We are grateful to the editor and referee for their time and energy in providing helpful comments and guidance that have improved the manuscript. In this document, we describe how we have addressed the reviewer's comments. Referee comments are shown in black italics and author responses are shown in blue regular text.

Reviewer #3:

The study has constructed a global dataset of fire-sourced $PM_{2.5}$ concentrations at a spatial resolution of 0.25 degree and daily scale covering the period of 2000-2023. The dataset is developed using global model simulations with two fire emission inventories, and further with bias-corrected using a machine learning algorithm applied to predict global surface $PM_{2.5}$ measurements. Differences between the fire-sourced $PM_{2.5}$ concentrations derived from the two fire emission inventories (GFED vs. QFED) are further analyzed.

Overall, I think the study is well conducted and the high-resolution fire-sourced $PM_{2.5}$ dataset is valuable for the community to further explore the impacts of fires on the environment, such as its use in the recent study (Xu et al., Nature 2023). Publishing the dataset (with reasonable extension relative to the previous study) on ESSD appears to fit the journal's scope.

Here I have several comments on the quality of the dataset that hope the authors can further address and refine.

➢ Thank you for your positive evaluations.

Comments

1) The differences between GFED vs. QFED derived fire $PM_{2.5}$ need to be better quantified. It seems that compared with the previous dataset of Xu et al. (Nature 2023), the datasets presented in this study apply two different fire emission inventories. Why were the two fire emission inventories selected? Did they represent the current fire emission uncertainty ranges? Section 3.3 discussed their differences but mainly focused on the mean values. How about the episodic fire events? Some comparisons based on the daily scale would be valuable.

➢ Thank you for your valuable suggestions. Xu et al. (2023) compared the uncertainties in fire-sourced [$PM_{2.5}$] from different inventories, but only for the year 2012. In contrast, our study provided datasets from both inventories spanning

2000-2023, enabling us to compare their spatiotemporal variations. Initially, we considered using the FINN and GFAS inventories as well. However, these datasets were slower to update and had incomplete emission data for the timeframe of our study. The GFED and QFED inventories, being more efficient in the data update, were ultimately chosen.

The inclusion of two inventories is one of the major contributions of our study to the community. In the revised version, we added Figure 4 to validate the derived fire [$PM_{2.5}$] from both inventories against estimates from Childs et al. (2022), and Figure S8 to compare the differences between them at various percentiles: "The probability density distributions of fire-sourced [$PM_{2.5}$] from the two inventories show notable differences (Fig. S8). During 2000-2023, fire [$PM_{2.5}$] from QFED is more than twice that from GFED below the 75th percentile, indicating that QFED predicts significantly higher [$PM_{2.5}$] for low to moderate fire events. However, this difference diminishes above the 90th percentile and becomes particularly constrained at the 99th percentile, where fire-sourced [$PM_{2.5}$] from GFED is 79.29% of that from QFED. It suggests that while both inventories yield comparable estimates for extreme fire episodes, GFED systematically underestimates emissions from smaller fires. This underestimation persists despite improvements in GFED's representation of small fires through additional implementations (Van Der Werf et al., 2017). Consequently, validations in the U.S. reveal substantial low values with GFED relative to observations (Fig. 4), whereas both inventories perform comparably during high-emission fire episodes (Figs. 3 and S7)." (Lines 244-254)

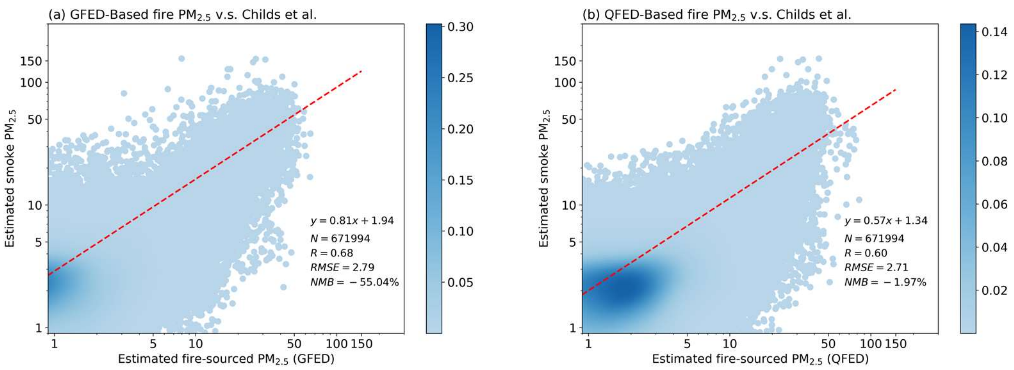

Figure 4. Comparison of fire-sourced $PM_{2.5}$ ($\mu g\ m^{-3}$) estimated using (a) GFED and (b) QFED inventories with smoke $PM_{2.5}$ observed by Childs et al. (2022) at 100156 polygons in U.S. during 2016–2019. Validation metrics of N, regression equation, R^2, RMSE, and NMB are calculated.

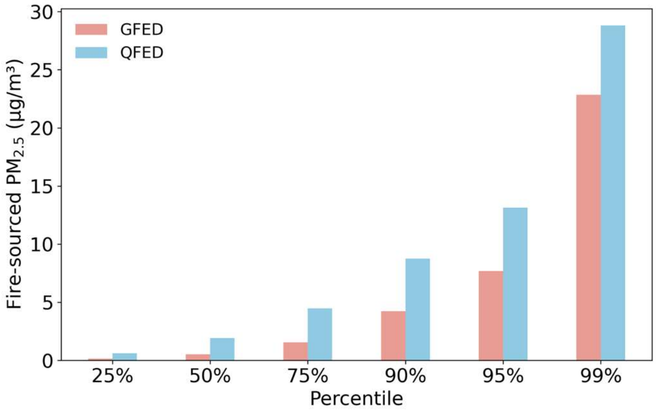

Figure S8. Comparison of daily fire-sourced [$PM_{2.5}$] at different percentiles between simulations with GFED and QFED inventories.

In the revised paper, we expanded our discussion on the causes of these uncertainties and offered recommendations on how to best use these datasets: "The two datasets derived from different inventories showed discrepancies in both the long-term mean and trend of fire-sourced [$PM_{2.5}$] (Fig. 5). In general, fire-related [$PM_{2.5}$] is much higher when using the QFED inventory compared to GFED, but the long-term trend is more negative with QFED. As expected, these discrepancies can be attributed to differences in the underlying fire emission inventories (Fig. 6), which stem from variations in their estimation methods, data sources, emission factors, and so on (Kaiser et al., 2012; Larkin et al., 2014; Jin et al., 2023). For example, QFED adjusts emission factors based on aerosol optical depth from MODIS (Petrenko et al., 2012; Li et al., 2022), resulting in significantly higher emissions in some regions compared to GFED. In contrast, GFED relies on burning pixels and changes in surface reflectance identified during satellite overpasses under relatively cloud-free conditions, which may lead to underestimating burned areas especially for some small fires (Pan et al., 2020). Further validations showed that all-source [$PM_{2.5}$] using GFED yielded an R value of 0.58±0.29 and an NMB of 10.68±24.96% averaged for the 12 fire episodes (Fig. 3). Slightly improved statistical metrics were achieved using QFED, with an R value of 0.63±0.26 and an NMB of 6.56±27.61% for the same events (Fig. S7). However, these differences are too minor to conclusively determine which dataset provides a better estimate of fire-sourced [$PM_{2.5}$]. Fire-sourced [$PM_{2.5}$] is generally lower in the GFED dataset compared to QFED; exceptions exist, such as the 2023 Canadian fires, in which fire-sourced [$PM_{2.5}$] from GFED (Fig. 7) was significantly higher than that from QFED (Fig. S9). Therefore, we recommend using the average of fire-sourced [$PM_{2.5}$] from both inventories to indicate the mean state, while using their difference as the range of uncertainties associated with fire-related air pollutants." (Lines 347-366)

As for the episodic fire events, we analyzed of the long-term trend of fire-sourced [$PM_{2.5}$] exceeding the WHO health standard with shadings to quantify the uncertainties from two inventories (Figure 8). Along with other figures (e.g., Figs 3 vs. S7, Figs 7 vs. S9), our study provided a thorough comparison and validation of fire [$PM_{2.5}$] during extreme events derived from two inventories.

"Extreme fire episodes pose significant threats to public health. The percentage of days and land grids with fire-sourced [$PM_{2.5}$] exceeding the World Health Organization's air quality standard of 15 μg m^3 showed a global decreasing trend of -0.03% yr^{-1} (Fig. 8a). Regionally, an increase of 0.04% yr^{-1} was found in North America, driven by the 2023 Canadian fire episode, though this change was not statistically significant. In other regions, the exposure risk to high levels of fire $PM_{2.5}$ declines, with the most notable declines of -0.22% yr^{-1} in South America and -0.13% yr^{-1} in Africa. While extreme fire [$PM_{2.5}$] in general decreased, a turning point occurred in 2017, with more pronounced fire events thereafter." (Lines 289-296)

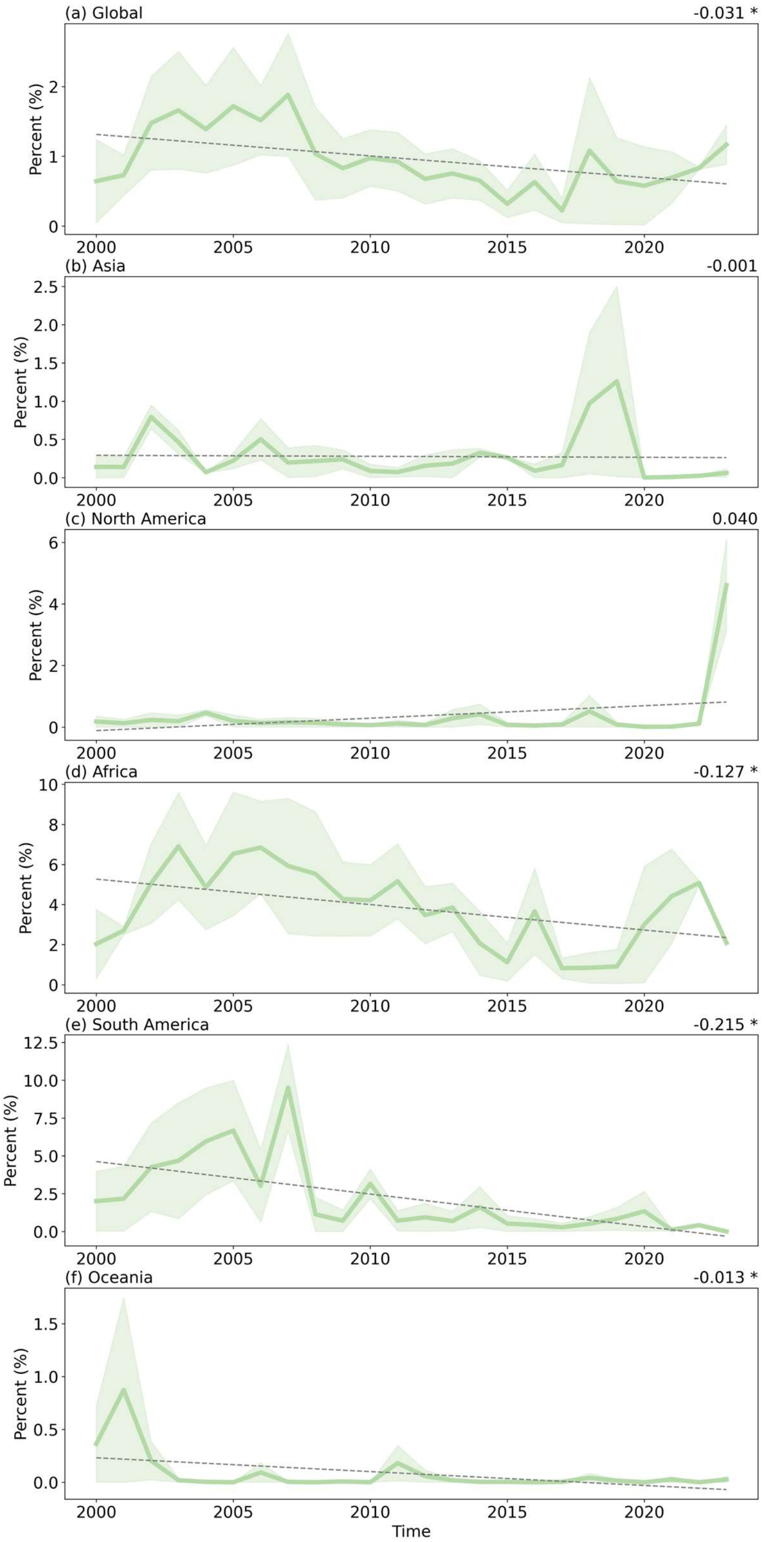

Figure 8. Annual percentage of days and land grids with fire-sourced [$PM_{2.5}$] exceeding 15 μg m^3 in (a) Global, (b) Asia, (c) North America, (d) Africa, (e) South America and (f) Oceania for 2000-2023. The average estimates from GFED and QFED are shown as bold lines, with shadings indicating their range. Regional trends are displayed on the top right of each panel, with an asterisk denoting significant (p < 0.05) changes.

2) As shown in Figure 4 and Figure S3, the model simulated all-source $PM_{2.5}$ concentrations were significantly biased high over many regions. How would these model biases affect the fire-sourced $PM_{2.5}$ estimates? According to Equ (3) in Section 2.4, if the biases were from the nofire model $PM_{2.5}$, then the resulting fire-sourced $PM_{2.5}$ would be underestimated. The impacts of the model biases shall be better discussed.

- In the revised paper, we added following discussion to acknowledge the uncertainties from chemical transport model: "Third, biases in the [$PM_{2.5}$] simulated by the GC model may significantly affect the accuracy of machine learning. Predicting air pollutants involves uncertainties due to variations in meteorological forcing, chemical and physical schemes, initial and boundary conditions, and so on. For example, Qiu et al. (2024) found that the GC model significantly overestimated [$PM_{2.5}$] during extreme wildfire events in 2020 over the western U.S. In contrast, our derived fire [$PM_{2.5}$], using the same GFED inventory, is much lower than the estimates of Childs et al. (2022) for low to median fire events (Fig. 4). These findings suggest that incorporating more validated fire inventories and/or chemical models is necessary to better quantify the uncertainties in derived air pollutant concentrations." (Lines 378-386)

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