Dear Editor and Reviewers,

We are so grateful to receive the valuable comments and suggestions from the reviewers which are essential for improving the quality of this paper and making our conclusions more convincing. We also appreciate you kindly giving us an opportunity to revise it. With the suggestions and comments from the reviewers, we added several parts to strengthen the results and discussion, such as calculating and integrating pixel-scale ensemble statistics (mean, standard deviation, maximum, and minimum) into the Multi-ensemble Biomass-burning Emissions Inventory (MBEI) dataset to explicitly quantify uncertainty. Additionally, we significantly expanded the discussion to address the trade-offs between temporal consistency (MODIS) and spatial resolution (VIIRS), as well as the physical limitations regarding small-fire detection and fuel load estimation. We have also condensed the abstract and improved the visual quality of the figures. We have carefully studied all precious comments and suggestions and did our best to revise this manuscript. The revised part has been highlighted in yellow color and the responses to reviewers’ comments are attached to this file. We hope that our responses are satisfactory for you and the reviewers. The dataset is publicly available at https://doi.org/10.5281/zenodo.18104830.

Yours sincerely,

Shuai Yin

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**Responds to the reviewer’s comments:**

**-------------------------------------------------------------------------------------------**

**Reviewer #1:**

This study presents a new framework (MBEI) that integrates top-down and bottom-up algorithms by combining two fire-detection products with four sets of key input variables, yielding eight distinct sub-inventories of biomass-burning emissions. Compared to existing inventories, these new datasets uniquely provide the maximum–minimum range of all eight sub-inventories, thereby quantifying estimation uncertainty. This rich information allows data users to directly incorporate sensitivity analyses into their own studies and thus provides critical support for exploring complex global biomass-burning dynamics. The paper is well written and offers new insight into biomass-burning research. However, a few points need to be addressed. Therefore, I recommend that the manuscript be accepted for publication after a revision.

Major concerns:

1. Although the new dataset includes eight groups of sub-inventories, the mean values and uncertainty information (e.g., standard deviation, minimum, and maximum) for these ensemble inventories are not provided at the pixel scale. I suggest that the authors calculate these statistics on a per-pixel basis and include them in the dataset. This information is highly valuable to data users and should be made publicly available.

**Response:** We sincerely thank the reviewer for this highly constructive suggestion regarding the accessibility of pixel-scale uncertainty information. We fully acknowledge that while the generation of eight independent sub-inventories constitutes the structural core of our ensemble framework, the practical utility of this dataset for downstream applications—such as atmospheric transport modeling and air quality assessment—relies heavily on the availability of synthesized statistical metrics at the grid scale. Providing the raw sub-inventories alone places an unnecessary computational burden on the user, whereas pre-calculated ensemble statistics provide immediate, actionable insight into the spatial reliability and variance of the emission estimates. The dataset is publicly available at https://doi.org/10.5281/zenodo.18104830.

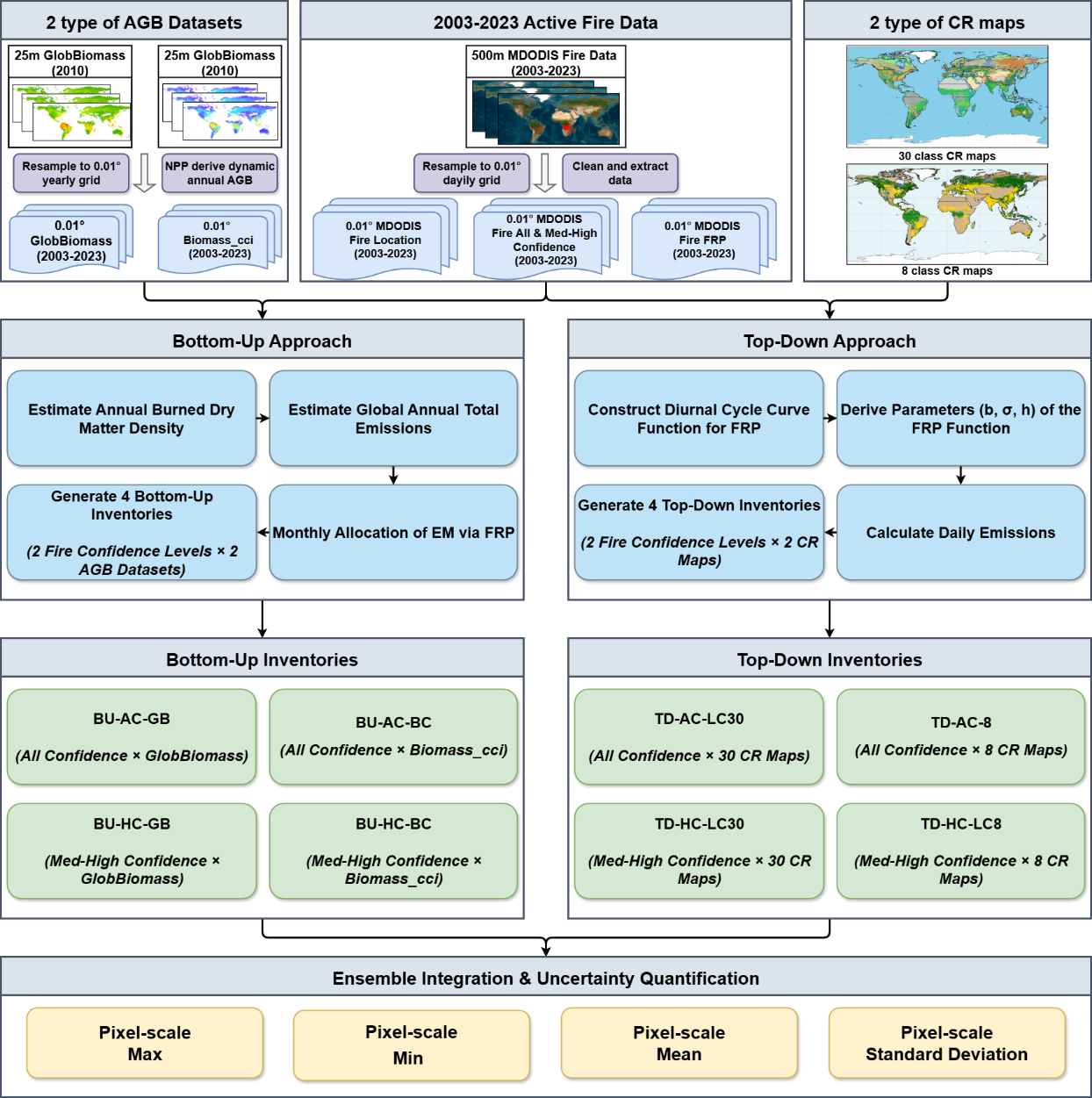
In direct response to this recommendation, we have rigorously post-processed the ensemble outputs to include pixel-level statistics for the entire study period (2003–2023). Specifically, for every 0.1° × 0.1° grid cell and for each month, we have calculated the ensemble mean to serve as the central estimate, along with the standard deviation to represent algorithmic dispersion, and the maximum and minimum values to define the full uncertainty range. These four statistical layers have been integrated into the updated MBEI dataset structure and are now publicly accessible via the repository link provided in the Data Availability section. This enhancement ensures that users can seamlessly incorporate both the central emission estimates and their associated uncertainty bounds into their analyses without needing to reconstruct the ensemble statistics manually.

Correspondingly, we have revised the manuscript to formally document this major improvement in data provision. As detailed in the updated introduction of Section 2.2, the description of the MBEI framework has been refined to explicitly state that the final dataset output includes these pixel-level ensemble statistics. We emphasize in the revised text that rather than obscuring differences through data fusion, the MBEI leverages the ensemble spread to define the uncertainty bounds, specifically providing "the ensemble mean as the central estimate, while delineating the uncertainty envelope through two metrics: the standard deviation, representing dispersion, and the maximum and minimum bounds, defining the uncertainty range." Furthermore, we have updated Table 2 to list these statistical metrics as integral components of the final dataset, and the workflow illustrated in Figure 1 has been modified to visually depict the aggregation of the eight sub-inventories into these final statistical layers.

Please refer to Page 10, Lines 243-252 and the following is the revised manuscript:

To quantify global biomass burning emissions and their associated uncertainties, we constructed the MBEI using a multi-source ensemble framework. Unlike conventional approaches that rely on a single algorithm, this framework operates by generating an ensemble of eight independent sub-inventories (see Table 2). This design is explicitly structured to capture the structural uncertainty stemming from the fundamental mechanistic discrepancies between bottom-up (burned area-based) and top-down (fire radiative power-based) methodologies. Rather than obscuring these differences through data fusion, the MBEI leverages them to define the uncertainty bounds of the estimates. Consequently, for each 0.1° grid cell, we provide the ensemble mean as the central estimate, while delineating the uncertainty envelope through two metrics: the standard deviation, representing dispersion, and the maximum and minimum bounds, defining the uncertainty range. The overall workflow is illustrated in Fig. 1.

Please refer to Fig. 1 and Table 2:



**Figure 1.Framework for the construction of MBEI.**

**Table 2. The detail of the eight biomass burning emission sub-inventories.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 4 Bottom-Up Inventories | | | 4 Top-Down Inventories | | |
| Name | Confidence Level | Datasets | Name | Confidence Level | Datasets |
| BU-AC-GB | All Confidence | GlobBiomass | TD-AC-LC30 | All Confidence | 30-class CR map |
| BU-AC-BC | All Confidence | Biomass\_cci | TD-AC-LC8 | All Confidence | 8-class CR map |
| BU-HC-GB | Medium-to-High confidence | GlobBiomass | TD-HC-LC30 | Medium-to-High confidence | 30-class CR map |
| BU-HC-BC | Medium-to-High confidence | Biomass\_cci | TD-HC-LC8 | Medium-to-High confidence | 8-class CR map |

Note: The final MBEI dataset also includes the pixel-level ensemble statistics (Mean, Std, Max, Min) calculated from these eight sub-inventories.

2. In this study, only MODIS fire products are used, while the higher-resolution VIIRS is not considered. As the successor to MODIS, VIIRS offers enhanced spatial resolution (375–750 m) and advanced day-night imaging capabilities for superior global monitoring of land, ocean, and atmospheric phenomena. The authors should explicitly state the reason for not including VIIRS observations in the manuscript.

**Response:** We sincerely appreciate the reviewer’s insight regarding the superior technical capabilities of the VIIRS sensor and the potential benefits of its inclusion. We fully agree with the reviewer’s assessment that VIIRS, serving as the designated successor to MODIS, offers significantly enhanced spatial resolution (375 m versus 1 km) and advanced day-night band capabilities, which are undoubtedly critical for improving the detection of small-scale thermal anomalies that MODIS might overlook. However, the decision to rely exclusively on MODIS active fire products (MCD14DL) for this specific study was driven by the overriding necessity to maintain rigorous temporal homogeneity across the entire 21-year study period (2003–2023).

The primary scientific objective of the MBEI is to analyze long-term trends and interannual variability in global biomass burning. Since the VIIRS record (via Suomi-NPP) only commences in 2012, integrating these data would necessitate splicing a higher-sensitivity sensor into the latter half of the time series. We argue that mixing the 1-km MODIS record (pre-2012) with the 375-m VIIRS record (post-2012) would introduce significant systematic inconsistencies. Specifically, the superior detection sensitivity of VIIRS would inevitably result in a distinct step-change increase in detected fire counts and radiant energy immediately following its introduction. Such an artificial discontinuity, arising solely from the change in instrumentation, could be easily misinterpreted as a climatological intensification of global fire activity, thereby compromising the validity of the trend analysis that is central to this research. Consequently, to avoid introducing artificial discontinuities into the time series, we prioritized the temporal consistency of the single-sensor MODIS record over the higher spatial resolution offered by VIIRS.

We have explicitly clarified this rationale in Section 4.2 of the revised manuscript to address the reviewer’s concern. In this revised discussion, we openly acknowledge the trade-offs inherent in this decision; while prioritizing temporal consistency allows for robust trend detection, it likely results in conservative emission estimates in regions dominated by small, fragmented fires, such as agricultural residues in India or the Middle East. Furthermore, looking ahead, we recognize the immense potential of VIIRS as its data record lengthens. As the VIIRS time series matures into a sufficient multi-decadal record, we plan to apply the MBEI framework to generate a dedicated, high-resolution VIIRS-based emission dataset, thereby fully leveraging its advanced detection capabilities for future monitoring.

Please refer to Page 29, Lines 643-652 and the following is the revised manuscript:

A key decision in this study was to use MODIS active fire products (MCD14DL) exclusively for the 2003–2023 period. Although the Visible Infrared Imaging Radiometer Suite (VIIRS), available since 2012, offers superior spatial resolution (375 m) compared to MODIS (1 km), applying it would have limited the consistent time series to the post-2012 era. Merging MODIS (2003–2011) and VIIRS (2012–2023) records introduces a risk of inconsistency; the higher detection sensitivity of VIIRS could result in an artificial increase in fire counts, which might be misinterpreted as a real upward trend in global fire activity. To maintain the homogeneity of the 21-year dataset for trend analysis, we prioritized sensor consistency. We acknowledge that this choice likely leads to an underestimation of emissions from small-scale agricultural fires, particularly in regions like the Middle East or India, where fires are often smaller than the MODIS detection threshold (Hantson et al., 2013; Justice et al., 2002; Vadrevu and Lasko, 2018).

3. To address the limitation of a static AGB benchmark map, net primary productivity (NPP) is used as a proxy to generate annual global AGB maps. Does this approach introduce inherent uncertainties? The authors should discuss these.

**Response:** We sincerely appreciate the reviewer’s critical assessment regarding the uncertainties associated with the fuel load estimation methodology. We fully acknowledge that the derivation of dynamic annual Aboveground Biomass (AGB) from static baseline maps using Net Primary Productivity (NPP) as a proxy is a methodological simplification that inevitably introduces inherent uncertainties into the bottom-up inventory. As correctly highlighted by the reviewer, and as we have now explicitly discussed in the revised manuscript, the relationship between these two variables is ecologically complex; fundamentally, AGB represents a cumulative carbon stock, whereas NPP represents an annual carbon flux. Consequently, their correlation is influenced by non-linear factors such as ecological lag effects, variable tree mortality rates, and decomposition processes, meaning that a year of high NPP does not necessarily translate into an immediate, proportional increase in standing biomass.

However, the decision to adopt this NPP-based proxy method was driven by the stringent constraints of current data availability. For the study period of 2003–2023, there exists no continuous, global, high-resolution annual AGB observational dataset. Faced with the choice between using a completely static AGB map—which would erroneously assume constant fuel loads despite significant climate variability—and using an NPP-driven dynamic adjustment, we determined that the latter represents the scientifically robust available strategy to approximate the interannual variability of fuel availability, despite its physical limitations.

In response to the reviewer’s suggestion, we have expanded Section 4.2 (Limitations and Future Perspectives) to include a dedicated discussion on these specific uncertainties. We clarified that while this approach allows us to capture the directional trends of interannual fuel dynamics, it remains a surrogate method. We further elaborated that future iterations of the MBEI aim to overcome this reliance on proxies by integrating direct vertical structure measurements from next-generation active remote sensing missions, such as NASA GEDI and ESA BIOMASS, once long-term records from these sensors become available to directly resolve dynamic fuel loads.

Please refer to Page 30, Lines 673-683 and the following is the revised manuscript:

Advancements in next-generation satellites will also enhance the MBEI’s capacity for fuel load estimation. In this study, due to the lack of high-resolution annual AGB observations, we adjusted static AGB maps using interannual variations in NPP. However, AGB is a cumulative stock variable, whereas NPP is an annual flux variable. Their relationship is complex and influenced by factors such as lag effects, tree mortality, and decomposition, meaning a high NPP year does not always result in an immediate biomass increase (Keeling and Phillips, 2007; Teets et al., 2022). Future versions of MBEI aim to improve this by integrating dynamic AGB datasets from active remote sensing missions. Specifically, spaceborne LiDAR (e.g., NASA GEDI) and P-band SAR (e.g., ESA BIOMASS mission) are expected to provide global measurements of forest vertical structure. This will allow MBEI to incorporate dynamic fuel loads, thereby reducing a major source of uncertainty in the bottom-up approach based on burned area (Cao et al., 2016; Liu et al., 2019; Rodríguez-Fernández et al., 2018).

4. The abstract is overly long and information-dense. I suggest to keep the most important findings and shorten the abstract to make the expression more concise.

**Response:** We sincerely appreciate the reviewer’s constructive feedback regarding the length and density of the abstract. We fully acknowledge that the original text, while comprehensive, was overly verbose in its contextualization and methodological detailing, which may have diluted the immediate impact of the study’s core contributions. We have accepted this suggestion and performed a rigorous editorial revision to significantly condense the abstract, thereby enhancing its concise expression and readability while retaining the critical scientific findings.

In the revised abstract, we have streamlined the narrative structure to prioritize the research gap and our specific contributions. First, we excised the generic background information regarding global climate change to focus immediately on the critical issue of discrepancies among existing inventories. Second, we compressed the methodological description; rather than listing every specific atmospheric pollutant, we focused on the innovative nature of the "ensemble framework" that integrates bottom-up and top-down approaches to quantify structural uncertainty. This allowed us to dedicate more space to the key empirical findings, which have been sharpened for clarity. Specifically, we retained the crucial quantitative results—such as the two-fold difference between maximum and minimum global estimates—and the distinct spatial heterogeneity of uncertainty, highlighting the contrast between high-uncertainty regions like Australia and lower-uncertainty regions like Africa. Furthermore, we refined the description of the temporal trends to clearly articulate the identified decadal shift: a decline in tropical burning (2003–2013) followed by a resurgence driven by high-latitude fires (2013–2023). These revisions ensure that the abstract now directly and effectively communicates the MBEI’s value in providing robust central estimates and explicit uncertainty bounds for atmospheric modeling.**Q5:** The Discussion section should be strengthened. Other factors are likely to bring the uncertainty in the estimation of biomass burning emission, for example the omission and commission errors in the satellite fire observations. Meanwhile, the existing bottom-up and up-down method is like to underestimate the emission for small-scale fire.

Please refer to Page 2, Lines 36-50 and the following is the revised manuscript:

**Abstract**. Large discrepancies among existing inventories hinder a consensus on the true magnitude and long-term trends of global biomass burning emissions. To address this, we developed the Multi-ensemble Biomass-burning Emissions Inventory (MBEI), a framework integrating bottom-up and top-down approaches with multi-source data to generate eight sub-inventories for the period 2003–2023. This ensemble approach allows for the explicit quantification of emission uncertainty at a 0.1° grid scale. We estimate global annual CO2 emissions at 7304 (4400–9657) Tg, with the maximum estimate exceeding the minimum by over two-fold. The uncertainty exhibits significant spatial heterogeneity: it is highest in low-emission regions like Australia and the Middle East (6.0–7.0 fold difference), whereas traditional hotspots like Africa show lower divergence (Approximately 2 fold). Temporally, a distinct decadal shift was identified: global emissions declined from 2003 to 2013 due to reduced tropical burning, but reversed to an increasing trend from 2013 to 2023, driven by intensified fires in northern high-latitudes and extreme events. Comparisons confirm that the MBEI mean provides a robust central estimate, while its max-min range effectively encompasses other major inventories. By providing explicit uncertainty bounds, MBEI enhances the reliability of atmospheric modeling and climate assessments. The dataset is publicly available at https://doi.org/10.5281/zenodo.18104830 (Liu and Yin, 2025).

5. The Discussion section should be strengthened. Other factors are likely to bring the uncertainty in the estimation of biomass burning emission, for example the omission and commission errors in the satellite fire observations. Meanwhile, the existing bottom-up and up-down method is like to underestimate the emission for small-scale fire.

**Response:** We sincerely appreciate the reviewer’s constructive critique regarding the comprehensiveness of our discussion on uncertainty sources. We fully agree with the reviewer’s assessment that beyond the structural uncertainties arising from algorithm choice, the fundamental physical limitations of satellite observations—specifically omission errors related to detection thresholds for small-scale fires—constitute significant sources of bias that necessitate rigorous examination. We acknowledge that existing bottom-up and top-down methods share these inherent physical constraints, which often lead to a systematic underestimation of emissions in specific fire regimes.

In direct response to this suggestion, we have substantially strengthened Section 4.2 to provide a deep-dive analysis of these physical limitations. A central focus of this revision is the explicit discussion of the trade-offs involved in sensor selection and the consequent impact on small-fire detection. We clarified that a key decision in this study was to use MODIS active fire products (MCD14DL) exclusively for the 2003–2023 period to ensure trend validity. We argue that although the Visible Infrared Imaging Radiometer Suite (VIIRS), available since 2012, offers superior spatial resolution (375 m) compared to MODIS (1 km), applying it would have limited the consistent time series to the post-2012 era. Furthermore, merging MODIS (2003–2011) and VIIRS (2012–2023) records introduces a substantial risk of inconsistency; the higher detection sensitivity of VIIRS could result in an artificial increase in fire counts, which might be misinterpreted as a real upward trend in global fire activity. To maintain the homogeneity of the 21-year dataset for trend analysis, we prioritized sensor consistency. However, in the revised discussion, we explicitly acknowledge that this choice likely leads to an underestimation of emissions from small-scale agricultural fires, particularly in regions like the Middle East or India, where fires are often smaller than the MODIS detection threshold.

In addition to sensor resolution, we also expanded the text to address omission errors driven by environmental heterogeneity, such as subsurface peat smoldering and canopy occlusion, which further constrain detection capabilities. By articulating these mechanisms, we highlight that the MBEI, while robust, is still bound by the physics of the input sensors. To conclude this discussion, we emphasized the adaptability of our system: in conclusion, while the current version of MBEI quantifies uncertainty by integrating established methods, its modular design serves as a platform for incorporating new data inputs as they become available. This ensures a feasible pathway for iterative refinement, supporting more comprehensive assessments of global biomass burning emissions.

Please refer to Page 29-30, Lines 643-672 and the following is the revised manuscript:

A key decision in this study was to use MODIS active fire products (MCD14DL) exclusively for the 2003–2023 period. Although the Visible Infrared Imaging Radiometer Suite (VIIRS), available since 2012, offers superior spatial resolution (375 m) compared to MODIS (1 km), applying it would have limited the consistent time series to the post-2012 era. Merging MODIS (2003–2011) and VIIRS (2012–2023) records introduces a risk of inconsistency; the higher detection sensitivity of VIIRS could result in an artificial increase in fire counts, which might be misinterpreted as a real upward trend in global fire activity. To maintain the homogeneity of the 21-year dataset for trend analysis, we prioritized sensor consistency. We acknowledge that this choice likely leads to an underestimation of emissions from small-scale agricultural fires, particularly in regions like the Middle East or India, where fires are often smaller than the MODIS detection threshold (Hantson et al., 2013; Justice et al., 2002; Vadrevu and Lasko, 2018).

In addition to sensor specifications, most current inventories relying on optical remote sensing face inherent physical limits driven by environmental heterogeneity. Complex surface conditions can constrain the effectiveness of estimation methods. For instance, in the peatlands of Equatorial Asia (e.g., Indonesia), fires often occur as subsurface low-temperature smoldering. The thermal radiation from these fires is frequently too weak to trigger standard satellite detection algorithms (Rein and Huang, 2021; Sofan et al., 2019). Similarly, in dense tropical rainforests, the canopy layer can occlude or absorb thermal radiation emitted by understory fires (East et al., 2023). These scenarios contribute to omission errors in top-down, FRP-based approaches (Morton et al., 2013; Tyukavina et al., 2022). Conversely, while bottom-up methods based on burned area can capture the spatial traces of these fires, they face challenges in accurately determining the depth of burn in organic soils (Ballhorn et al., 2009; Wiggins et al., 2018). Therefore, despite the integration of multiple algorithms in MBEI, these physical constraints suggest a potential underestimation in our emission estimates for these specific biomes.

Looking forward, the flexible architecture of MBEI is designed to incorporate emerging datasets to address these limitations. As the observational record of VIIRS extends, future versions of MBEI will integrate these data to improve the detection of small-scale fires once a sufficiently long and consistent record is established. Furthermore, data from new-generation geostationary satellites (e.g., FY-4, Himawari-8/9, GOES-R) offer a significant improvement in temporal resolution. Minute-level observations from these platforms will enable the direct integration of the Fire Radiative Power (FRP) diurnal cycle, reducing the reliance on Gaussian extrapolation from sparse polar-orbiter snapshots and enhancing the physical realism of Fire Radiative Energy (FRE) estimation.

Minor comments:

1. Line 67-68: add references to support this statement.

**Response**: We sincerely thank the reviewer for pointing out the need for supporting citations to substantiate this foundational statement. We agree that referencing authoritative literature is essential for establishing the context of biomass burning as a key ecosystem disturbance. Accordingly, we have inserted citations to Bowman et al. (2020) and Jones et al. (2022) in the revised manuscript to support the text: "Biomass burning, encompassing forest fires, grassland fires, and the burning of agricultural residues, is a key disturbance in terrestrial ecosystems."

Please refer to Page 3, Lines 69-70 and the following is the revised manuscript:

Biomass burning, encompassing forest fires, grassland fires, and the burning of agricultural residues, is a key disturbance in terrestrial ecosystems (Bowman et al., 2020; Jones et al., 2022).

2. Lines 90–91: An extraneous period appears after “Karanasiou et al (2021)”. Please remove it to ensure proper punctuation.

**Response**: We appreciate the reviewer’s meticulous attention to detail regarding punctuation. We have removed the extraneous period following "Karanasiou et al. (2021)" to ensure grammatical correctness and proper sentence flow.

Please refer to Page 3, Lines 92 and the following is the revised manuscript:

A meta-analysis of 81 studies (1980–2020) (Karanasiou et al., 2021).

3. There are some grammar issues and please proofread the entire manuscript carefully before resubmission. For example, Line 102-103, “Atmospheric Chemistry Transport Models used for air quality forecasting and source apportionment, rely on emission inventories with high spatiotemporal resolution and reliability”.

**Response:** We apologize for the grammatical oversight in Lines 102–103 and for any other linguistic imperfections in the original draft. We have corrected the specific sentence to read: "Atmospheric Chemistry Transport Models, which are used for air quality forecasting and source apportionment, rely on emission inventories with high spatiotemporal resolution and reliability." Furthermore, prior to this resubmission, we have conducted a comprehensive proofreading of the entire manuscript to eliminate grammatical errors and enhance the overall clarity and fluency of the English text.

Please refer to Page 3, Lines 92 and the following is the revised manuscript:

Atmospheric Chemistry Transport Models, which are used for air quality forecasting and source apportionment, rely on emission inventories with high spatiotemporal resolution and reliability.

4. Line 182: The current format is cluttered and hard to read. Please reformat it.

**Response:** We thank the reviewer for noting the formatting issues in Table 1. We agree that a cluttered presentation hinders readability and have therefore completely reformatted Table 1. The revised table now presents the dataset information in a clean, organized, and reader-friendly manner.

Please refer to the following is the revised Table 1:

**Table 1. Datasets used in this study.**

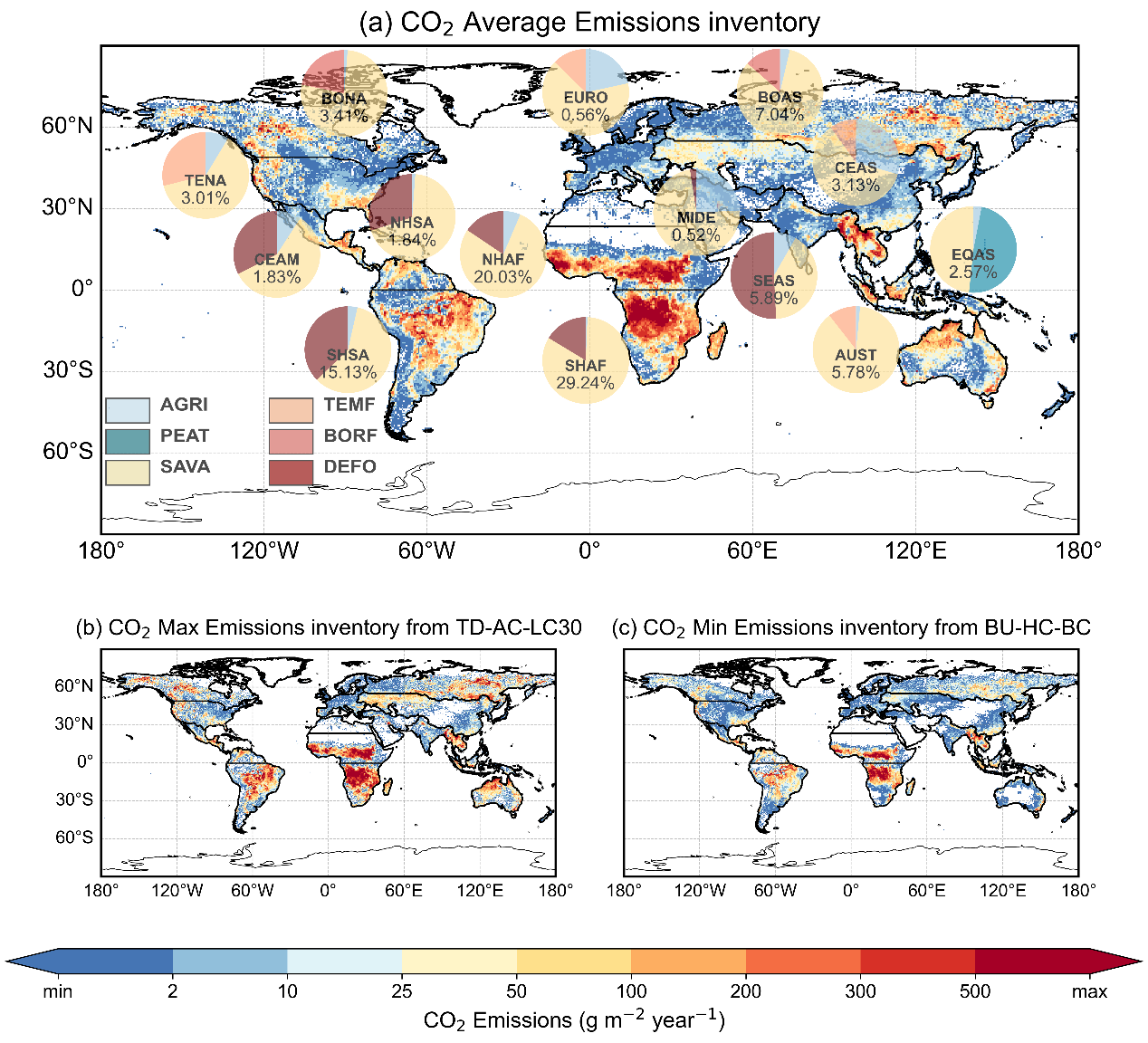
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Data types | Name | Temporal Coverage | Spatial Resolution | Temporal Resolution | Reference |
| Active Fire Data | Aqua  MCD14DL | 2003-2023 | 1 km × 1 km | daily | (NASA VIIRS Land Science Team, 2021) |
| Terra  MCD14DL | 2003-2023 | 1 km × 1 km | daily | (NASA VIIRS Land Science Team, 2021) |
| Burning Efficiency (BE) & Emission Factor (EF) Data | EF Classification Source Data GFED | \ | 0.25° × 0.25° | \ | (van der Werf et al., 2006) |
| EF Coefficients | \ | \ | \ | (van der Werf et al., 2017) |
| BE Coefficients | \ | \ | \ | (Shi et al., 2015) |
| AGB Data | GlobBiomass | 2010 | 25 m × 25 m | \ | (Santoro, 2018) |
| Biomass\_cci | 2010/2015-2021 | 100 m × 100 m | yearly | (Santoro and Cartus, 2024) |
| Conversion Factor (CR) Data | 30-class CR map | \ | 0.1° × 0.1° | \ | (Kaiser et al., 2023) |
| 8-class CR map | \ | 0.1° × 0.1° | \ | (Kaiser et al., 2012) |
| Ancillary & Validation Data | Net Primary Production (NPP)  MYD17A3HGF v061 | 2003-2023 | 500 m × 500 m | yearly | (Running and Zhao, 2021) |
| Land Cover Type  MCD12Q1.061 | 2003-2023 | 500 m × 500 m | yearly | (Friedl and Sulla-Menashe, 2022) |
| Validation Inventory Data | Global Fire Emissions Database 5 (GFED 5) | 2003-2022 | 0.25° × 0.25° | daily | (Binte Shahid et al., 2024; Vernooij et al., 2023; Wiggins et al., 2021) |
| Fire INventory from NCAR 2.5 (FINN 2.5) MODIS | 2002-2022 | 0.1° × 0.1° | daily | (Wiedinmyer et al., 2023) |
| Global Fire Assimilation System 1.2 (GFAS 1.2) | 2003-2022 | 0.1° × 0.1° | daily | (Kaiser et al., 2012) |
| Quick Fire Emissions Dataset 3.1 (QFED 3.1) | 2003-2022 | 0.1° × 0.1° | daily | (Koster et al., 2015) |

Note: The 8-class biome map is derived from the 30-class biome map. See Fig. S1 for its spatial distribution.

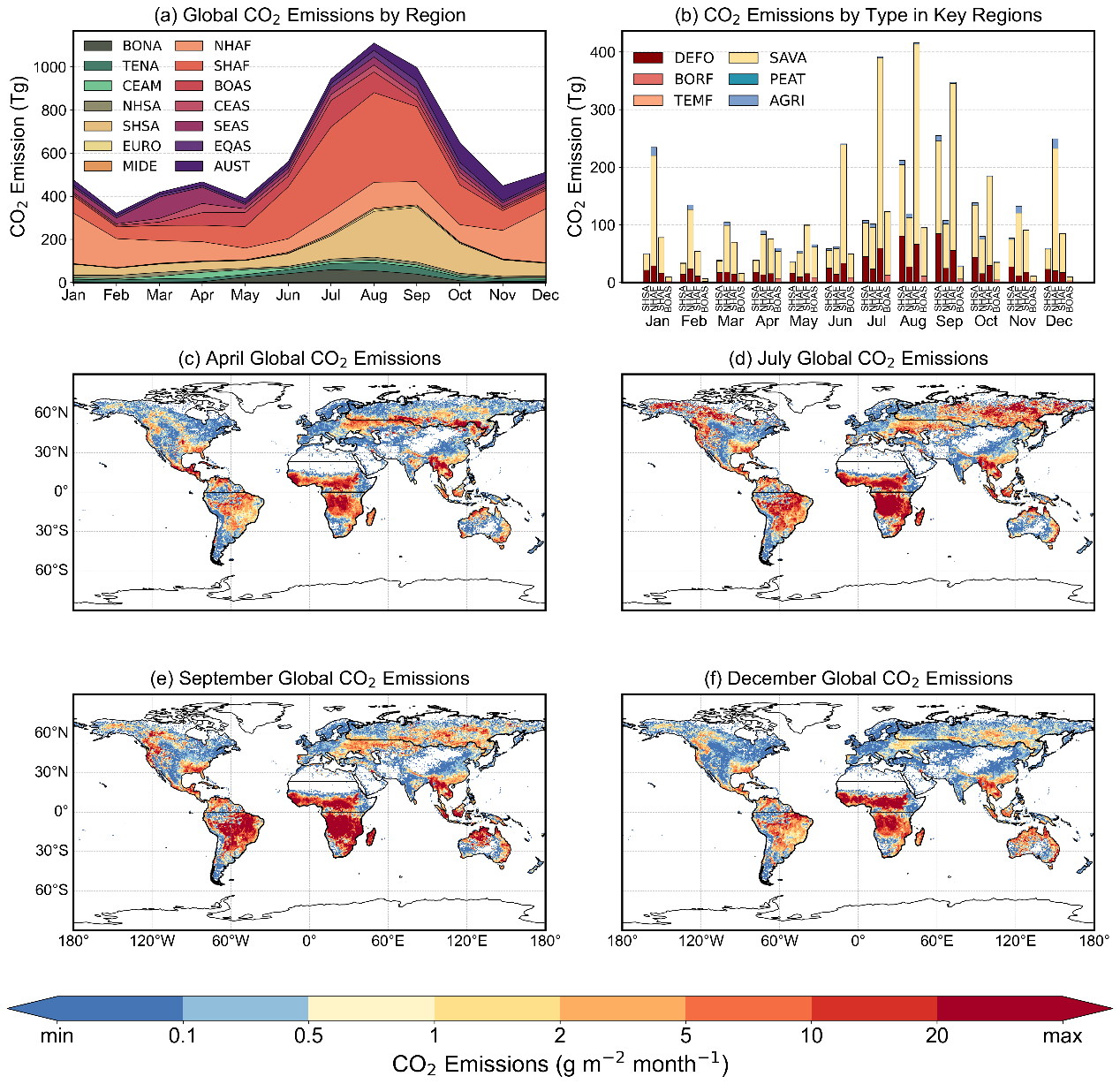
5. Figures 2a and 3a,b: Fonts are too small, reducing readability. Please enlarge them and ensure consistent styling across panels.

**Response:** We appreciate the reviewer’s feedback regarding the visual clarity of our figures. We acknowledge that the font sizes in Figures 2a and 3a,b were insufficient for easy reading. We have redrawn these panels with significantly enlarged fonts and have ensured that the styling is consistent across all figures to improve the overall graphical quality of the manuscript.

Please refer to the following is the revised Figure 2 and 3:



**Figure 2. Spatial patterns and regional composition of global biomass burning CO2 emissions (mean of 2003–2023). (a) Spatial distribution of the annual mean CO2 emission flux estimated from the mean of the eight inventories in this study. The embedded pie charts show the emission composition for 14 major regions, where: 1) the number in the pie chart indicates the percentage of that region's emissions relative to the global total; and 2) the sectors of the pie chart represent the proportional contribution of six major fire types to the region's total emissions. (b) and (c) show the spatial emission patterns corresponding to the inventory with the highest global total annual emissions (TD-AC-LC30) and the lowest global total annual emissions (BU-HC-BC) among the eight inventories over the entire study period, respectively.**



**Figure 3. Seasonal cycle and spatial dynamics of global biomass burning CO2 emissions (mean of 2003–2023). (a) Global monthly emissions partitioned by source region. (b) Monthly emissions for the four primary contributing regions, showing the composition by fire type. (c-f) Spatial distribution of mean monthly emission flux during key seasonal phases: April, July, September, and December.**

6. Two extraneous spaces appear between “high” and “biomass”. Please delete them for clean typesetting.

**Response:** We thank the reviewer for spotting this typographical error. We have removed the extraneous spaces between "high" and "biomass" to ensure clean and professional typesetting. The sentence now correctly reads: "Importantly, high biomass burning emission uncertainty is not found in traditional biomass burning hotspots."

Please refer to Page 17, Lines 396 and the following is the revised manuscript:

Importantly, high biomass burning emission uncertainty is not found in traditional biomass burning hotspots. Instead, some of the highest uncertainties are found in regions with lower overall emissions.

7. Table 3: please do not use the short name for maximum, minimum, and average.

**Response:** We accept the reviewer’s suggestion to use formal terminology in our data presentation. We have revised the headers in Table 3 to use the full terms "Maximum," "Minimum," and "Average" instead of abbreviations, ensuring clarity and adherence to academic standards.

Please refer to the following is the revised Table 3:

**Table 3. Total annual CO2 emissions (Maximum, Minimum, and Average, unit: Tg) for 2003–2023.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Maximum | Minimum | Average | Year | Maximum | Minimum | Average |
| 2003 | 10882.90 | 4487.65 | 7673.68 | 2014 | 9258.62 | 4489.87 | 7265.29 |
| 2004 | 10842.08 | 4271.50 | 7522.16 | 2015 | 9688.74 | 5035.46 | 7701.46 |
| 2005 | 10391.58 | 4350.62 | 7328.15 | 2016 | 8476.61 | 4059.68 | 6789.30 |
| 2006 | 9663.37 | 4160.83 | 7077.83 | 2017 | 9250.64 | 4436.15 | 7042.77 |
| 2007 | 11063.35 | 4641.22 | 7751.48 | 2018 | 8727.34 | 4160.93 | 6911.22 |
| 2008 | 9725.05 | 4030.68 | 6925.95 | 2019 | 9747.60 | 4971.22 | 7657.46 |
| 2009 | 8661.02 | 3930.36 | 6669.83 | 2020 | 9295.62 | 4375.98 | 7249.50 |
| 2010 | 10253.23 | 4748.50 | 7554.59 | 2021 | 10696.69 | 4767.44 | 7705.11 |
| 2011 | 9653.73 | 4119.74 | 7205.26 | 2022 | 7289.55 | 3348.45 | 6442.83 |
| 2012 | 10537.30 | 4721.32 | 7895.63 | 2023 | 10527.88 | 5206.72 | 8506.96 |
| 2013 | 8161.82 | 4087.36 | 6489.87 | Mean | 9656.89 | 4400.08 | 7303.16 |

8. Line 469: use a consistent format for the term “max-min band”.

**Response:** We appreciate the reviewer’s guidance on maintaining terminological consistency. We have carefully reviewed the entire manuscript and standardized the usage of the term "max-min band" throughout the text to avoid any confusion.

Please refer to Page 22, Lines 475 and the following is the revised manuscript:

Alongside these climate-driven variations, the MBEI is characterized by a broad uncertainty range, stemming from differences in algorithm structures and input data. The spread between MBEI estimates (the max-min band in Figs. 4a, c, e) is considerable, with the difference between the highest and lowest annual totals exceeding 2600 Tg in some years (e.g., 2004, 2022).

9. Line 477-479: Is there any tables or figures in the supplementary material to support these results?

**Response:** We thank the reviewer for suggesting the inclusion of supporting data for these results. We agree that providing the underlying data enhances the robustness of our claims. Therefore, we have added new supplementary tables (Table S6–S8) to the Supplementary Material, which explicitly support the results discussed in Lines 477–479.

Please refer to Page 22-23, Lines 482-512 and the following is the revised manuscript:

Over the full 21-year period, statistically significant trends were concentrated in Asia. BOAS exhibited a strong and significant increasing trend in emission flux at a rate of 15.71 g m-2 yr-1 (p < 0.01). In contrast, CEAS and SEAS showed significant decreasing trends of -1.72 g m-2 yr-1 (p < 0.01) and -2.08 g m-2 yr-1 (p < 0.05), respectively (Table S6). Fig. 4b suggests decreases in equatorial Africa and central-southern South America, and increases in BONA, these trends were not statistically significant when aggregated over the entire 14 GFED regions for the 2003–2023 period. This highlights an offsetting pattern, where declining emissions in some regions are partially balanced by increases elsewhere, contributing to the lack of a significant global trend.

A decadal comparison between 2003–2013 and 2013–2023 reveals substantial evolution in these spatial patterns, indicating a major shift in the global distribution of biomass burning emissions (Figs. 4d, f).

During the first decade (2003–2013), a slight but statistically non-significant global decrease (p > 0.05; Fig. 4c) masked a profound spatial redistribution of fire activity. The dominant feature was a significant increase in fire emissions in SHAF, which saw an upward trend of 4.41 g m-2 yr-1 (p < 0.05). By contrast, South America experienced significant decreases, particularly in NHSA where emissions declined at a rate of -4.97 g m-2 yr-1 (p < 0.05). Simultaneously, a strong decreasing trend was observed in CEAS, with a rate of -2.96 g m-2 yr-1 (p < 0.05). Boreal regions and Southeast Asia showed no statistically significant regional trends during this period (Fig. 4d and Table S7).

In the subsequent decade (2013–2023), this pattern shifted markedly. Although the global emission trajectory did not exhibit a statistically significant linear trend (p > 0.05), it transitioned from a slight decline to an overall increase (Fig. 4e), signaling a clear decadal change in biomass burning dynamics. This shift is more appropriately characterized as a structural transformation rather than a linear progression, driven by a marked increase in both the frequency and intensity of extreme emission years (e.g., 2015, 2019, 2023). The 2015–2016 ENSO cycle exemplifies this mechanism, as the super El Niño event in 2015 induced catastrophic PEAT in Indonesia (EQAS) and elevated global emissions to a record peak, which was subsequently followed by a pronounced decline in 2016 with the onset of a strong La Niña (Whitburn et al., 2016; Yin et al., 2020a). The 2023 fire season was even more pronounced, as an unprecedented wildfire season in boreal Canada (BONA) coincided with a developing El Niño, jointly driving global annual emissions to the highest level in our 21-year record. Detailed regional statistics, including the annual mean CO2 emission fluxes and their corresponding Theil-Sen slope trends across the 14 study regions for the 2013–2023 period, are summarized in Table S8 (Jain et al., 2024; Luo et al., 2025).

Please refer to the following is the revised Table S6-8 in Supplementary material:

**Table S6. Mean annual CO2 emission fluxes and their corresponding Theil-Sen slope trends across 14 regions from 2003 to 2023. (unit: g m-2).**

|  |  |  |
| --- | --- | --- |
| Region | Mean Emission Flux | Theil Sen Slope value |
| BONA | 543.72 | 12.12 |
| TENA | 114.04 | 2.67 |
| CEAM | 98.28 | -0.61 |
| NHSA | 115.33 | 1.06 |
| SHSA | 173.34 | 1.24 |
| EURO | 52.05 | -0.02 |
| MIDE | 77.65 | 0.64 |
| NHAF | 266.74 | 0.37 |
| SHAF | 330.52 | 1.24 |
| BOAS | 371.02 | 15.71 |
| CEAS | 56.89 | -1.72 |
| SEAS | 137.16 | -2.08 |
| EQAS | 163.81 | -4.78 |
| AUST | 195.02 | -1.30 |

**Table S7. Mean annual CO2 emission fluxes and their corresponding Theil-Sen slope trends across 14 regions from 2003 to 2013. (unit: g m-2).**

|  |  |  |
| --- | --- | --- |
| Region | Mean Emission Flux | Theil Sen Slope value |
| BONA | 418.62 | -4.65 |
| TENA | 99.06 | 0.73 |
| CEAM | 103.17 | -0.10 |
| NHSA | 105.58 | -4.97 |
| SHSA | 170.75 | -6.13 |
| EURO | 44.50 | -1.11 |
| MIDE | 73.12 | 0.09 |
| NHAF | 264.05 | 2.57 |
| SHAF | 325.09 | 4.41 |
| BOAS | 279.94 | 9.10 |
| CEAS | 61.30 | -2.96 |
| SEAS | 150.13 | -0.02 |
| EQAS | 172.99 | -6.91 |
| AUST | 195.80 | 0.44 |

**Table S8. Mean annual CO2 emission fluxes and their corresponding Theil-Sen slope trends across 14 regions from 2013 to 2023. (unit: g m-2).**

|  |  |  |
| --- | --- | --- |
| Region | Mean Emission Flux | Theil Sen Slope value |
| BONA | 663.77 | 11.93 |
| TENA | 128.43 | 3.78 |
| CEAM | 94.85 | 0.47 |
| NHSA | 123.83 | 3.72 |
| SHSA | 170.02 | 8.01 |
| EURO | 58.03 | -0.30 |
| MIDE | 80.63 | 0.61 |
| NHAF | 269.14 | -5.14 |
| SHAF | 337.60 | -1.77 |
| BOAS | 460.83 | 17.48 |
| CEAS | 50.72 | -0.30 |
| SEAS | 125.39 | -2.72 |
| EQAS | 154.30 | -11.19 |
| AUST | 189.94 | 0.85 |

10. Supplementary material: Please ensure all figures and tables are explicitly referenced in the main text.

**Response:** We appreciate this important reminder regarding the linkage between the main text and the supplementary information. We have performed a systematic check of the manuscript to ensure that every figure and table included in the Supplementary Material is explicitly and correctly referenced within the main text.

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Finally, we express our sincere gratitude to the reviewer for identifying the issues and providing us with the opportunity to revise this paper. These comments are essential to improve the quality of the paper. We have rigorously post-processed the ensemble outputs to include pixel-level statistics, ensuring users can access immediate uncertainty information. The Discussion part has been strengthened to explicitly analyze the omission errors in satellite observations and the rationale for prioritizing temporal homogeneity in trend analysis. In addition, we have added more tables in the supplementary materials to support the regional trend results and completely reformatted the dataset descriptions for clarity. Following the major revision, the abstract has become more precise, and the limitations of the methodology are now transparently addressed. Besides aforementioned revision, some parts and descriptions are also changed. We have highlighted the revised part in yellow color, for more details, please refer to the manuscript and supplementary material. Sincerely hope the revision is satisfying.