant relationships with VIs and VI-based APARchl (Doughty et al., 2021b).

Line 75: *Define ecoregions.*

Response: We have added the following statement to the beginning of Section 2.7 Ecoregions in the methods section:

An ecoregion is a substantial geographic area characterized by a unique composition of natural communities and ecosystems, where the majority of its species, ecological interactions, and environmental conditions are distinct and unified. These regions reflect the historical distribution of specific species and ecosystems and are categorized within broader biomes like forests, grasslands, or deserts, encompassing the diversity of terrestrial life on Earth.

Methods:

Sections 2.1, 2.2, and 2.5: *Not sure how the authors gridded these data to match climate reanalysis.*

Response: Actually, all data was used as-is. We did not grid the ungridded data and we did not re-grid any of the data. We have clarified this by moving Section 2.6 Copernicus Forest Cover to the beginning of the methods section and clarifying our approach:

We used both gridded and ungridded data in our analyses and these datasets are explicitly described below. All data were filtered using the 100-m Copernicus Land Cover dataset for the year 2019 (data after 2019 is not available) (Buchhorn et al., 2020), thus we only used data that fell within the forested areas. All data was used as-is without gridding or re-gridding, and values were aggregated to monthly timesteps at the ecoregion scale. To help ensure that our spaceborne data were acquired over forest and to reduce the likelihood of mixed pixels and soundings with mixed land cover types, we converted the forest land cover raster data to polygon and created a 2.5 km inner buffer.

Section 2.4 ERA5 Reanalysis: *I am not sure whether the author used CHIRPS Precipitation instead of ERA5 precipitation.*

Response: Thanks, we have clarified that we used CHIRPS precipitation data in what is now section 2.4 CHIRPS Precipitation:

Our precipitation data came from Climate Hazards group InfraRed Precipitation with Stations (CHIRPS), which is a long-term, near-global, daily data set.

Section 2.7 Ecoregions: *Please expand the description. It would be good to provide a map of ecoregions of the study area. How many types of Africa's tropical forest types do you have? How are they defined?*

Response: We have added a definition for Ecoregion, have elaborated on how ecoregions are defined, and now note how many forest ecogreions there are in Tropical Africa:

An ecoregion is a substantial geographic area characterized by a unique composition of natural communities and ecosystems, where the majority of its species, ecological interactions, and environmental conditions are distinct and unified. These regions reflect the historical distribution of specific species and ecosystems and are categorized within broader biomes like forests, grasslands, or deserts, encompassing the diversity of terrestrial life on Earth. We used the Terrestrial Ecoregions of the World boundaries (Olson et al., 2001) to distinguish between Africa's tropical forest types (Fig. 1), of which there are twelve. We combined the Nigerian Lowland Forests and the Niger Delta Swamp Forest ecoregions, which are adjacent to each other, in our analyses due to the sparsity of forest and spaceborne data for these forests.

Results:

Lines 212, 215, and 216: *"Sites" -> "ecoregions"?*

Response: Great catch, we have made these changes.

Figure 4: *Why don't you show the scattering plot at the pixel level?*

Response: As we now clarify in section 2.1 of the methods, all data was aggregated to monthly at the ecoregion scale. SIF data is not gridded, and is provided at the sounding level. There are no official gridded SIF datasets, as gridding SIF data is generally not advised. Variability and trends in SIF at a pixel level would be extremely biased by differences in spatial and temporal sampling, sun-sensor geometry, and sampling frequency. Also, uncertainty can be very high and variable at the pixel level for SIF data. I discuss these issues more fully in Section 5 of my paper on GOSAT, OCO, and OCO-2 SIF data (Doughty et al. 2021), and the regional-scale aggregation of SIF data is an approach that I have employed in nearly all of my papers.

Section 3.3 Robustness of the SIF Signal: *I think this part should go into Discussion or Supplementary. Also, there is no unit in Fig. 7.*

Response: We agree and have moved this section to the Discussion as section 4.4. There is not room on the y-axis for the label, so we included it in the legend. To further clarify, we have also added it to the figure caption.

Discussion:

Line 271: *Why suddenly discuss Amazon vs. African forests? I think the paper does not intend to compare Amazon and African forests since the authors did not mention any results of Amazon before.*

Response: Thank you for your opinion. We have responded to this concern in detail.

Line 305: *Not sure whether the authors have defined physiology and phenology.*

Response: We delineated this difference by adding the underlined text to our manuscript:

Recent advancements in the retrieval of solar-induced chlorophyll fluorescence (SIF) from space provides an observation-based method for monitoring plant physiology and the amount of PAR absorbed by chlorophyll ($APAR_{chl}$) and has been described as a proxy of photosynthesis (Doughty et al., 2019, 2021b). SIF is a small amount of energy that is re-emitted by chlorophyll (1%-2%) and is sensitive to leaf physiology, <u>which are the functions and processes within a plant leaf, including how it absorbs sunlight, exchanges gases through stomata, transports water and nutrients, and carries out photosynthesis</u> (Johnson and Berry, 2021; Porcar-Castell et al., 2021, 2014). <u>Because SIF is emitted during the light reactions of photosynthesis, it is directly sensitive to both the quantity of light absorbed and the efficiency with which that light is used for carbon fixation. This makes SIF a more direct proxy of photosynthetic activity and plant productivity compared to traditional vegetation indices, which primarily capture canopy greenness and structure.</u>

Additional Suggestion:

The authors may add a paragraph to describe the uncertainty or limitation of this study.

Response: Thank you for this important suggestion. We have added this section to the Discussion:

4.4 Uncertainties and Limitations

While our study advances the understanding of photosynthetic seasonality in African tropical forests using spaceborne SIF data, we acknowledge that there are several uncertainties and limitations of our study.

First, satellite-based SIF measurements, although powerful for large-scale observations, come with inherent uncertainties due to sensor characteristics and retrieval algorithms. Differences between OCO-2, OCO-3, and TROPOMI—such as spatial resolution, overpass time, viewing geometry, and retrieval methods—can introduce biases and inconsistencies in the SIF data (Doughty et al., 2021a). The higher bias observed in OCO-2 and OCO-3 relative to TROPOMI may be attributed to these factors, potentially affecting the comparability of our results across different sensors.

Second, atmospheric conditions prevalent in tropical regions, particularly cloud cover and aerosols, can impact the accuracy of SIF retrievals despite efforts to mitigate these effects (Guanter et al., 2015). Although we avoided applying a cloud fraction threshold to prevent clear sky bias, residual atmospheric disturbances may still influence the SIF signals, leading to possible overestimation or underestimation of photosynthetic activity.

Third, the lack of ground-based validation data poses a significant limitation. The scarcity of eddy covariance towers and other in situ measurements in structurally intact African tropical forests restricts our ability to validate satellite-derived SIF data and to calibrate the relationships between SIF, GPP, and environmental variables (Malhi, 2012; Williams et al., 2007). Without ground truthing, it remains challenging to disentangle the contributions of leaf physiology, phenology, and canopy structure to the observed SIF signals, and to attribute observed variations in SIF to specific environmental drivers with high confidence.

Fourth, our assumption that SIF is a reliable proxy for photosynthetic activity may not fully capture the complexity of plant physiological responses. SIF is influenced by multiple factors, including canopy structure, leaf area index, chlorophyll content, and fluorescence yield, which can vary independently of GPP (Porcar-Castell et al., 2014; Magney et al., 2020). The relationship between SIF and GPP can be affected by environmental stressors, such as VPD and temperature, which may alter fluorescence efficiency without a proportional change in photosynthesis (Gonçalves et al., 2020). Without concurrent measurements of leaf-level physiological parameters, attributing changes in SIF to specific processes remains challenging.

Additionally, the climate and environmental data used in our analyses introduce their own uncertainties. Reanalysis products like ERA5 may not capture localized microclimatic variations and can be less accurate in regions with sparse observational data (Beck et al., 2017). Satellite-derived vegetation indices may suffer from saturation effects in dense canopies and can be influenced by sensor noise and atmospheric conditions (Huete et al., 1997b). These uncertainties may affect our assessments of the relationships between SIF, vegetation indices, and environmental factors.

Furthermore, our spatial analysis at the ecoregion level may mask heterogeneity within ecoregions due to variations in species composition, soil properties, topography, and anthropogenic disturbances. The coarse spatial resolution of some datasets may lead to mixed pixels, especially near forest edges or in fragmented landscapes, potentially confounding the interpretation of SIF signals.

Addressing these limitations requires the integration of additional ground-based observations, improved satellite retrieval algorithms, higher-resolution datasets, and extended time series. Establishing a network of eddy covariance towers and phenological monitoring sites across African tropical forests would greatly enhance the validation and interpretation of satellite-derived SIF data. Future studies should also explore advanced modeling approaches that account for the complexity of plant physiological processes and incorporate data from upcoming satellite missions with enhanced capabilities.

Once again, we appreciate your constructive feedback and believe that these revisions will significantly strengthen our manuscript. We are committed to addressing all your comments thoroughly and look forward to submitting a revised version for your consideration.