Interactive discussion for egusphere-2026-2906

We sincerely thank Referee #1 for the careful and constructive review. We have addressed all comments below and have prepared corresponding revisions for the manuscript to be submitted after the discussion phase. Reviewer comments are reproduced below, followed by our responses and a concise description of the changes. Page and line numbers refer to the revised manuscript. Exact revised text is quoted only where it is needed to document a substantive correction. We believe these revisions substantially improve the scientific accuracy, balance, and clarity of the manuscript.

[Comment #1] Review of "Spatiotemporal Dynamics, Drivers, and Uncertainties of Global Wildfire Carbon Dioxide Emissions" by Liang and co-authors. This paper synthesizes evidence on global wildfire carbon dioxide emissions (WCEs) from 1700 to 2100 by integrating multiple sources of analyses, including satellite-based fire emission products, fire-enabled dynamic vegetation and Earth system models, and paleoenvironmental proxies such as charcoal and ice-core black carbon records. Using these complementary datasets, the authors evaluate historical trends, contemporary spatial patterns, future projections, key drivers, associated uncertainties, and they come up with ways to improve this.

Review papers are very helpful but I felt the authors are not fully up to speed with the research field they reviewed (mostly concerning the description of the contemporary satellite-based era), and therefore may cause more confusion than clarity. That is a major concern which is not one that can be easily addressed. Another major concern - which can be addressed- is that the paper is outdated. Simple example, since Roteta et al. (2019, https://doi.org/10.1016/j.rse.2018.12.011) we know the coarse resolution burned area datasets -and their derived emissions- are biased low, but in this review paper those coarse resolution datasets are still described and averaged as the best available knowledge.

[Response #1] We appreciate the reviewer's critical comment, especially insufficiency accounting for biases of the coarse-resolution fire products. We therefore substantially restructured and reanalyzed the contemporary satellite-era component of the review, as summarized below.

(1) Updated the literature and interpretation of satellite-based fire observations. We incorporated recent high-resolution burned-area studies, including Roteta et al. (2019), and now explicitly recognize that coarse-resolution products systematically omit many small and fragmented fires, leading to low biases in burned area and derived emissions. (Introduction, Lines 45–54; Section 2.3, Lines 309–331)

Revised text:

Satellite-based estimates of global burned area vary substantially among products (Jones et al., 2022; van der Werf et al., 2017; Zheng et al., 2021), with recent high-resolution mapping estimating a mean annual burned area of 774 ± 63 Mha during 2001–2020, equivalent to 5.9 ± 0.5% of global ice-free land (Chen et al., 2023). In this review, wildfire CO_2 emissions (WCEs) refer to gross emissions released during biomass combustion rather than net ecosystem carbon loss or the net contribution of fire to atmospheric CO_2 growth. Estimates of the magnitude and spatiotemporal dynamics of WCEs nevertheless remain highly uncertain because of differences in burned-area detection, fuel consumption, combustion completeness, emission factors, as well as structural differences among fire-enabled models (van der Werf et al., 2017; Zheng et al., 2021; Li et al., 2024; Hantson et al., 2020). These uncertainties highlight the need for a systematic synthesis and critical evaluation of current fire-emission estimates.

Burned-area products differ markedly in their ability to detect small agricultural fires, crop-residue burning, fragmented burn scars, and events obscured by cloud cover (Randerson et al., 2012; Kaiser et al., 2012). MODIS Collection 6 and FireCCI improved the detection of small and spatially fragmented burns through revised algorithms and finer-resolution reflectance observations, although substantial omissions remain in regions dominated by small fires, particularly African savannas (Lizundia-Loiola et al., 2020; Ramo et al., 2021; Liu et al., 2020; Giglio et al., 2018).

These limitations are particularly evident when GFED5 is compared with earlier coarse-resolution products. GFED5 MODIS Collection 6 burned area with high-resolution Landsat- and Sentinel-2-based corrections for omission and commission errors and revises the treatment of cropland fires, producing substantially larger burned-area and emission estimates than GFED4.1s in many fragmented and human-dominated landscapes (Chen et al., 2023; van der Werf et al., 2025; Roteta et al., 2019). In the present analysis, GFED5.1 was used for 2001–2022 and extended to 2025 using GFED5NRT estimates for 2023–2025.

(2) Updated and extended the contemporary WCE analysis. We added GFED5 to the original four-product ensemble, extended the analysis from 2001–2022 to 2001–2025 using the GFED5 near-real-time extension for the most recent years, and reprocessed the five datasets within a consistent analytical framework. All global and regional WCE estimates, spatial patterns, temporal trends, figures, and associated interpretations in Section 2 were recalculated and replaced where necessary. (Section 2.1, Lines 105–180; Section 2.2, Lines 215–275; Table 1; Figs. 1–4)

Revised text:

The five-product ensemble of fire-emission datasets (Table 1), including the Global Fire Emissions Dataset version 5 (GFED5, extended with GFED5NRT for 2023–2025), Global Fire Emissions Dataset version 4.1 with small fires (GFED4s), the Global Fire Assimilation System Dataset (GFAS), the Quick Fire Emissions Dataset (QFED), and the Fire Energetics and Emissions Research Dataset (FEER). GFED5, GFED4s, and QFED were available for 2001–2002. All five products were used for 2003–2025, with equal weights among the products available in each year. The pooled product yielded mean annual WCEs of 9.42 ± 0.86 (annual ensemble means ± interannual standard variation) Pg CO_2 yr^{-1} during 2001–2025. Burned area was assessed separately rather than as an ensemble quantity. GFED4s-based estimates indicate a mean global burned area of 440 ± 50 Mha yr^{-1} (Bowman et al., 2020), whereas GFED5 reports a higher value of 774 ± 63 Mha yr^{-1}, or 5.9 ± 0.5% of global ice-free land (Chen et al., 2023), mainly because GFED5 better detects small and fragmented fires.

Moving from model-based reconstructions to the satellite era, contemporary satellite-derived fire emission datasets capture consistent magnitudes and interannual variability of WCEs, with pronounced peaks during El Niño–induced droughts and reductions in La Niña years (van der Werf et al., 2017). Between 2001 and 2025, the five widely used datasets (GFED5, GFED4s, QFED, GFAS, and FEER) reveal broadly comparable global averages but exhibit substantial discrepancies in interannual dynamics and long-term trends (Fig. 3). Notably, this mean-level consensus reflects shared methodological roots (e.g., GFAS calibrated to GFED3.1), thus the narrow range of global averages vastly underestimates true emission uncertainty as evidenced by the ~61% burned area jump from GFED4s to GFED5 (van der Werf et al., 2025). Several products suggest a modest decline in global fire emissions during the early 21st century, largely linked to reductions in burned area across savanna regions of Africa and South America (Andela et al., 2017; Zheng et al., 2021), whereas others indicate relatively stable emissions, underscoring their strong dependence on dataset choice and the continuing uncertainties associated with satellite retrievals and emission modeling.

(3) Revised the interpretation of the multi-product ensemble. The manuscript no longer presents the simple product average as the "best available estimate." The ensemble mean is now used only to characterize central tendency, whereas inter-product spread is interpreted as a partial and potentially conservative representation of structural uncertainty because several products share satellite inputs, calibration information, methodological components, and parameterizations. (Section 2.2, Lines 215–225; Section 2.3, Lines 337–348)

Revised text:

Notably, this mean-level consensus reflects shared methodological roots (e.g., GFAS calibrated to GFED3.1), thus the narrow range of global averages vastly underestimates true emission uncertainty as evidenced by the ~61% burned area jump from GFED4s to GFED5 (van der Werf et al., 2025). Several products suggest a modest decline in global fire emissions during the early 21st century, largely linked to reductions in burned area across savanna regions of Africa and South America (Andela et al., 2017; Zheng et al., 2021), whereas others indicate relatively stable emissions, underscoring their strong dependence on dataset choice and the continuing uncertainties associated with satellite retrievals and emission modeling.

These products are not fully independent because they share some satellite inputs, calibration information, methodological components, or literature-derived parameters (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020). Their inter-product spread is therefore a partial and potentially conservative representation of structural uncertainty rather than a complete estimate of total uncertainty. Atmospheric inversions provide a more independent top-down constraint, but remain sensitive to observational coverage, prior assumptions, and atmospheric transport and cannot be treated as an absolute benchmark (Chevallier et al., 2019; van der Werf et al., 2025).

(4) Expanded the methodological and uncertainty assessment. The revised manuscript distinguishes the burned-area and modeled-fuel-consumption framework of GFED products from approaches relying more strongly on FRP or FRE observations and product-specific conversion schemes, including GFAS, QFED, and FEER. It also evaluates uncertainties associated with fire detection, fuel consumption, combustion completeness, CO_2 emission factors, land-cover representation, and model structure. Atmospheric inversions are discussed as a more independent, although not absolute, top-down constraint on contemporary fire-emission estimates. (Section 2.3, Lines 309–365)

Revised text:

For the contemporary satellite era, uncertainty arises throughout the emission-estimation chain, from fire detection to the conversion of observed fire activity into CO_2 emissions (van der Werf et al., 2017; Pan et al., 2020). Burned-area products differ markedly in their ability to detect small agricultural fires, crop-residue burning, fragmented burn scars, and events obscured by cloud cover (Randerson et al., 2012; Kaiser et al., 2012). MODIS Collection 6 and FireCCI improved the detection of small and spatially fragmented burns through revised algorithms and finer-resolution reflectance observations, although substantial omissions remain in regions dominated *by small fires, particularly African savannas (Lizundia-Loiola et al., 2020; Ramo et al., 2021; Liu et al., 2020; Giglio et al., 2018). Further uncertainty is introduced when detected fire activity is converted into emissions. Fuel-consumption estimates depend on modeled fuel loads and combustion completeness, which vary among ecosystems, fuel types, moisture conditions, and fire behavior (van der Werf et al., 2017; van Wees et al., 2022). Combustion completeness denotes the fraction of available fuel consumed and is particularly uncertain where burning extends into litter, organic soils, or peat (van der Werf et al., 2017; Che Azmi et al., 2021). CO_2 emission factors also vary among fuel and vegetation types and with the relative contributions of flaming and smoldering combustion (Andreae, 2019). Fire-radiative-power-based inventories are additionally sensitive to cloud-related observation gaps, sensor characteristics, and biome-specific conversion coefficients (Kaiser et al., 2012). These uncertainties propagate through the estimation chain and contribute to substantial regional and interannual differences between burned-area-based and FRP-based inventories (Nguyen and Wooster, 2020; Pan et al., 2020).*

Differences among GFED5, GFED4s, GFAS, QFED, and FEER also reflect contrasting representations of fire activity and emission estimation. GFED products combine burned area with modeled fuel consumption, whereas GFAS, QFED, and FEER derive emissions primarily from fire radiative power or energy using product-specific conversion factors, land-cover classifications, and emission factors (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020). These products are not fully independent because they share some satellite inputs, calibration information, methodological components, or literature-derived parameters (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020). Their inter-product spread is therefore a partial and potentially conservative representation of structural uncertainty rather than a complete estimate of total uncertainty. Atmospheric inversions provide a more independent top-down constraint, but remain sensitive to observational coverage, prior assumptions, and atmospheric transport and cannot be treated as an absolute benchmark (Chevallier et al., 2019; van der Werf et al., 2025).

Collectively, these changes constitute a substantial revision of the contemporary satellite-era component of the manuscript. They replace the previous four-product averaging framework with an updated five-product analysis and a more explicit evaluation of shared biases, methodological dependencies, and independent atmospheric constraints. (Sections 2.1–2.3, Lines 105–378)

Revised text:

In summary, WCE estimates remain highly uncertain across historical reconstructions, contemporary satellite inventories, and future projections. These uncertainties arise from three interacting sources: observational limitations in detecting burned area and fire activity; parameter uncertainty in fuel loads, combustion completeness, and CO_2 emission factors; and structural uncertainty in the representation of fire–climate–vegetation–human interactions, land-use change, and extreme-fire behavior. Because many inventories and models share satellite inputs, calibration datasets, and parameterizations, agreement among products does not necessarily indicate low uncertainty, and inter-product spread should be interpreted as a partial and potentially conservative representation of total uncertainty. Reducing these uncertainties will require coordinated integration of high-resolution multi-sensor observations, ground measurements, atmospheric inversions, and paleofire proxies; improved parameterizations of combustion, multiday fire dynamics, and vegetation–fuel feedbacks; and more explicit representation of socioeconomic processes and land management in fire-enabled Earth system models.

[Comment #2] Please find below a list of examples of verbose, outdated, and occasionally unfocused writing. Simply addressing these would not make this paper publishable in my opinion (also because this is just a subset of the issues). Converting this paper to a publishable version requires a major overhaul, providing much more depth, including analysing the literature that provides independent information on fire patterns compared to the models (e.g., fire proxies), but most of all becoming familiar with the most recent literature. I apologize for being so negative as I do realize the authors have done their best.

[Response #2] To address this comment, we undertook a manuscript-wide revision. Repetitive and unfocused text was removed or condensed, the historical, contemporary, and future sections were reorganized, and the literature was updated throughout with recent studies of fire observations, paleofire reconstruction, and fire-enabled modeling. (Introduction, Lines 40–90; Sections 2–5, Lines 92–679)

Revised text:

This Review synthesizes the spatiotemporal dynamics of global wildfire carbon dioxide emissions (WCEs) across historical (1700–2000), contemporary (2001–2025), and future (2026–2100) periods by integrating evidence from satellite-based products, process-based models, and scenario projections. We compare the major drivers regulating WCEs across spatial and temporal scales and examine recent extreme wildfire seasons (EWS), which contribute to interannual variability in regional and global WCEs. We also evaluate methodological differences, evidence gaps, and *uncertainty across observational, proxy, and modeling frameworks. Building on this synthesis, we delineate research priorities for improving predictability, representing climate–wildfire feedbacks in fire-enabled Earth system models, and constraining post-fire carbon recovery. Collectively, these advances provide framework to support more robust projections and to inform wildfire management and climate mitigation strategies.*

The revised manuscript now compares methodologically distinct lines of evidence rather than presenting datasets and model outputs separately. We distinguish the model-derived pre-1850 stability in FireMIP from reconstructions based on sedimentary charcoal, ice-core CO, and ice-core $\delta^{13}CH_4$ records, and explain how spatial coverage, temporal resolution, preservation, and proxy sensitivity affect their interpretation. We also added a model-specific comparison of fire-process representations, subsequent developments, and remaining limitations across FireMIP DGVMs (Table 2). Section 2.2, Lines 199–213; Section 2.3, Lines 278–305; Table 2)

Revised text:

Historical WCEs (1700–2000) in this study were derived from DGVMs participating in FireMIP (Fig. 3). The weak pre-1850 change in the model ensemble (approximately ± 0.1% yr⁻1) is partly a consequence of the experimental protocol, including repeated 1901–1920 climate and lightning forcing before 1900, and should not be interpreted as an observation-based reconstruction of actual centennial climate variability. After 1850, period exhibits strong divergence among models, which are largely attributable to accelerating land-use change (e.g., tropical deforestation for agriculture), human ignition, suppression, and fire processes are represented differently (van Marle et al., 2017; Li et al., 2024). Models that explicitly incorporate anthropogenic ignitions (e.g., LPJ-GUESS-SIMFIRE-BLAZE) or Bayesian optimization (FINAL) simulate declining WCEs, consistent with CMIP6 projections emphasizing fire suppression in converted landscapes. In contrast, process-based models such as ORCHIDEE-SPITFIRE and paleo reconstructions from ice-core black carbon and sedimentary charcoal point to marked increases in fire emissions (Yue et al., 2015; Ferretti et al., 2005; Wang et al., 2010). This divergence underscores a key uncertainty: many DGVMs underestimate the extent of human–fire interactions, whereas empirical reconstructions suggest enhanced burning linked to deforestation, peatland drainage, vegetation feedback, and land-use intensification (Li et al., 2024; Marlon et al., 2008).

A major source of uncertainty in historical WCE simulations lies in both the structural formulation of dynamic global vegetation models (DGVMs) and the experimental design of FireMIP. The weak pre-1850 trends simulated by the FireMIP ensemble (<0.015% yr^{-1}) should therefore be interpreted as a model-derived pattern rather than *an observation-based historical constraint (Li et al., 2019; Rabin et al., 2017). Before 1900, the models were driven by repeated 1901–1920 climate and lightning forcing, which suppresses the actual sequence of interdecadal and centennial-scale climate variability. Many fire modules also use empirical or semi-empirical parameterizations of fire occurrence and burned area, further limiting their sensitivity to historical climate extremes. The resulting model-derived stability contrasts with reconstructions based on sedimentary charcoal, ice-core CO, and ice-core $\delta^{13}CH_4$ records, several of which indicate increasing biomass burning between approximately 1700 and 1850 (Wang et al., 2010; Ferretti et al., 2005; Marlon et al., 2008; Marlon et al., 2016). These proxies, however, differ in spatial coverage, temporal resolution, preservation processes, and the aspects of fire activity they record, and cannot be translated directly into CO_2 emissions. After 1850, intermodel divergence is further amplified by inconsistent representations of anthropogenic fire processes. For example, CLM4.5 explicitly represents crop, deforestation, and peat fires, although soil organic matter combustion from peat fires was excluded from the FireMIP outputs. CLM4.5 and LPJ-GUESS-SIMFIRE-BLAZE represent suppression effects on both fire occurrence and spread, whereas other configurations represent suppression through fire duration or alternative empirical constraints (Li et al., 2019; Rabin et al., 2017). Subsequent developments and remaining limitations are summarized by model in Table 2 and the references therein.*

The uncertainty analysis was also reorganized to distinguish observational, parameter, and model-structural sources across historical reconstruction, contemporary estimation, and future projection. The revised manuscript therefore moves beyond a descriptive compilation by critically evaluating the evidential basis, agreement, divergence, and limitations of conclusions across the three periods. (Section 2.3, Lines 278–378; Section 5, Lines 625–679)

Revised text:

In summary, WCE estimates remain highly uncertain across historical reconstructions, contemporary satellite inventories, and future projections. These uncertainties arise from three interacting sources: observational limitations in detecting burned area and fire activity; parameter uncertainty in fuel loads, combustion completeness, and CO_2 emission factors; and structural uncertainty in the representation of fire–climate–vegetation–human interactions, land-use change, and extreme-fire behavior. Because many inventories and models share satellite inputs, calibration datasets, and parameterizations, agreement among products does not necessarily indicate low uncertainty, and inter-product spread should be interpreted as a partial and potentially conservative representation of total uncertainty. Reducing these uncertainties will *require coordinated integration of high-resolution multi-sensor observations, ground measurements, atmospheric inversions, and paleofire proxies; improved parameterizations of combustion, multiday fire dynamics, and vegetation–fuel feedbacks; and more explicit representation of socioeconomic processes and land management in fire-enabled Earth system models.*

Specific Comments:

[Comment #3] L23: "8.72 ± 0.67 Pg CO_2 yr^{-1}" does not refer to the trend but is the average I assume? That makes it a somewhat confusing sentence. Also, it may be good to have fewer significant digits for numbers so uncertain. And it is not clear where the 0.67 refers to. Guess spread between inventories? Good to clarify.

[Response #3] We agree that the original wording did not clearly distinguish the mean annual emissions from the temporal trend or define the meaning of the "±" term. We have therefore reported the two quantities separately, corrected the trend unit to Pg CO_2 yr^{-2}, and reduced the number of significant digits. The "± 0.86" value is now explicitly defined as the interannual standard deviation of the annual five-product ensemble means, rather than the spread among inventories. (Abstract, Lines 24–27)

Revised text:

Contemporary satellite observations showed a non-significant negative global WCE tendency during 2001–2025, with a trend slope of -0.1 Pg CO_2 yr^{-2} (confidence interval = 95%; $p > 0.05$). Mean annual WCEs over this period were 9.42 ± 0.86 (annual ensemble means ± interannual standard deviation) Pg CO_2 yr^{-1}, with approximately 83% originating from tropical ecosystems, mainly due to extensive burned area and high gross CO2 emissions per unit burned area.

[Comment #4] L25: "high combustion efficiency". In the fire literature combustion efficiency usually refers to the fraction of total carbon emitted as CO2, but I doubt that is what you mean here?

[Response #4] Thank you for pointing this out. We agree that "combustion efficiency" has a specific meaning in the fire-emissions literature and was not the quantity intended here. We therefore replaced "high combustion efficiency" with "high CO_2 emissions per unit area burned," which more accurately describes the intended meaning and avoids confusion with combustion efficiency as conventionally defined. (Abstract, Lines 26–28)

Revised text:

Mean annual WCEs over this period were 9.42 ± 0.86 (annual ensemble means ± interannual standard deviation) Pg CO_2 yr^{-1}, with approximately 83% originating from *tropical ecosystems, mainly due to extensive burned area and high gross CO_2 emissions per unit burned area.*

[Comment #5] L25: "Importantly, these fluxes represent a critical shift in the net carbon balance of tropical and boreal biome". One can argue that fires in tropical forests change the carbon balance, but fires in savannas and the Boreal zone have been there for a long time and there needs to be some discussion about background versus elevated fire levels.

[Response #5] Thanks for the comment. In the revised main text, we distinguish background fire regimes from elevated or changing fire activity. We now clarify that fire is more likely to alter biome-scale carbon balance when fire frequency or intensity exceeds its historical range, fire-return intervals become shorter than the time required for ecosystem recovery or burning affects carbon-dense or recovery-limited ecosystems. These conditions include tropical forests and peatlands, as well as degraded forests that are vulnerable to repeated burning, incomplete recovery, and vegetation-state transitions. (Section 2.1, Lines 131–140)

Revised text:

WCEs should not be interpreted directly as changes in net carbon balance, because WCEs represent gross fire CO_2 emissions and their net effect depends on post-fire recovery and ecosystem carbon residence time (van der Werf et al., 2010). In tropical savannas and many boreal ecosystems, fire is part of the long-term background fire regime, and post-fire regrowth can partly offset CO_2 emissions over time (van der Werf et al., 2010; Lipsett-Moore et al., 2018). However, elevated or altered fire activity can substantially affect biome-scale carbon balance when burned area, fire frequency, or fire severity exceeds historical background levels, when recovery intervals shorten, or when fires occur in carbon-dense systems such as tropical forests, degraded forests, and peatlands (Walker et al., 2019; Turetsky et al., 2015). These distinctions are essential for interpreting WCEs as gross fire emissions rather than direct indicators of net ecosystem carbon loss.

[Comment #6] L30: "Despite regional heterogeneity, climate change emerges as the primary regulator of interannual variability in WCE". In the main text you rightfully state that interannual variability is related to ENSO, but that is not climate change.

[Response #6] We agree that ENSO represents interannual climate variability rather than climate change. We have revised the sentence to refer to climate variability, particularly ENSO-related hydroclimatic anomalies, as a major driver of interannual variability in WCEs. We also distinguish this from longer-term climate-change effects on fire-weather extremes and future fire risk in section 3.1. (Abstract, Lines 31–33;

Section 3.1, Lines 415–439)

Revised text:

Despite regional heterogeneity, climate variability, particularly ENSO-related hydroclimatic anomalies, is a major driver of interannual WCE variability.

Climate exerts a significant influence on both wildfire occurrence and WCEs over short- and long-term timescales. At a short-term timescale (spanning days to weeks), climatic anomalies such as droughts and heatwaves directly affect fire weather (e.g., temperature, humidity, and winds) (Abram et al., 2021). These sudden shifts in climate can significantly enhance wildfire occurrence risk, creating conditions where vegetation becomes drier, more flammable, and more susceptible to ignition, thereby increasing the likelihood of wildfires and their associated WCEs (Liu and Wimberly, 2015). In contrast, long-term (decadal to centennial) climatic trends in temperature and precipitation affect broader vegetation productivity, fuel accumulation, and landscape heterogeneity (Jones et al., 2022). These long-term climatic trends shape wildfire regimes by determining the types and distribution of fuels across large areas, which in turn influences both the frequency and intensity of wildfires and thus CO_2 *emissions (Liu et al., 2012; Schoennagel et al., 2017).*

With global warming, the frequency of such extreme climatic conditions is expected to increase, which is likely to result in larger, more intense, and more frequent wildfires (Schoennagel et al., 2017; Senande-Rivera et al., 2022; Gutierrez et al., 2021). The trend is already evident in many fire-prone regions, with models projecting significant increases in wildfire activity under future climate scenarios. Specifically, the global land area exposed to frequent fire-prone climatic conditions is projected to expand by 29% at the end of 21st century, with particularly sharp increases in boreal (+111%) and temperate (+25%) forests, alongside a lengthening of fire seasons (Senande-Rivera et al., 2022). This result describes climatic suitability for frequent fire, not realized burned area.

[Comment #7] L43 “dominant source of the atmospheric CO_2 “ -> dominant source of the rise in atmospheric CO_2.

[Response #7] Thanks for pointing it out, and we have accepted it in the revised manuscript. (Introduction, Lines 44–45)

Revised text:

In the post-industrial era, fossil-fuel combustion has become the dominant source of the sustained increase in atmospheric CO_2 *(Friedlingstein et al., 2023).*

[Comment #8] L44: "Meanwhile, satellite observations from this period suggest that wildfires annually burned 3.8–4.8% of global vegetated land and wildfire carbon dioxide emissions (WCEs) emitted approximately 20% of CO_2 released from fossil fuel combustion (Jones et al., 2022; Van Der Werf et al., 2017; Zheng et al., 2021)". Chen et al. (2023, https://doi.org/10.5194/essd-15-5227-2023) reports 5.9%. To me it looks the authors are not aware of the latest literature and developments which is crucial when writing a review. In addition, comparing WCE with fossil fuel emissions or with annual CO2 increases is comparing apples and oranges; the vast majority of fire emissions are balanced by regrowth and not a net source of CO2. The way it is framed now ("WCEs accounted for 35–52% of the net annual atmospheric CO_2 increase") is simply wrong. What are the insights from recent studies using higher resolution burned area (for example Sentinel-2 or Landsat)? How do the estimated emissions compare to atmospheric inversion studies? Why is the recent version of GFED (GFED5) so much higher, etc. That is the kind of information that would be good to focus a review paper on and would push the field forwards. The same counts for a proper discussion and evaluation of fire models.

[Response #8] We thank the reviewer for this important and constructive comment. We agree that the original burned-area estimate was outdated and that directly comparing gross wildfire CO_2 emissions with fossil-fuel emissions or net atmospheric CO_2 growth was inappropriate. We have updated the Introduction using the recent high-resolution estimate of Chen et al. (2023), which reports a mean annual burned area of 774 ± 63 Mha during 2001–2020, equivalent to 5.9 ± 0.5% of global ice-free vegetated land. We have also removed the statements that WCEs represented approximately 20% of fossil-fuel emissions and 35–52% of annual atmospheric CO_2 growth, and now explicitly define WCEs as gross combustion emissions rather than net ecosystem carbon loss or the net contribution of fire to atmospheric CO_2 growth. (Introduction, Lines 45–54)

Revised text:

Satellite-based estimates of global burned area vary substantially among products (Jones et al., 2022; van der Werf et al., 2017; Zheng et al., 2021), with recent high-resolution mapping estimating a mean annual burned area of 774 ± 63 Mha during 2001–2020, equivalent to 5.9 ± 0.5% of global ice-free land (Chen et al., 2023). In this review, wildfire CO_2 emissions (WCEs) refer to gross emissions released during biomass combustion rather than net ecosystem carbon loss or the net contribution of fire to atmospheric CO_2 growth. Estimates of the magnitude and spatiotemporal dynamics of WCEs nevertheless remain highly uncertain because of differences in burned-area detection, fuel consumption, combustion completeness, emission factors, as well as structural differences among fire-enabled models (van der Werf et al., 2017;

Zheng et al., 2021; Li et al., 2024; Hantson et al., 2020). These uncertainties highlight the need for a systematic synthesis and critical evaluation of current fire-emission estimates.

More substantially, we have added GFED5 to the previous four-product ensemble and extended the analysis period from 2001–2022 to 2001–2025. We consequently recalculated and updated all results in Section 2, including global and regional WCE magnitudes, spatial patterns, temporal trends, figures, and corresponding interpretations. (Section 2.1, Lines 105–180; Section 2.2, Lines 215–275; Table 1; Figs. 1–4)

Revised text:

The five-product ensemble of fire-emission datasets (Table 1), including the Global Fire Emissions Dataset version 5 (GFED5, extended with GFED5NRT for 2023–2025), Global Fire Emissions Dataset version 4.1 with small fires (GFED4s), the Global Fire Assimilation System Dataset (GFAS), the Quick Fire Emissions Dataset (QFED), and the Fire Energetics and Emissions Research Dataset (FEER). GFED5, GFED4s, and QFED were available for 2001–2002. All five products were used for 2003–2025, with equal weights among the products available in each year. The pooled product yielded mean annual WCEs of 9.42 ± 0.86 (annual ensemble means ± interannual standard variation) Pg CO_2 yr^{-1} during 2001–2025. Burned area was assessed separately rather than as an ensemble quantity. GFED4s-based estimates indicate a mean global burned area of 440 ± 50 Mha yr^{-1} (Bowman et al., 2020), whereas GFED5 reports a higher value of 774 ± 63 Mha yr^{-1}, or 5.9 ± 0.5% of global ice-free land (Chen et al., 2023), mainly because GFED5 better detects small and fragmented fires.

We have also expanded the uncertainty analysis to compare GFED5 with GFED4s, GFAS, QFED, and FEER, focusing on the effects of Landsat- and Sentinel-2-based burned-area results, small-fire detection, fuel consumption, combustion completeness, emission factors, and model structure. In addition, we strengthened the discussion of comparisons with atmospheric inversion constraints and the evaluation of fire-enabled models. These revisions provide a more current and critical synthesis of recent observational and modelling developments. (Section 2.3, Lines 309–365)

Revised text:

For the contemporary satellite era, uncertainty arises throughout the emission-estimation chain, from fire detection to the conversion of observed fire activity into CO_2 emissions (van der Werf et al., 2017; Pan et al., 2020). Burned-area products differ markedly in their ability to detect small agricultural fires, crop-residue burning, fragmented burn scars, and events obscured by cloud cover (Randerson et al., 2012; Kaiser et al., 2012). MODIS Collection 6 and FireCCI improved the detection of small *and spatially fragmented burns through revised algorithms and finer-resolution reflectance observations, although substantial omissions remain in regions dominated by small fires, particularly African savannas (Lizundia-Loiola et al., 2020; Ramo et al., 2021; Liu et al., 2020; Giglio et al., 2018). Further uncertainty is introduced when detected fire activity is converted into emissions. Fuel-consumption estimates depend on modeled fuel loads and combustion completeness, which vary among ecosystems, fuel types, moisture conditions, and fire behavior (van der Werf et al., 2017; van Wees et al., 2022). Combustion completeness denotes the fraction of available fuel consumed and is particularly uncertain where burning extends into litter, organic soils, or peat (van der Werf et al., 2017; Che Azmi et al., 2021). CO_2 emission factors also vary among fuel and vegetation types and with the relative contributions of flaming and smoldering combustion (Andreae, 2019). Fire-radiative-power-based inventories are additionally sensitive to cloud-related observation gaps, sensor characteristics, and biome-specific conversion coefficients (Kaiser et al., 2012). These uncertainties propagate through the estimation chain and contribute to substantial regional and interannual differences between burned-area-based and FRP-based inventories (Nguyen and Wooster, 2020; Pan et al., 2020).*

These limitations are particularly evident when GFED5 is compared with earlier coarse-resolution products. GFED5 MODIS Collection 6 burned area with high-resolution Landsat- and Sentinel-2-based corrections for omission and commission errors and revises the treatment of cropland fires, producing substantially larger burned-area and emission estimates than GFED4.1s in many fragmented and human-dominated landscapes (Chen et al., 2023; van der Werf et al., 2025; Roteta et al., 2019). In the present analysis, GFED5.1 was used for 2001–2022 and extended to 2025 using GFED5NRT estimates for 2023–2025. The two series were joined directly with no bias correction and uncertainty associated with this transition is considered when interpreting the most recent trends (Chen et al., 2026). Increases in detected burned area do not translate proportionally into CO_2 emissions because fuel loads, combustion completeness, and fire characteristics vary among ecosystems and fire types. Differences among GFED5, GFED4s, GFAS, QFED, and FEER also reflect contrasting representations of fire activity and emission estimation. GFED products combine burned area with modeled fuel consumption, whereas GFAS, QFED, and FEER derive emissions primarily from fire radiative power or energy using product-specific conversion factors, land-cover classifications, and emission factors (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020). These products are not fully independent because they share some satellite inputs, calibration information, methodological components, or literature-derived parameters (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020).

Their inter-product spread is therefore a partial and potentially conservative representation of structural uncertainty rather than a complete estimate of total uncertainty. Atmospheric inversions provide a more independent top-down constraint, but remain sensitive to observational coverage, prior assumptions, and atmospheric transport and cannot be treated as an absolute benchmark (Chevallier et al., 2019; van der Werf et al., 2025).

[Comment #9] L94: "The ensemble mean of four fire emission datasets (Table 1), including the Global Fire Emissions Dataset with small fires (GFEDv4s), the Global Fire Assimilation System Dataset (GFASv1.2), the Quick Fire Emissions Dataset (QFEDv2.6r1), and the Fire Energetics and Emissions Research Dataset (FEER), indicates that the global burned area averaged 440 ± 50 Mha yr-1 from 2001 to 2020". Then Table 1 shows that only one of those databases is based on burned area, can one call this an ensemble estimate then? And how should I interpret the ± 50 Mha? Please be crystal clear with your writing and take the reader by the arm so (s)he does not have to guess what you mean.

[Response #9] We agree that the original wording was unclear and incorrectly implied that global burned area was estimated as an ensemble mean of the four fire-emission datasets. In the revised manuscript, we have separated burned-area estimates from WCE estimates. (Section 2.1, Lines 105–116)

Revised text:

The five-product ensemble of fire-emission datasets (Table 1), including the Global Fire Emissions Dataset version 5 (GFED5, extended with GFED5NRT for 2023–2025), Global Fire Emissions Dataset version 4.1 with small fires (GFED4s), the Global Fire Assimilation System Dataset (GFAS), the Quick Fire Emissions Dataset (QFED), and the Fire Energetics and Emissions Research Dataset (FEER). GFED5, GFED4s, and QFED were available for 2001–2002. All five products were used for 2003–2025, with equal weights among the products available in each year. The pooled product yielded mean annual WCEs of 9.42 ± 0.86 (annual ensemble means ± interannual standard variation) Pg CO_2 yr^{-1} during 2001–2025. Burned area was assessed separately rather than as an ensemble quantity.

Specifically, burned area is now reported from burned-area products only. We report the earlier GFEDv4s-based estimate of 440 ± 50 Mha yr^{-1} and the updated GFED5 estimate of 774 ± 63 Mha yr^{-1}. We clarify that the ± values represent interannual standard deviations over the study period, not inter-dataset spread or formal uncertainty. (Section 2.1, Lines 110–116)

Revised text:

Burned area was assessed separately rather than as an ensemble quantity. GFED4s-based estimates indicate a mean global burned area of 440 ± 50 Mha yr^{-1} (Bowman et al., 2020), whereas GFED5 reports a higher value of 774 ± 63 Mha yr^{-1}, or 5.9 ± 0.5% of global ice-free land (Chen et al., 2023), mainly because GFED5 better detects small and fragmented fires.

For WCEs, we recalculated the ensemble mean using five fire-emission products: GFEDv4s, GFASv1.2, QFEDv2.6r1, FEER, and GFED5. We also revised Table 1 to distinguish datasets used for burned-area estimates from those used for WCE estimates. (Section 2.1, Lines 105–111; Table 1)

Revised text:

The five-product ensemble of fire-emission datasets (Table 1), including the Global Fire Emissions Dataset version 5 (GFED5, extended with GFED5NRT for 2023–2025), Global Fire Emissions Dataset version 4.1 with small fires (GFED4s), the Global Fire Assimilation System Dataset (GFAS), the Quick Fire Emissions Dataset (QFED), and the Fire Energetics and Emissions Research Dataset (FEER). GFED5, GFED4s, and QFED were available for 2001–2002. All five products were used for 2003–2025, with equal weights among the products available in each year. The pooled product yielded mean annual WCEs of 9.42 ± 0.86 (annual ensemble means ± interannual standard variation) Pg CO_2 yr^{-1} during 2001–2025.

[Comment #10] L103: "Tropical fires, primarily within 20°S-15° N, account for approximately 83% of global WCEs (Fig. 1), largely due to tropical dry forests in Amazonia." In most datasets African fire emissions exceed those from South America, and tropical dry forests may be a relatively small fraction of South American forests.

[Response #10] We have revised the manuscript to emphasize extensive burning in tropical savannas and woodlands, particularly in Africa, and high per-area carbon losses from tropical forests, deforestation/degradation fires, and peatlands. (Section 2.1, Lines 121–130)

Revised text:

Tropical fires, primarily within 20°S-15° N, account for approximately 83% of global WCEs (Fig. 1). This dominance is consistent with previous fire-emission studies and mainly reflects extensive burned area in tropical savannas and woodlands, particularly in Africa, together with high seasonal fuel availability and high gross CO_2 emissions per unit burned area from tropical forests, deforestation/degradation fires, and peatlands (Jones et al., 2024b; van der Werf et al., 2025; Crawford et al., 2024). In addition, tropical forest fire occurrence has marked spatial and temporal heterogeneity, *especially in Southeast Asia (1.65 ± 0.62 Pg CO_2 yr^{-1}) which contributes more than two-thirds of total Asian WCEs. Temperate and boreal regions above 45°N contribute approximately 12% of global WCEs (Fig. 1) and have experienced increasing fire activity and carbon emissions in recent decades, especially during EWSs associated with climate warming (Jones et al., 2024b; Zheng et al., 2023; de Groot et al., 2013).*

[Comment #11] L117 "–32.92 Tg CO_2 yr^{-1}, significant" So the other ones are not significant? I guess so, but please be clear in how you write things down.

[Response #11] You are correct. Only the trends in North America and Africa were statistically significant, whereas the trends for the other continents were not significant. We have revised the sentence to make this explicit. (Section 2.1, Lines 145–150)

Revised text:

The change rates of annual WCEs were quantified using the Theil–Sen slope estimator and Mann–Kendall test (95% confidence interval; Fig. 2). At the continental scale, WCEs increased significantly in North America (+35.54 Tg CO_2 yr^{-2}; $p < 0.05$) and decreased significantly in Africa (−54.90 Tg CO_2 yr^{-2}; $p < 0.05$) and Europe (−5.69 Tg CO_2 yr^{-2}; $p < 0.05$). Other continents showed non-significant tendencies, with negative slopes in South America (−10.32 Tg CO_2 yr^{-2}; $p > 0.05$) and Asia (−10.42 Tg CO_2 yr^{-2} ; $p > 0.05$), and negative slopes in Oceania (−10.17 Tg CO_2 yr^{-2}; $p > 0.05$).

[Comment #12] L119 "seven major positive hotspots" Not clear what you are after and how these are defined.

[Response #12] We have revised the text to explicitly state the quantitative criteria used for identifying these clusters. Specifically, hotspots were identified using the DBSCAN algorithm (15 km search radius). Positive hotspots (red boxes) are defined as spatially contiguous clusters exceeding 2,000 km² with a cluster-averaged trend of pixels >0.005 Tg CO_2 yr^{-2}. Negative hotspots (blue boxes) are defined similarly but require a cluster-averaged trend of pixels <−0.005 Tg CO_2 yr^{-2}. Applying these filters resulted in six positive and four negative hotspots, respectively. (Section 2.1, Lines 150–159; Fig. 2)

Revised text:

Using the density-based spatial clustering algorithm (DBSCAN, 150 km search radius, min_samples = 2), six major positive hotspots (red boxes, defined as area of contiguous clusters > 200,000 km² with mean trends of pixels > 0.005 Tg CO_2 yr^{-2}) were identified in Alaska (+1.03 Tg CO_2 yr^{-2}, sum of trend within cluster), the Canadian Boreal Forest and Pacific Coast of the United States (+10.99 Tg CO_2 yr^{-2}), Central America (+0.52 Tg CO_2 yr^{-2}), northern South America (+1.07 Tg CO_2 yr^{-2}), Southeast Asia (+1.05 Tg CO_2 yr^{-2}), and eastern Siberia (+16.43 Tg CO_2 yr^{-2}). Three negative hotspots *(blue boxes, defined as area of contiguous clusters > 200,000 km² with mean trends of pixels < -0.005 Tg CO_2 yr^{-2}) are located in the Amazon Rainforest (–16.6 Tg CO_2 yr^{-2}), sub-Saharan Africa (–28.02 Tg CO_2 yr^{-2}), and northern Australia (–10.3 Tg CO_2 yr^{-2}).*

[Comment #13] L137-147 is very confusing and to me it is not clear what you want to say here, also because there is a downward trend in burned area in Africa.

[Response #13] We have revised this paragraph to improve its logical flow and clarity. Our intention was to show that burned area and WCE trends are not always proportional. The revised paragraph now states that both burned area and WCEs declined in Africa, but at different rates, and uses Africa and Oceania as examples of non-proportional burned area–emission relationships. We also clarified the underlying mechanism by explaining that WCEs depend not only on burned area, but also on fuel load, combustion completeness, emission factors, and ecosystem carbon density. (Section 2.1, Lines 169–180)

Revised text:

Trends in WCEs and burned area exhibited divergent spatial patterns (Bowman et al., 2020; Zheng et al., 2021). Increases in burned area do not necessarily result in increasing WCEs (e.g. in Africa and Oceania), since vegetation flammability and biomass density critically mediate carbon release efficiency (Bowman et al., 2020). In herbaceous-dominated ecosystems (e.g., grasslands and savannas), the expansion of burned areas typically amplifies CO2 emissions. This pattern likely reflects their low aboveground biomass density (<5 t/ha) and spatially homogeneous fuel loads, which promote combustion completeness (>90%) (van der Velde et al., 2021; Vernooij et al., 2023). Conversely, in high-biomass ecosystems like boreal forests (>150 t·C·ha^{-1}) or tropical forests, elevated moisture content (vegetation >30%, soil >25%) suppresses flammability and limits the deep ignition of soil organic carbon (SOC) pools (Pan et al., 2011; Prior et al., 2020; Soro et al., 2025). Consequently, when critical moisture thresholds are exceeded, larger burned areas in these systems may release less CO2 than theoretical models predict (Chen et al., 2010; Walker et al., 2020).

[Comment #14] L167 "Although global emissions remained relatively stable prior to 1850 (±0.1% yr^{-1}), reflecting predominantly natural climate variability". Please make sure readers understand that the emissions being stable is a model output. In a review I expect also to get some background on why climate anomaloies like the Medieval Warm Period do not show up, and why some reconstructions based on proxies give different results. For the post 1850 period you do give some insight in potential dynamics and deficiences later on which is great, but there (L177-178) you also draw very firm conclusions. Please elaborate which DGVM's have these deficiencies, have they been improved over time, etc.

[Response #14] To address this concern, we revised both the Section 2 and the uncertainty analysis. The pre-1850 stability is now explicitly described as a FireMIP model-ensemble result rather than an observed historical pattern. We also tempered the corresponding trend attribution in the Results. (Section 2.2, Lines 199–205; Section 2.3, Lines 278–289)

Revised text:

Historical WCEs (1700–2000) in this study were derived from DGVMs participating in FireMIP (Fig. 3). The weak pre-1850 change in the model ensemble (approximately ± 0.1% yr^{-1}) is partly a consequence of the experimental protocol, including repeated 1901–1920 climate and lightning forcing before 1900, and should not be interpreted as an observation-based reconstruction of actual centennial climate variability.

The weak pre-1850 trends simulated by the FireMIP ensemble (<0.015% yr^{-1}) should therefore be interpreted as a model-derived pattern rather than an observation-based historical constraint (Li et al., 2019; Rabin et al., 2017). Before 1900, the models were driven by repeated 1901–1920 climate and lightning forcing, which suppresses the actual sequence of interdecadal and centennial-scale climate variability. Many fire modules also use empirical or semi-empirical parameterizations of fire occurrence and burned area, further limiting their sensitivity to historical climate extremes. The resulting model-derived stability contrasts with reconstructions based on sedimentary charcoal, ice-core CO, and ice-core $\delta^{13}CH_4$ records, several of which indicate increasing biomass burning between approximately 1700 and 1850 (Wang et al., 2010; Ferretti et al., 2005; Marlon et al., 2008; Marlon et al., 2016). These proxies, however, differ in spatial coverage, temporal resolution, preservation processes, and the aspects of fire activity they record, and cannot be translated directly into CO2 emissions.

The revised uncertainty section explains why major pre-industrial climate anomalies, including the Medieval Climate Anomaly, are weak or absent from these simulations. In the FireMIP protocol, pre-1900 simulations used repeated 1901–1920 climate forcing, which suppresses centennial-scale climatic variability. In addition, many fire modules rely on simplified empirical relationships and therefore have limited sensitivity to historical climate anomalies. We now contrast this model-derived stability with proxy evidence from charcoal and ice-core black carbon records, while noting that proxy reconstructions differ in spatial representativeness, temporal resolution, preservation processes, and the aspects of fire activity they record. (Section 2.3, Lines 278–289)

Revised text:

Before 1900, the models were driven by repeated 1901–1920 climate and lightning forcing, which suppresses the actual sequence of interdecadal and centennial-scale climate variability. Many fire modules also use empirical or semi-empirical parameterizations of fire occurrence and burned area, further limiting their sensitivity to historical climate extremes. The resulting model-derived stability contrasts with reconstructions based on sedimentary charcoal, ice-core CO, and ice-core $\delta^{13}CH_4$ records, several of which indicate increasing biomass burning between approximately 1700 and 1850 (Wang et al., 2010; Ferretti et al., 2005; Marlon et al., 2008; Marlon et al., 2016). These proxies, however, differ in spatial coverage, temporal resolution, preservation processes, and the aspects of fire activity they record, and cannot be translated directly into CO_2 emissions.

We also expanded the model-specific evaluation of post-1850 divergence. The revised text identifies which models represent agriculture, deforestation, peat, ignition, and fire-suppression processes, and discusses how these representations have changed in later model versions. For example, CLM4.5 includes crop, deforestation, and peat fires, whereas explicit human fire suppression is represented only in a subset of the FireMIP models examined. We have summarized these differences in a new model-comparison table and clarified that several structural limitations remain despite subsequent model development. (Section 2.3, Lines 290–305; Table 2)

Revised text:

After 1850, intermodel divergence is further amplified by inconsistent representations of anthropogenic fire processes. For example, CLM4.5 explicitly represents crop, deforestation, and peat fires, although soil organic matter combustion from peat fires was excluded from the FireMIP outputs. CLM4.5 and LPJ-GUESS-SIMFIRE-BLAZE represent suppression effects on both fire occurrence and spread, whereas other configurations represent suppression through fire duration or alternative empirical constraints (Li et al., 2019; Rabin et al., 2017). Subsequent developments and remaining limitations are summarized by model in Table 2 and the references therein. In addition, all FireMIP configurations limit individual fires in natural vegetation to no more than one day, restricting their ability to represent prolonged drought-driven events (Li et al., 2019). These structural and protocol-related limitations constrain the attribution of historical WCE trends and direct comparisons among models.

These revisions distinguish model output from proxy-based evidence and provide a more cautious, model-specific interpretation of both pre- and post-1850 fire-emission trends. (Section 2.2, Lines 199–213; Section 2.3, Lines 278–305)

Revised text:

The weak pre-1850 change in the model ensemble (approximately ± 0.1% yr^{-1}) is partly a consequence of the experimental protocol, including repeated 1901–1920 climate and lightning forcing before 1900, and should not be interpreted as an observation-based reconstruction of actual centennial climate variability.

These structural and protocol-related limitations constrain the attribution of historical WCE trends and direct comparisons among models.

[Comment #15] L182 “Between 2001 and 2020, the four widely used datasets (GFED, QFED, CAMS, and FEER) reveal broadly comparable global averages” This is not fully surprising as CAMS is tuned to GFED3, and QFED also underwent tuning. Therefore the range is also something completely different than the uncertainty. A discussion about this (and include GFED5) would be useful for the readers.

[Response #15] We have added a discussion in Section 2.3 clarifying that CAMS-GFAS calibrates to GFED3.1, QFED (pre-v2.5) adopts GFAS cloud-correction logic, and FEER uses overlapping emission coefficients. Their similar global averages thus reflect shared methods, not unrelated independent estimates aligning by chance. We further note GFED5_Beta emits ~60% more CO_2 and organic carbon than GFED4.1s, proving the inter-dataset range is only a lower uncertainty bound, not a measure of true error. (Section 2.2, Lines 215–225; Section 2.3, Lines 327–348)

Revised text:

Between 2001 and 2025, the five widely used datasets (GFED5, GFED4s, QFED, GFAS, and FEER) reveal broadly comparable global averages but exhibit substantial discrepancies in interannual dynamics and long-term trends (Fig. 3). Notably, this mean-level consensus reflects shared methodological roots (e.g., GFAS calibrated to GFED3.1), thus the narrow range of global averages vastly underestimates true emission uncertainty as evidenced by the ~61% burned area jump from GFED4s to GFED5 (van der Werf et al., 2025).

These products are not fully independent because they share some satellite inputs, calibration information, methodological components, or literature-derived parameters (Kaiser et al., 2012; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; Pan et al., 2020). Their inter-product spread is therefore a partial and potentially conservative representation of structural uncertainty rather than a complete estimate of total uncertainty.

[Comment #16] L195: The use of SSP5-85 requires a bit of discussion, it is not just a “high emission scenario”. Best to avoid using it or provide a very strong disclaimer (see Van Vuuren et al., 2026, https://doi.org/10.5194/gmd-19-2627-2026).

[Response #16] We agree that SSP5-8.5 should not be described simply as a "high-emission scenario" or treated as a likely future pathway. We have revised the wording and now refer to SSP5-8.5 as a high-end climate-risk scenario, used to explore upper-bound of WCE responses under strong radiative forcing and fossil-fueled socioeconomic development. We also added a disclaimer that results under SSP5-8.5 should be interpreted as a high-end sensitivity case rather than a central projection. (Section 2.2, Lines 232–240)

Revised text:

After mid-century, projections diverge across socioeconomic pathways: high-end climate-risk scenario (e.g., SSP5-8.5) amplify boreal fire–carbon feedbacks through permafrost thaw and peatland drying, leading to up to 40% greater cumulative carbon loss in Canadian boreal forests by 2060 than under low-emission pathways (e.g., SSP1-2.6) (McCarty et al., 2020; Turetsky et al., 2015). Under low-emission scenarios (e.g., SSP1-2.6 and SSP2-4.5), projected fire carbon emissions increase more modestly, with part of the increase potentially buffered by enhanced vegetation regrowth and strengthened fire-suppression policies (Bowman et al., 2020; Park et al., 2023). We retain SSP5-8.5 as a high-end sensitivity scenario to explore upper-bound WCE responses under strong radiative forcing and fossil-fueled socioeconomic development, rather than treating it as a likely or representative future pathway.

[Comment #17] Figure 4; trends for Canada will change dramatically when adding 2023-2025. This also highlights how sensitive the trends are to individual years.

[Response #17] We agree that the inclusion of recent extreme fire years can substantially affect regional trend estimates, especially for Canada. We have therefore extended the analysis to 2025 where data availability allows and recalculated the trends in Figure 4. The revised results now explicitly show how the inclusion of the 2023–2025 Canadian fire seasons changes the estimated trend, highlighting the sensitivity of short-period regional trends to individual extreme years. We have also added text in the Results and Discussion to clarify that these trends should be interpreted as period-specific estimates rather than stationary long-term trajectories. (Section 2.2, Lines 257–270; Fig. 4)

Revised text:

China, Canada, and the USA show substantial rises in WCEs (Fig. 4b, c, f). As vegetation types are also relevant to WCEs, increased WCEs in Canada (0.31 ± 0.32 Pg CO_2 yr^{-1}) and Russia (0.84± 0.31 Pg CO_2 yr^{-1}) mainly from increased forest fires linked to elevated regional temperature (Drobyshev et al., 2021; Flannigan et al., 2016; Jain et al., 2017), especially in 2023-2025 with Canadian extreme forest fire which *change WCE dramatically.*

[Comment #18] L245 “and fire emission inventories”. So uncertainties in fire emissions inventories are uncertain because of assumption in fire emissions inventories?

[Response #18] We have revised the sentence to replace the circular wording with the specific sources of uncertainty, including fuel-load and fuel-consumption estimates, combustion completeness, CO_2 emission factors, land-cover and sensor characteristics, and product-specific conversion coefficients. (Section 2.3, Lines 308–325)

Revised text:

For the contemporary satellite era, uncertainty arises throughout the emission-estimation chain, from fire detection to the conversion of observed fire activity into CO_2 emissions (van der Werf et al., 2017; Pan et al., 2020). Burned-area products differ markedly in their ability to detect small agricultural fires, crop-residue burning, fragmented burn scars, and events obscured by cloud cover (Randerson et al., 2012; Kaiser et al., 2012). MODIS Collection 6 and FireCCI improved the detection of small and spatially fragmented burns through revised algorithms and finer-resolution reflectance observations, although substantial omissions remain in regions dominated by small fires, particularly African savannas (Lizundia-Loiola et al., 2020; Ramo et al., 2021; Liu et al., 2020; Giglio et al., 2018). Further uncertainty is introduced when detected fire activity is converted into emissions. Fuel-consumption estimates depend on modeled fuel loads and combustion completeness, which vary among ecosystems, fuel types, moisture conditions, and fire behavior (van der Werf et al., 2017; van Wees et al., 2022). Combustion completeness denotes the fraction of available fuel consumed and is particularly uncertain where burning extends into litter, organic soils, or peat (van der Werf et al., 2017; Che Azmi et al., 2021). CO_2 emission factors also vary among fuel and vegetation types and with the relative contributions of flaming and smoldering combustion (Andreae, 2019). Fire-radiative-power-based inventories are additionally sensitive to cloud-related observation gaps, sensor characteristics, and biome-specific conversion coefficients (Kaiser et al., 2012). These uncertainties propagate through the estimation chain and contribute to substantial regional and interannual differences between burned-area-based and FRP-based inventories (Nguyen and Wooster, 2020; Pan et al., 2020).

[Comment #19] L245 combustion completeness refers to more than burning depth

[Response #19] We revised the sentence to define combustion completeness broadly and treat burning depth as one contributing factor in litter, organic soils, and peat. (Section 2.3, Lines 316–322)

Revised text:

Fuel-consumption estimates depend on modeled fuel loads and combustion completeness, which vary among ecosystems, fuel types, moisture conditions, and fire behavior (van der Werf et al., 2017; van Wees et al., 2022). Combustion completeness denotes the fraction of available fuel consumed and is particularly uncertain where burning extends into litter, organic soils, or peat (van der Werf et al., 2017; Che Azmi et al., 2021).

[Comment #20] Table 2 would benefit from possible a general part (factors that are everywhere the same) and a region specific part. Also, a figure may be better here.

[Response #20] We agree that the original Table 2 did not clearly distinguish between controls that operate broadly across regions and those whose importance or direction varies among regions, and that a graphical synthesis provides a more intuitive presentation. (Section 3, Fig. 6 caption, Lines 406–414)

Revised text:

Figure 6. Global and region-specific controls of wildfire activity. The framework synthesizes evidence from previous global and regional studies on climatic, vegetation/fuel, and anthropogenic controls of wildfire activity (Jones et al., 2022; Wu et al., 2021; Tang et al., 2021; Ganteaume et al., 2013; Archibald et al., 2009; Ali et al., 2012; Alencar et al., 2015; Deb et al., 2020).Black text indicates controls that have been identified broadly at the global scale, whereas colored text indicates the factors, directions, or relative strengths specifically reported for individual regions.

Accordingly, we have replaced the original Table 2 with a new conceptual synthesis presented as Figure 6. Black text indicates controls identified broadly at the global scale, whereas colored text indicates the factors and effect directions specifically reported for individual regions. Positive and negative symbols indicate the reported direction of the relationships, and repeated symbols provide a qualitative indication of the relative strength of the reported effects. We have clarified these graphical conventions in the figure legend. (Section 3, Fig. 6 caption, Lines 406–414)

Revised text:

Positive (+) and negative (−) symbols indicate the reported direction of each effect. Repeated symbols provide a qualitative indication of the relative strength or importance of the reported effects across the literature, rather than standardized effect sizes and cannot be compared quantitatively among regions. The symbols represent the authors' qualitative synthesis of the cited literature.

[Comment #21] L322: "Specifically, projections suggest a 29% global increase in area burned due to climate change". Which projections? How do they fit in the earlier story wrt future fire?

[Response #21] The 29% estimate was derived from Senande-Rivera et al. (2022), who used an ensemble of 22 CMIP5 models under the RCP8.5 scenario to compare climatic conditions during 2070–2099 with those during 1996–2016. Importantly, the study projected a 29% expansion in the global land area exposed to frequent fire-prone climatic conditions, rather than a 29% increase in realized burned area. We have corrected this distinction in the revised manuscript. This result complements the future WCE projections discussed earlier, while actual burned area and emissions remain dependent on fuel availability, ignition, land-use change, vegetation dynamics, and fire suppression. (Section 3.1, Lines 431–434)

Revised text:

Specifically, the global land area exposed to frequent fire-prone climatic conditions is projected to expand by 29% at the end of 21st century, with particularly sharp increases in boreal (+111%) and temperate (+25%) forests, alongside a lengthening of fire seasons (Senande-Rivera et al., 2022). This result describes climatic suitability for frequent fire, not realized burned area.

[Comment #22] L344: In a paper about WCE I would expect this equation to be mentioned much earlier, and then a systematic discussion about the various parameters.

[Response #22] We moved the WCE equation to the beginning of the contemporary section and defined each term. Section 2.3 then systematically discusses uncertainty in fire detection, fuel consumption, combustion completeness, emission factors, and the different structures of burned-area- and FRP/FRE-based products. (Section 2, Lines 93–103; Section 2.3, Lines 308–348)

Revised text:

For burned-area-based inventories, the WCE is conventionally estimated using the equation: $WCE = A \times B \times CC \times EF$, where A is burned area, B is the available fuel load per unit area, CC is the fraction of available fuel consumed, and EF is the mass of CO_2 emitted per unit dry matter burned (Chen et al., 2024). FRP-based products use observed radiative energy and product-specific conversion coefficients rather than an explicit burned-area calculation.

For the contemporary satellite era, uncertainty arises throughout the emission-estimation chain, from fire detection to the conversion of observed fire activity into CO_2 emissions (van der Werf et al., 2017; Pan et al., 2020). Burned-area products differ *markedly in their ability to detect small agricultural fires, crop-residue burning, fragmented burn scars, and events obscured by cloud cover (Randerson et al., 2012; Kaiser et al., 2012). MODIS Collection 6 and FireCCI improved the detection of small and spatially fragmented burns through revised algorithms and finer-resolution reflectance observations, although substantial omissions remain in regions dominated by small fires, particularly African savannas (Lizundia-Loiola et al., 2020; Ramo et al., 2021; Liu et al., 2020; Giglio et al., 2018). Further uncertainty is introduced when detected fire activity is converted into emissions. Fuel-consumption estimates depend on modeled fuel loads and combustion completeness, which vary among ecosystems, fuel types, moisture conditions, and fire behavior (van der Werf et al., 2017; van Wees et al., 2022). Combustion completeness denotes the fraction of available fuel consumed and is particularly uncertain where burning extends into litter, organic soils, or peat (van der Werf et al., 2017; Che Azmi et al., 2021). CO_2 emission factors also vary among fuel and vegetation types and with the relative contributions of flaming and smoldering combustion (Andreae, 2019). Fire-radiative-power-based inventories are additionally sensitive to cloud-related observation gaps, sensor characteristics, and biome-specific conversion coefficients (Kaiser et al., 2012). These uncertainties propagate through the estimation chain and contribute to substantial regional and interannual differences between burned-area-based and FRP-based inventories (Nguyen and Wooster, 2020; Pan et al., 2020).*

[Comment #23] L367: So the warming will be around 4 degree (50% / 12%) over this century? Or does that depend on the climate scenario? This could be a misunderstanding from my part, apologies, but it would help to write this down in a different way.

[Response #23] The reported 50% increase was projected under a specific future climate scenario and should not be interpreted as a universal warming threshold. We have revised the text to clarify that lightning responses are temperature-dependent and scenario-specific. (Section 3.3, Lines 475–485)

Revised text:

Future lightning strikes across the conterminous United States are projected to increase by approximately 50% at the end of this century under the high-emission RCP8.5 scenario, based on an estimated increase of 12 ± 5% per degree Celsius of global warming, which may increase ignition opportunities to further escalate WCEs (Romps et al., 2014). However, alternative study employing upward cloud ice flux as a predictor suggests that lightning flash rates could decrease by approximately 15% in 2100, owing to alterations in atmospheric dynamics under high-warming scenarios (Finney et al., 2018). The key igniter for lightning wildfires is proposed to be Long-Continuing-

Current (LCC) lightning flashes and the rate of LCC is projected to increase by 41% by the 2090s under RCP 6.0 scenario (Perez-Invernon et al., 2023). These differing projections highlight the uncertainty in predicting future lightning activity and its impact on WCEs, underscoring the need for further research to refine our understanding of how climate change will influence lightning strikes and the frequency of lightning-induced WCEs.

[Comment #24] L355: 7% in all types of forests?

[Response #24] The reported 7% reduction was specific to a fuel-reduction study conducted in a dry *Eucalyptus* forest in southeastern Australia and should not be generalized across forest types. We have revised the text to specify the ecosystem and geographical context. (Section 3.2, Lines 460–467)

Revised text:

For instance, a study in a dry Eucalyptus forest in southeastern Australia reported that fuel-reduction treatment was associated with 7% lower CO_2 emissions and 50% lower non-CO_2 greenhouse-gas emissions than unmanaged forest stands (Volkova et al., 2014).

[Comment #25] L408: "This operational definition identifies wildfire seasons characterized by exceptionally large, fast-spreading, and intense wildfires that deviate markedly from the historical range of variability in burned area, fire severity, and associated carbon emissions. " How do we know this?

[Response #25] We agree that the original wording overstated what a WCEs-only threshold can identify. We have revised the text to: (1) explicitly frame the definition as identifying anomalously high-carbon-emission years within the 2001-2025 climatology; (2) acknowledge that a single WCEs threshold cannot directly infer burned area extent or spread rate, rather is supported by evidence that high-WCE years coincide with exceptionally large and intense fires (Zheng et al., 2023); and (3) note that one standard deviation is a permissive threshold chosen for consistency with conventional climate anomaly detection, while acknowledging stricter alternatives exist (e.g., the 3σ threshold used by Zheng et al. (2023) for boreal fire anomalies). We believe this revision provides a more honest and defensible operational definition. (Section 4, Lines 515–530)

Revised text:

Climate extremes (such as heatwaves and droughts) and human activity have greatly increased the frequency of extreme wildfire seasons (EWS) (Bowman et al., 2017). No universally accepted definition of EWS currently exists. We therefore define an EWS *here as the year in which WCEs exceed one interannual standard deviation over the mean of WCEs during 2001-2025. This operational definition identifies wildfire seasons with anomalously high carbon emissions relative to the 2001-2025 climatology, which often coincide with exceptionally large and intense fires (Yang et al., 2026; Cunningham et al., 2024). The choice of one standard deviation follows the method of identifying anomalous years in climate time series, though this yields a permissive threshold relative to stricter definition and no sensitivity analysis using alternative standard-deviation or percentile thresholds was performed. It should be mentioned that the threshold was specified for this analysis rather than adopted as a universal physical definition. The resulting event frequency, affected area, and hotspots should therefore be interpreted specifically under this one-standard-deviation definition. Satellite observations and atmospheric inversion products reveal that, since 2000, several EWS have markedly amplified the interannual variability of global WCEs, with some EWS even exerting a single-event impact capable of altering the global annual gross fire CO2 emissions (Zheng et al., 2023; Jones et al., 2024a; Kolden et al., 2024). Such events can substantially amplify annual WCEs, alter regional carbon balance, and generate profound ecological and societal consequences (Bowman et al., 2017; Tedim et al., 2018).*

Zheng, B., Ciais, P., Chevallier, F., Yang, H. et al. Record-high CO_2 emissions from boreal fires in 2021. Science 379, 912–917. https://doi.org/10.1126/science.ade0805. (2023)

[Comment #26] L456: "far exceeding typical annual Canadian emissions". From fires or from fossil fuel burning?

[Response #26] The comparison was intended to refer to typical annual Canadian wildfire CO_2 emissions, not fossil-fuel emissions. We revised the sentence to use "Canada's typical annual WCEs". (Section 4.2, Lines 571–580)

Revised text:

Total emissions were estimated at around 2.37 Pg CO_2 (Byrne et al., 2024), far exceeding Canada's typical annual WCEs.

[Comment #27] L467: Greenpeace Internaional (2021) is not scientific literature, please be careful with using grey literature.

[Response #27] We agree and have removed the Greenpeace International reference. The revised statement is now supported by Chebykina et al. (2022), who reported that forest fires burned approximately 18.2 million hectares across Russia in 2021, the largest annual forest fire area recorded since reliable and comparable satellite observations began in 2001. (Section 4.2, Lines 584–595)

Revised text:

2021 Russian Wildfires: The 2021 wildfire season in Russia was unprecedented, with extensive burning across Siberia and the Russian Far East. Record-breaking heat and prolonged drought created extreme fire conditions (Voronova et al., 2022). Approximately 18.2 million hectares of forests were affected, making it one of the largest fire seasons since the beginning of satellite monitoring in 2001 (Chebykina et al., 2022).

[Comment #28] L480: "The fires burned an estimated 24 to 33 million hectares and emitted about 0.72 Pg CO_2 (Binskin et al., 2020; Van Der Velde et al., 2021), accounting for approximately one quarter of global WCEs in 2019." How should I reconcile your text that 0.72 Pg C is a quarter of global WCE (which would thus be 4 x 0.72 = 2.88 Pg CO2) with your earlier number of 8.7 Pg CO2?

[Response #28] Thank you for pointing out this inconsistency. We note that the 8.72 Pg CO_2 yr^{-1} value reported earlier represents the mean annual global WCE during 2001–2020, rather than the global WCE in 2019 specifically. The estimate of 0.72 Pg CO_2 refers to southeastern Australia during November 2019–January 2020 and spans two calendar years, making a direct comparison with global emissions for 2019 inappropriate. We have therefore removed this percentage and clarified the spatial and temporal scope of the emission estimate. (Abstract, Lines 24–27; Section 4.2, Lines 597–607)

Revised text:

Mean annual WCEs over this period were 9.42 ± 0.86 (annual ensemble means ± interannual standard deviation) Pg CO_2 yr^{-1}, with approximately 83% originating from tropical ecosystems, mainly due to extensive burned area and high gross CO_2 emissions per unit burned area.

The fires burned an estimated 24 to 33 million hectares, while CO_2 emissions from Southeast Australia during November 2019 to January 2020 were estimated at approximately 0.72 Pg CO_2 (Binskin et al., 2020; van der Velde et al., 2021).

[Comment #29] L491: "representing an 83 percent increase compared with 2018" Yes, but 2018 was a very low fire year. In total, 2019 was not exceptional in the Amazon and according to most of the datasets used even below average.

[Response #29] Thank you for this clarification. We agree that comparison with unusually low 2018 season may overstate the overall anomaly of the 2019 fire season.

We have therefore replaced the single-year comparison with long-term burned-area statistics. Kelley et al. (2021) showed that approximately 11% of the active-deforestation area experienced its highest early-season burned area since 2002, while August burned area across the entire region was 45% above the long-term average and ranked third after 2007 and 2010. The revised text therefore distinguishes pronounced regional anomalies from the broader regional pattern. (Section 4.2, Lines 609–620)

Revised text:

In August, approximately 11% of the active-deforestation area recorded its highest burned area since observations began in 2002. Across that area, burned area was 45% above the 2002–2019 August average and was the third highest on record, after 2007 and 2010 (Kelley et al., 2021). The 2019 fires affected large areas across Brazil, Bolivia, Paraguay, and Peru, with approximately 47 million hectares burned across these four countries, including about 33.6 million hectares in Brazil alone (Artes et al., 2020).

[Comment #30] Figure 6b is mentioned in the caption but I do not see it.

[Response #30] Figure 6b was mistakenly mentioned in the caption. We have revised the caption accordingly and removed the reference to panel (b). (Section 3, Fig. 6 caption, Lines 406–414)

Revised text:

Figure 6. Global and region-specific controls of wildfire activity. The framework synthesizes evidence from previous global and regional studies on climatic, vegetation/fuel, and anthropogenic controls of wildfire activity (Jones et al., 2022; Wu et al., 2021; Tang et al., 2021; Ganteaume et al., 2013; Archibald et al., 2009; Ali et al., 2012; Alencar et al., 2015; Deb et al., 2020).Black text indicates controls that have been identified broadly at the global scale, whereas colored text indicates the factors, directions, or relative strengths specifically reported for individual regions. Positive (+) and negative (−) symbols indicate the reported direction of each effect. Repeated symbols provide a qualitative indication of the relative strength or importance of the reported effects across the literature, rather than standardized effect sizes and cannot be compared quantitatively among regions. The symbols represent the authors' qualitative synthesis of the cited literature.

[Comment #31] Finally, I was wondering why the paper is about carbon dioxide and not simply carbon? There is no discussion about CO2 emission factors and all the text refers to the carbon dynamics of fires.

[Response #31] We focus on CO_2 because it is the dominant carbon-containing gas released during biomass combustion and is directly relevant to atmospheric CO_2

budgets and long-term climate forcing. In addition, the major global fire-emission products evaluated in this review provide CO_2-specific emission estimates, enabling more consistent comparisons across inventories, models, and scenarios. A broader assessment of fire-related carbon would also require consideration of CO, CH_4, organic and black carbon, pyrogenic carbon residues, and post-fire ecosystem uptake, which is beyond the scope of this review.

In the revised manuscript, we now define WCEs explicitly as gross CO_2 emissions released during wildfire combustion, rather than total fire-related carbon emissions or net ecosystem carbon loss. Where emissions were reported as the mass of carbon contained in CO_2 (CO_2–C), we converted them to CO_2 mass using the molecular mass ratio of 44/12. We also added a discussion of CO_2 emission factors and their variability among fuel types, biomes, and combustion phases, including flaming and smoldering combustion. Finally, we revised the terminology throughout the manuscript to distinguish broader fire-related carbon dynamics from the specific CO_2 fluxes analyzed here. (Introduction, Lines 49–54; Section 2, Lines 93–103; Section 2.3, Lines 316–324)

Revised text:

In this review, wildfire CO_2 emissions (WCEs) refer to gross emissions released during biomass combustion rather than net ecosystem carbon loss or the net contribution of fire to atmospheric CO_2 growth.

For burned-area-based inventories, the WCE is conventionally estimated using the equation: $WCE = A \times B \times CC \times EF$, where A is burned area, B is the available fuel load per unit area, CC is the fraction of available fuel consumed, and EF is the mass of CO_2 emitted per unit dry matter burned (Chen et al., 2024). FRP-based products use observed radiative energy and product-specific conversion coefficients rather than an explicit burned-area calculation.

CO_2 emission factors also vary among fuel and vegetation types and with the relative contributions of flaming and smoldering combustion (Andreae, 2019).

References newly added in the revised manuscript

The following 45 references were newly added to the revised manuscript:

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