Responses to the reviewer comments for manuscript egusphere-2025-804 (Global patterns and drivers of climate-driven fires in a warming world).

We thank the reviewers for their thoughtful and constructive feedback on our manuscript. In this document, we provide detailed responses to all comments and suggestions. For ease of reference, the responses are compiled into one single file.

In each section, the reviewer comments are shown in **black**, followed by our responses in **blue**.

Response to Reviewer #1

This paper presents a timely and important study on how future climate change may affect global wildfire patterns and carbon emissions. Using CLM5 with interactive biogeochemistry and fire components, the authors simulate burned area and emissions under two future scenarios (SSP1-2.6 and SSP3-7.0). The inclusion of global and seasonal analyses helps capture broad patterns in future fire dynamics.

However, several aspects require further clarification or development. In particular, regional model evaluation is limited, interpretation relies heavily on correlations, and the machine learning analysis lacks methodological details. While the paper is well-structured and relevant to *Biogeosciences*, substantial revisions are needed before publication.

We thank the reviewer for their thoughtful and encouraging feedback. We are pleased that the reviewer found our study timely and recognized the value of our modeling framework, scenario design, and the inclusion of global and seasonal analyses to assess future wildfire dynamics.

We appreciate the identification of key areas for improvement. We have carefully considered each of these points and provided detailed point-to-point responses.

Major Comments

1. **Model Evaluation**

The model evaluation is only performed at the global scale, overlooking regional and seasonal differences in fire regimes. Many regions, such as boreal forests or the tropics, exhibit distinct fire behaviors that should be validated individually. Including regional comparisons with GFED data and assessing fire seasonality would increase confidence in the model's ability to project future trends.

We appreciate the reviewer's comment. Now, we have extended our evaluation to include seasonal comparisons of monthly burned area (BA) for the Global, Tropical (20°S–20°N), and Northern extratropics (NET: 30°N–70°N) regions. These are now presented in newly added panels (Figure 1e–g). This addition allows us to demonstrate the model's ability to capture not only spatial but also temporal trends in fire activity, thereby strengthening confidence in its use for future projections. The following paragraph has been added to **Section 2.4** of the revised manuscript:

"To further assess the ability of CLM5 to capture temporal fire dynamics, we compared monthly BA across global, tropical (20°S–20°N), and northern extratropical (NET: 30°N–70°N) regions (Figure 1e–g). CLM5 reproduces the observed double-peak seasonal cycle in the tropics, which is also reflected in the global mean due to the dominance of tropical fire activity. This pattern, visible in both GFED4.1 and GFED5, likely reflects distinct early and late dry season burning phases, though with some discrepancies in the timing and magnitudes of the peaks, likely due to known precipitation biases or underrepresentation of early dry season fires and differences in the fuel build-up season (Hantson et al., 2020; Li et al., 2024). In NET regions, CLM5 overestimates BA (1.09 million km^2 vs. 0.37 and 0.81 million km^2 in GFED4.1 and GFED5, respectively), particularly during summer months, potentially due to over-sensitivity to fire weather or fuel availability. Despite these regional biases, CLM5 broadly reproduces key spatiotemporal patterns of global fire regimes. While CLM5 retains the core structure of CLM4.5, key updates to fuel moisture sensitivity and agricultural fire treatment improve fire sensitivity (Lawrence et al., 2019). Comparison of CLM performance with other fire models within the Fire Model Intercomparison Project (FireMIP) also reported that CLM reasonably reproduces the spatiotemporal variability in global fires (Li et al., 2019; Hantson et al., 2020). Importantly, Hantson et al. (2020) reported CLM as the only model to reproduce the double-peak fire season, while all other models produce a single summer peak, indicating its improved ability to simulate fire dynamics. Recent studies have further compared different Earth system models and found CESM estimates closer to observations (e.g., Li et al., 2024)." **(Section 2.4)**

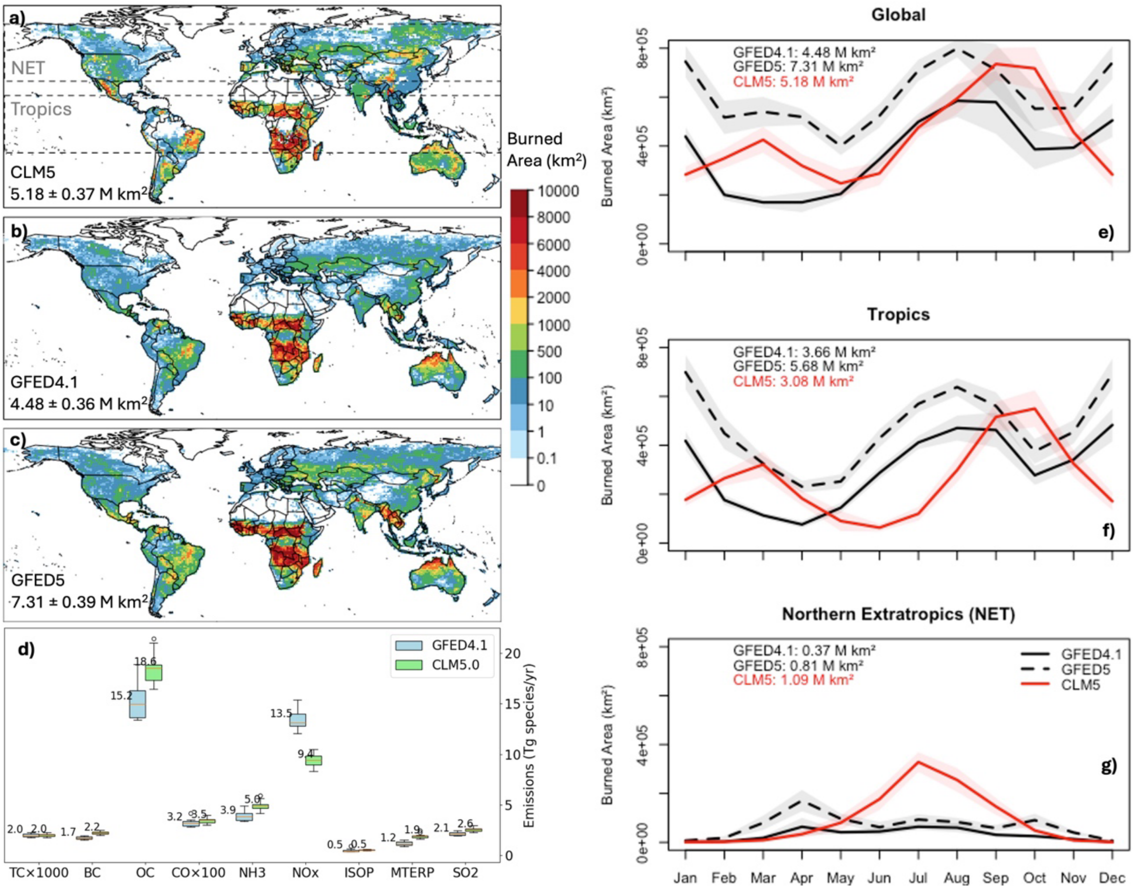

Figure 1. Model validation (added panels e–g and changed ‘boreal’ to ‘northern extratropics (NET)’).

Figure caption is modified adding, “Monthly climatology of BA for (e) global, (f) tropical (20°S–20°N), and (g) northern extratropics (NET: 30°N–70°N) regions are compared for CLM5 with GFED4.1 and GFED5. Shaded areas represent interannual variability (±SD).”

2. Correlation Metrics

The paper draws many conclusions based on correlations between BA, meteorological variables, and vegetation carbon. While statistically strong, some statements read as causal—e.g. suggesting that increased vegetation directly “fuels more intense fires” (Lines 372–373), or that precipitation enhances BA in boreal forests (Line 331). These interpretations rely solely on correlations from model outputs without supporting observational references. A more cautious framing, supported by literature or alternative statistical methods, would strengthen this section.

We thank the reviewer for this observation. As Reviewer #3 suggested to use annual gridded data (instead of previously used monthly data to avoid seasonal effect on correlation), we replotted the correlation map (Figure 5) and we have carefully refined our language to avoid causal interpretations. Where applicable, we have referenced relevant literature to support our analysis. We believe these revisions provide a more balanced and robust presentation of the results. **(Section 3.2)**

“To identify the main factors influencing climate-driven wildfires, we analyzed the spatial variations (Figure S3) and correlations between BA and meteorological factors, vegetation dynamics, and carbon emissions. To isolate interannual variability and minimize the influence of long-term trends, we performed a Pearson correlation coefficient analysis on detrended annual mean data for each grid cell from 2015 to 2100. We found strong correlations of BA with meteorological variables, total vegetation carbon (TOTVEGC), and TC emissions for both SSP1 (Figure 5) and SSP3 (Figure S6) scenarios. BA is positively correlated with surface temperature across most fire-prone regions ($R > 0.6$), consistent with the role of warming in enhancing fuel flammability and increasing fire risks (e.g., Abatzoglou and Williams, 2016; Wu et al., 2021). A strong positive correlation also appears between BA and total vegetation carbon in Eurasian (Steppe) and tropical grasslands (e.g., African savanna, parts of Australia), where warmer and wetter conditions stimulate plant productivity, thereby increasing the fuel supply and fire risks. This is also likely amplified under future elevated CO_2, which enhances photosynthesis and fuel accumulation via fertilization effects (Lawrence et al., 2019; Walker et al., 2021; Allen et al., 2024). Meanwhile, in forested regions, the correlation between BA and vegetation carbon is often negative, suggesting that dense woody vegetation may suppress fire through improvement in plant water use efficiency, thereby retaining soil moisture and lowering fuel flammability. These findings support the notion that herbaceous fuels respond more rapidly to fire-conducive weather, while forests may buffer such effects due to slower drying and deeper rooting (Jones et al., 2022). Effects of these individual forcing factors, such as climate, CO_2, and land use, on fuel availability and combustibility have also been previously discussed for historical fires using several climate models under FireMIP (Li et al., 2019).

BA shows widespread negative correlations with moisture-related variables (e.g., RH, 10-cm soil moisture, precipitation, and CWA), consistent with their role in suppressing fire through increased fuel moisture and reduced flammability (Jolly et al., 2015). Soil moisture, in particular, has a key indirect control on wildfire activity, influencing both vegetation stress and fuel moisture content. Although the model does not simulate dead fuel moisture explicitly, soil moisture serves as a proxy for fuel combustibility. Drier soil conditions reduce live fuel moisture and increase the likelihood of ignition and fire spread. However, persistently dry conditions may also suppress vegetation growth and thus reduce fuel availability, which can lead to lower fire activity in some cases (Turco et al., 2017).

In tropical forests, high precipitation and soil moisture continue to reduce BA, consistent with fuel combustibility suppression. However, in semiarid savannas, modest precipitation enhancements promote grass growth, boosting fire-prone fine fuel loads. However, upper soil moisture (10 cm) may not fully represent deeper root zones in forests and can vary in flammability (Markewitz et al., 2010; Lawrence et al., 2019). These contrasting relationships demonstrate region-specific climate-fire dynamics, mediated by vegetation types and fuel responses to water availability.

Wind speed shows mixed correlations with BA. In fire-prone regions such as Australia and parts of South America, positive correlations indicate that stronger winds enhance fire spread. In contrast, in some high-latitude northern regions, increased wind is possibly associated with the influx of cooler, moister air masses, leading to a suppression of fire activity.

BA shows a strong spatial correlation with TC emissions ($R > 0.80$) across most regions, highlighting the model-inherent link between area burned and carbon output. Further analysis of the differences in carbonaceous species also corroborates the robust correlation with differences in BA ($0.56 < R < 0.71$, $p < 0.05$; Figure S7), underscoring the synergetic effect of

BA on carbon emissions. Although increased BA generally leads to higher emissions, a reduction in grassland BA accompanied by forest fire increases may result in higher emissions despite declining total BA (Zheng et al., 2021)."

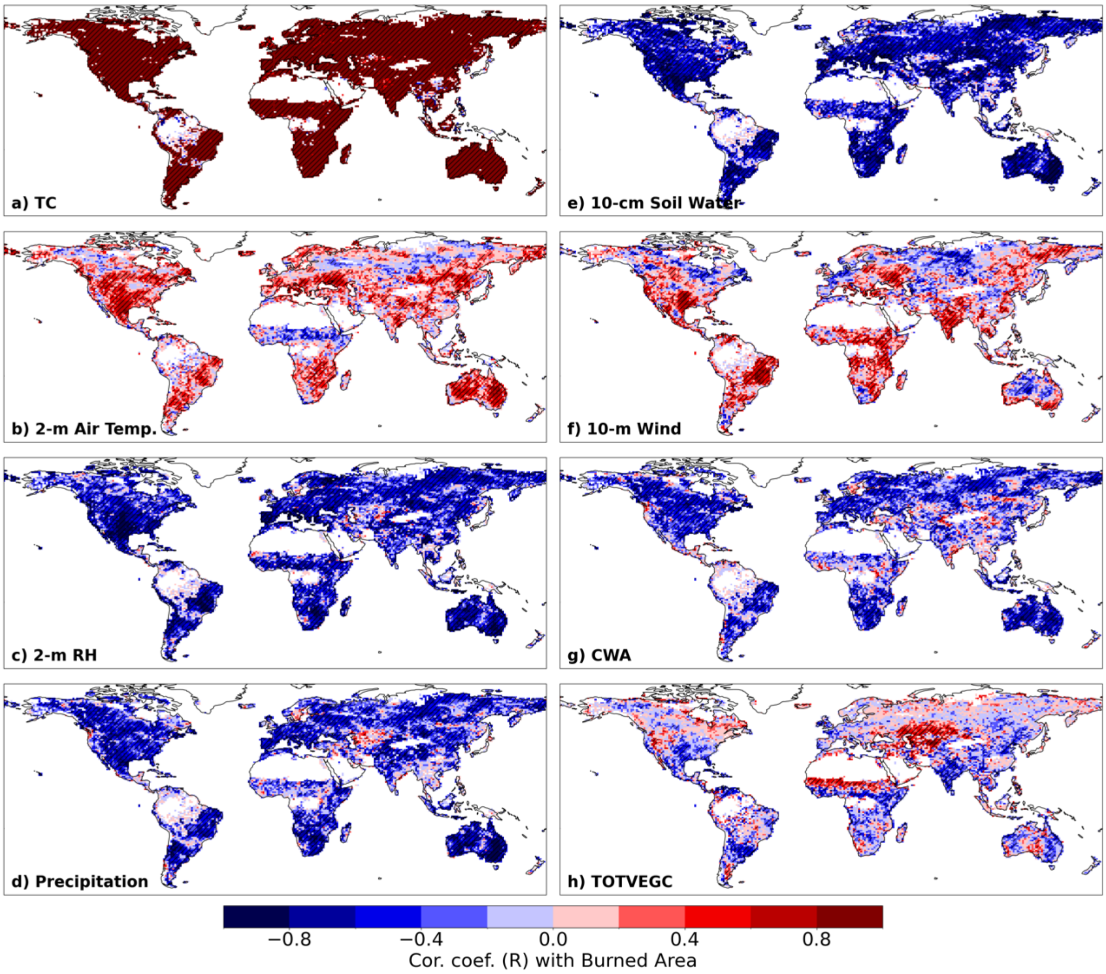

Figure 5. Pearson correlation (*R*) on annual mean time series data (2015 to 2100). Hatch lines are shown over regions with a 95% significance level.

Additionally, we have also rephrased initial Line 372–373 as:

"… Increased vegetation, while potentially serving as a carbon sink, may contribute to higher fire risks by increasing fuel availability, especially under warmer and drier conditions (Flannigan et al., 2009)." **(Section 3.3)**

3. **Machine Learning**

The use of XGBoost, LightGBM, and Random Forest for feature importance appears redundant, as all are tree-based methods with similar structures. The methodology lacks details on how feature importance was computed (e.g. permutation, SHAP), and no evaluation of model performance is provided. Without validation metrics, it is unclear whether the models are accurate enough to support reliable interpretation of variable importance. This section should be either better justified or revised with appropriate technical detail.

Thanks for pointing this out. We recognize and first test which ML model performs best, and choose the best-performing model for feature importance and SHAP values as discussed below. We have added **Section 2.5** (Method) to describe the comprehensive technical details of the machine learning approach:

"**2.5 Machine learning models**

To assess the relative contribution of climate and vegetation drivers to high latitudes (≥40°N) summer (JJA) BA, we trained three supervised machine learning models: XGBoost, LightGBM, and Random Forest. These models were trained on monthly grid cell-level data using predictors from CLM5 simulations: 10-cm soil moisture, total vegetation carbon (TOTVEGC), 2-m air temperature, 2-m RH, 10-m wind speed, precipitation, and climate water availability (CWA = precipitation – evapotranspiration).

Each model was trained using an 80/20 train-test split, with Bayesian hyperparameter optimization and 5-fold cross-validation. Predictive performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE) on held-out test sets for both SSP1 and SSP3 scenarios. XGBoost demonstrated the best performance across both scenarios and was selected for further interpretation (Table 1). To interpret the model outputs, we used both gain-based built-in feature importance and SHAP (Shapley Additive exPlanations) values to capture the marginal effects of each feature and their nonlinear interactions with BA.

Table 1. Performance metrics (R^2 and RMSE) for XGBoost, LightGBM, and Random Forest models in predicting boreal summer burned area under SSP1 and SSP3 scenarios.

ML model	SSP1		SSP3	
	R^2	RMSE	R^2	RMSE
XGBoost	0.70	957.48	0.62	1111.06
LightGBM	0.59	1112.72	0.54	1215.03
Random Forest	0.52	1202.24	0.49	1284.20

"

We also updated Figure 8 and the analysis in **Section 3.3**:

"Feature importance results consistently identify 10-cm soil water content (influencing fuel availability and dryness) and vegetation carbon (influencing canopy and surface fuel loads) as primary predictors of wildfire activity (Figure 8). These two factors alone explain over 40–50% of model variance. While CLM5 does not explicitly simulate dead fuel moisture, lower soil moisture is often associated with drier fuels, increasing fire susceptibility.

SHAP analysis further reveals the nonlinear and context-dependent behavior of environmental drivers. Low soil moisture and high vegetation carbon values substantially increase predicted BA, underscoring the critical role of dry and abundant fuels. Surface temperature and RH show moderate yet consistent effects: higher temperatures and lower RH are associated with elevated fire risks. In contrast, precipitation and wind speed exhibit weaker and more variable influences, often depending on local fuel conditions. Moreover, high CWA contributes to elevated BA as it may facilitate vegetation growth and thus indirectly accumulate fuel required for fires, reflecting fuel accumulation during wetter conditions followed by subsequent drying. These insights emphasize both the dominant controls and complex interdependencies shaping wildfire risks in boreal regions. Although these ML results provide useful diagnostic insights into feature importance, they are inherently limited by the underlying correlations in the input variables and model structure. Future work should explore process-level attribution through sensitivity simulations using fixed climate forcings within CLM5."

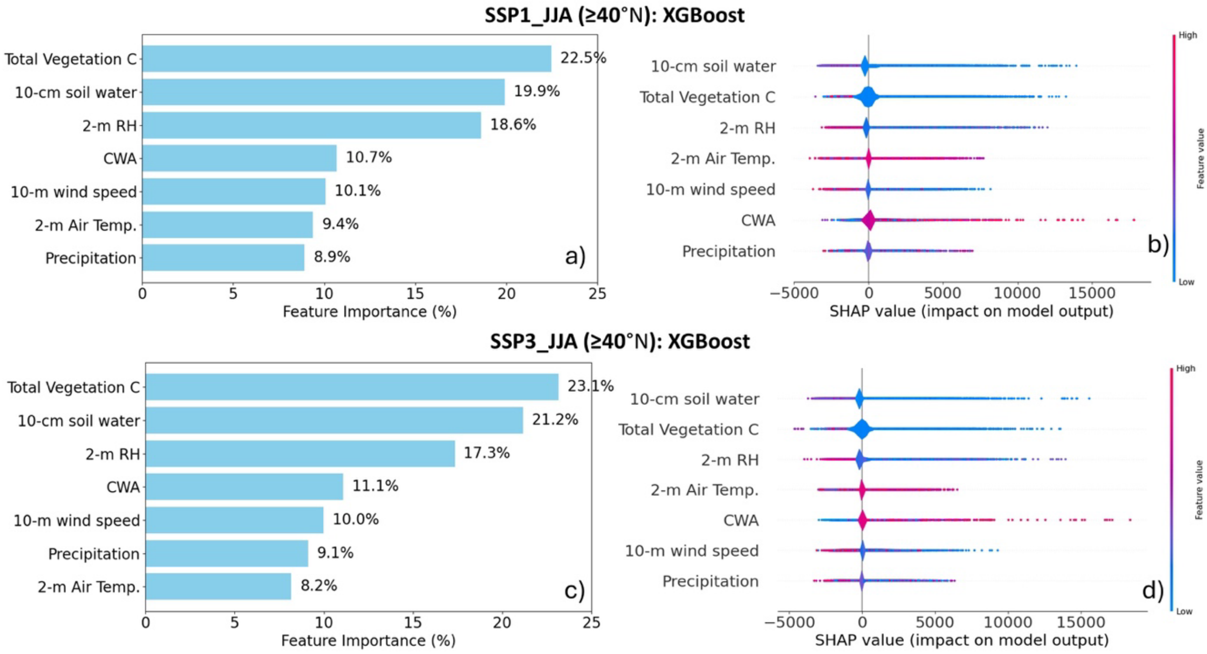

Figure 8. Feature importance and SHAP summary plots showing analysis of environmental drivers of wildfire activity during boreal summer (JJA) over northern latitudes (≥40°N) using XGBoost machine learning model under (a, b) SSP1 and (c, d) SSP3 scenarios."

4. **Model Uncertainty**

Although standard deviations are reported in some figures, they only reflect interannual variability, not actual modeling uncertainty. The paper does not quantify uncertainties related to model structure, parameter choices, or scenario assumptions. A discussion of these limitations, or references to uncertainty estimates from comparable studies, would improve the robustness of the conclusions.

We acknowledge that the standard deviations reported in our figures capture interannual variability but do not fully represent structural or parametric modeling uncertainty. In the revised manuscript, we have added discussion in **Section 2.4** (as indicated in response to **comment #1**) citing studies considering FireMIP (Li et al., 2019; Hantson et al., 2020) and Earth system models (Li et al., 2024).

Moreover, we have now added a paragraph in the limitations point explicitly addressing key sources of uncertainty, including model structure, parameter choices, and scenario assumptions. We clarify that our single-model framework does not account for internal climate variability or multi-model spread, and we reference relevant uncertainty-focused studies. We believe this addition helps contextualize our conclusions within the broader landscape of fire modeling uncertainty.

"Uncertainty quantification: Our single-model approach does not explicitly account for model structural uncertainty, parameter sensitivity, or internal variability from ensemble simulations. While our study using CLM5 provides a controlled framework to isolate climate-driven fire responses, multi-model comparisons such as those conducted in the FireMIP initiative (Hantson et al., 2016; Teckentrup et al., 2019; Burton et al., 2024) have shown that inter-model differences can lead to considerable spread in regional and global BA estimates. Additionally, Jones et al. (2022) demonstrated that uncertainty in fire emissions can stem from interactions between land cover change and fire suppression assumptions. Future studies should incorporate ensemble simulations or model intercomparison frameworks to more robustly assess projection uncertainty and guide policy-relevant interpretation." **(Section 4)**

Minor Comments

- The spatial resolution of CLM5 (~100 km) may miss small-scale fires. A brief discussion on its implications would be useful.

We agree with the reviewer that the coarse spatial resolution of CLM5 (~100 km) limits its ability to capture small-scale and short-lived fires, which can be significant in certain ecosystems. We have now included a discussion in the limitations paragraph of the Discussion **(Section 4)** to acknowledge this issue and discuss its implications.

"Model resolution and representation: The CLM5 model, with its relatively coarse spatial resolution (~100 km), may lead to underrepresentation of short-term and small-scale fires, particularly those driven by local ignition sources, land use changes, or fine-scale vegetation patterns. These fires, although individually small, can have cumulative ecological and atmospheric impacts, especially in fragmented landscapes or human-dominated regions. …"

- Although land use and population are held constant, it would help to briefly discuss how their future changes might affect BA and emissions.

While we have expanded Section 2.2 explaining our rationale for holding land use and population constant and their possible impacts on BA and emissions, we have now added a brief discussion in the limitations (Section 4) outlining how potential changes in these factors could influence BA and fire emissions. Specifically, we discuss how land use change and population dynamics could alter ignition patterns, fire suppression, and fuel continuity–thereby modifying regional fire risk in ways not captured in this study.

Modification in **Section 2.2**:

"In this study, to focus on the impacts of future climate change on wildfires, land use and populations were held constant at present-day levels, allowing only climate to evolve over time. This introduces a partial decoupling from the SSP framework but allows us to attribute changes in BA and emissions directly to climate-driven factors, independent of socioeconomic and land use shifts. While fixing land use change directly affects fuel availability, fixing population change is associated with fire management (suppress or ignite), thereby affecting BA and carbon emissions. …"

Modification in **Section 4**:

"Several limitations of this study warrant further investigation and consideration when interpreting our results:

Attribution experiments: Our study isolates the climate effect by holding anthropogenic influence (changes in land use and population density) constant. While this provides a controlled framework for evaluating climate-driven wildfire risks, real-world fire dynamics are shaped by a broader set of factors. Future land use changes – such as agricultural expansion, forest fragmentation, or abandonment – can alter fuel continuity and flammability. For instance, fragmentation may reduce fire spread by breaking fuel connectivity, while deforestation or abandonment could increase fire risk by creating more open, combustible landscapes. Similarly, population growth and urbanization may lead to more frequent human ignitions or enhanced suppression capacity, depending on regional context. These socioeconomic dynamics, which have already contributed to declining BA in recent decades (e.g., Andela et al., 2017; Forkel et al., 2019), are not captured in our simulations. In addition, our interpretation of fire-climate relationships is based on statistical methods, which are inherently correlative. Future research would benefit from targeted sensitivity simulations that systematically vary climate drivers (e.g., CO_2, temperature, precipitation) or land use parameters, either independently or in combination. Such factorial experiments would enable more rigorous causal attribution and improve confidence in regional fire projections under complex future scenarios."

- Using only 10-cm soil moisture may overlook deeper rooting in forests. A note on subsoil moisture would improve the interpretation.

We agree that 10-cm soil moisture may not fully capture root-zone water availability, particularly in forests and deeper rooting systems. We have now acknowledged this limitation in **Section 3.2** of the manuscript to clarify that deeper soil layers can influence vegetation water stress and thus fire susceptibility.

"… However, the 10-cm soil moisture may not fully represent deeper root zones in forests (Markewitz et al., 2010; Lawrence et al., 2019). …"

Additionally, we have also discussed it in the limitations part in **Section 4** as:

"… Additionally, our analysis relies on 10-cm topsoil moisture as a proxy for assessing fuel dryness, which may not fully reflect water availability for deep-rooted vegetation in forest ecosystems. However, CLM5 fire module internally relies on root-zone soil wetness to estimate fuel combustibility, which captures moisture availability over a deeper soil profile. This distinction introduces some approximation in our interpretation, especially in ecosystems where deeper soil layers better reflect vegetation water access and fire susceptibility."

- The strong correlation between BA and total carbon emissions (Lines 346–347) reflects a direct model dependency. This could be reframed more cautiously.

As also stated in response to **comment #2**, we have reframed and revised **Section 3.2**. Specifically, the paragraph with BA and carbon emissions correlation has been revised to:

"BA shows a strong spatial correlation with TC emissions (R > 0.80) across most regions, highlighting the model-inherent link between area burned and carbon output. Further analysis of the differences in carbonaceous species also corroborates the robust correlation with differences in BA ($0.56 < R < 0.71$, $p < 0.05$; Figure S7), underscoring the synergetic effect of BA on carbon emissions. Although increased BA generally leads to higher emissions, a reduction in grassland BA accompanied by forest fire increases may result in higher emissions despite declining total BA (Zheng et al., 2021)."

- While climate forcings are based on SSP1 and SSP3 scenarios, land use and population are held constant. Clarifying this partial inconsistency in the CLM5 setup would help readers understand the scope.

We agree that using SSP-based climate forcings while holding land use and population constant introduces a partial decoupling from the SSP framework. This modeling design choice was intentional to isolate climate-driven impacts on fire activity. We have clarified this explicitly in **Section 2.2** and **Section 4** of the revised manuscript (as detailed previously in response to **#second minor comment**).

Response to Reviewer #2

This is a very well-written and clear article. The conclusions are of scientific interest, however, before publication further validation of the temporal trends under current conditions as well as the impact of holding socio-economic variables constant is needed.

We thank the reviewer for their positive assessment of our manuscript. We appreciate the constructive suggestions regarding validation of temporal trends and discussion on holding socioeconomic variables constant. These are important considerations, and we have carefully addressed each point along with revisions to the manuscript where appropriate, and provided point-by-point responses.

Major comments

The authors have chosen to hold socio-economic activity constant in this paper, to isolate out the climate and vegetation effects of climate change on burnt area. Whilst this is a defendable and useful counter-factual set up, more discussion is needed as to the effect of this choice on the results. More specifically:

- The authors state that the model can reproduce current patterns in burnt area, but this validation appears to be only spatial. However, a validation of the temporal trends and the model's ability to reproduce current trends is needed given that this study performs a transient temporal analysis.

As suggested, we have expanded our model evaluation to include seasonal (monthly) burned area (BA) comparisons between CLM5 simulations and GFED4.1/GFED5 observations over the Global, Tropical (20°S–20°N), and northern extratropics (NET: 30°N–70°N) regions (new panels e-g in Figure 1). Additionally, we have also discussed the evaluation by comparing with FireMIP and other relevant studies in further polishing our comparison. This additional validation confirms that CLM5, while having some biases, captures not only spatial patterns but also core temporal dynamics of fire activity.

"To further assess the ability of CLM5 to capture temporal fire dynamics, we compared monthly BA across global, tropical (20°S–20°N), and northern extratropical (NET: 30°N–70°N) regions (Figure 1e–g). CLM5 reproduces the observed double-peak seasonal cycle in the tropics, which is also reflected in the global mean due to the dominance of tropical fire activity. This pattern, visible in both GFED4.1 and GFED5, likely reflects distinct early and late dry season burning phases, though with some discrepancies in the timing and magnitudes of the peaks, likely due to known precipitation biases or underrepresentation of early dry season fires and differences in the fuel build-up season (Hantson et al., 2020; Li et al., 2024). In NET regions, CLM5 overestimates BA (1.09 million km^2 vs. 0.37 and 0.81 million km^2 in GFED4.1 and GFED5, respectively), particularly during summer months, potentially due to over-sensitivity to fire weather or fuel availability. Despite these regional biases, CLM5 broadly reproduces key spatiotemporal patterns of global fire regimes. While CLM5 retains the core structure of CLM4.5, key updates to fuel moisture sensitivity and agricultural fire treatment improve fire sensitivity (Lawrence et al., 2019). Comparison of CLM performance with other fire models within the Fire Model Intercomparison Project (FireMIP) also reported that CLM reasonably reproduces the spatiotemporal variability in global fires (Li et al., 2019; Hantson et al., 2020). Importantly, Hantson et al. (2020) reported CLM as the only model to reproduce the double-peak fire season, while all other models produce a single summer peak, indicating its improved ability to simulate fire dynamics. Recent studies have further compared different

Earth system models and found CESM estimates closer to observations (e.g., Li et al., 2024)."
(Section 2.4)

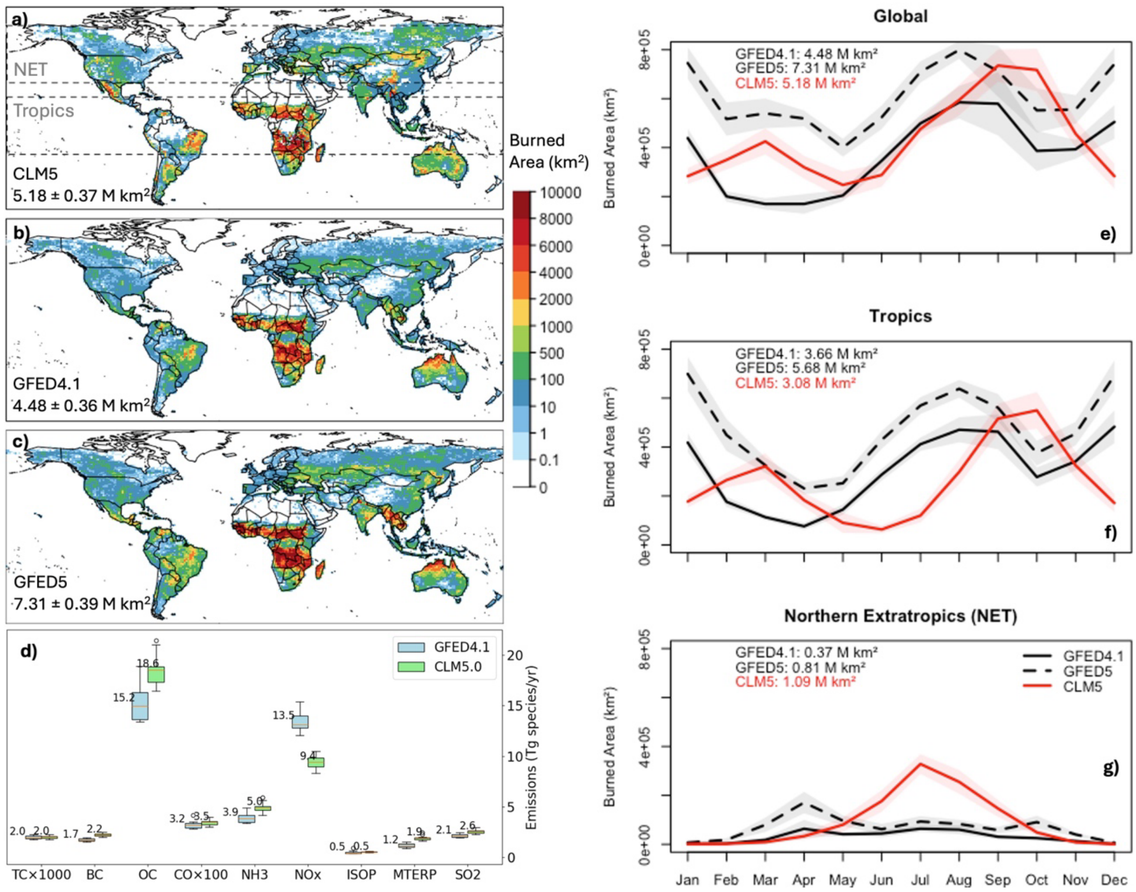

Figure 1. Model validation (added panels e–g and changed 'boreal' to 'northern extratropics (NET)').

Figure caption is modified adding, "Monthly climatology of BA for (e) global, (f) tropical (20°S–20°N), and (g) northern extratropics (NET: 30°N–70°N) regions are compared for CLM5 with GFED4.1 and GFED5. Shaded areas represent interannual variability (±SD)."

- Furthermore, given the fact that the current declining global trend in burnt area has been attributed to changes in human activity, and that this study holds human activity constant, a quantification is needed to assess the impact this choice will have on trends.

We have expanded Section 2.2 and also explained in the Discussion (Section 4) that our setup isolates climate-driven impacts and their possible impacts in BA and carbon emissions, backed up with the relevant studies. Specifically, we discuss how land use change and population dynamics could alter ignition patterns, fire suppression, and fuel continuity–thereby modifying regional fire risk in ways not captured in this study.

"In this study, to focus on the impacts of future climate change on wildfires, land use and populations were held constant at present-day levels, allowing only climate to evolve over time. This introduces a partial decoupling from the SSP framework but allows us to attribute changes in BA and emissions directly to climate-driven factors, independent of socioeconomic and land use shifts. While fixing land use change directly affects fuel availability, fixing population change is associated with fire management (suppress or ignite), thereby affecting BA and carbon emissions. …" **(Section 2.2)**

In addition, we have outlined this approach as a key direction for future work in the revised Discussion **(Section 4).**

"Several limitations of this study warrant further investigation and consideration when interpreting our results:

Attribution experiments: Our study isolates the climate effect by holding anthropogenic influence (changes in land use and population density) constant. While this provides a controlled framework for evaluating climate-driven wildfire risks, real-world fire dynamics are shaped by a broader set of factors. Future land use changes – such as agricultural expansion, forest fragmentation, or abandonment – can alter fuel continuity and flammability. For instance, fragmentation may reduce fire spread by breaking fuel connectivity, while deforestation or abandonment could increase fire risk by creating more open, combustible landscapes. Similarly, population growth and urbanization may lead to more frequent human ignitions or enhanced suppression capacity, depending on regional context. These socioeconomic dynamics, which have already contributed to declining BA in recent decades (e.g., Andela et al., 2017; Forkel et al., 2019), are not captured in our simulations. In addition, our interpretation of fire-climate relationships is based on statistical methods, which are inherently correlative. Future research would benefit from targeted sensitivity simulations that systematically vary climate drivers (e.g., CO_2, temperature, precipitation) or land use parameters, either independently or in combination. Such factorial experiments would enable more rigorous causal attribution and improve confidence in regional fire projections under complex future scenarios."

- It would be nice to see the temporal trend of simulated BA between 2015 and 2024 with a) the socio-economic variables varying, b) the socio-economic variables held constant.

In this study, we designed our simulations to isolate the impacts of future climate change on fire activity by holding land use and population constant at present-day levels. As such, we did not perform a parallel simulation with evolving socioeconomic forcings, and therefore cannot directly compare the effects within our current framework. However, previous studies (e.g., Andela et al., 2017; Jones et al., 2022) have shown that changes in land use and fire management significantly contributed to observed declines in burned area over recent decades. We have clarified this point in the Discussion section (as discussed in response to the above comment) and referenced relevant literature to provide context on the potential influence of socioeconomic changes, which are beyond the scope of our current study design.

- The impact of human activity in each region could then be quantified by taking the difference in these two simulations. This would allow a discussion of regions in which we expect that the results shown here (climate effect only) to be the driving trend and regions in which, given that human activity is a significant driver, the results presented here should be taken with more caution.

We appreciate this suggestion. However, as explained above, this is beyond the scope of this research design. We acknowledge that the influence of human activities on fire dynamics is highly region-specific. For example, boreal regions are expected to be more strongly influenced by climate-driven factors such as fuel availability and fire weather, while tropical and subtropical regions are more sensitive to land use change and fire management practices (e.g., Andela et al., 2017; Forkel et al., 2019). As indicated above, we have now clarified these points in the Discussion section and highlighted that future modeling studies integrating evolving socioeconomic factors would enable a more complete regional attribution of fire trends.

Given that the largest increases of burnt area and emissions are in the northern latitudes, regions in which we expect human activity to have very little impact, this exercise would strengthen your conclusions. Furthermore, another interesting result is the fact that this analysis shows decreases in many regions, including the tropics, *despite* holding human activity constant.

We agree that boreal regions are primarily driven by climatic factors such as temperature, soil moisture, and vegetation productivity, and thus our climate-only setup is particularly relevant for interpreting projected increases in these regions. We also acknowledge that the simulated decreases in tropical BA, despite holding human activity constant, suggest a strong climate influence (e.g., increased precipitation leading to reduced fire activity). We have now emphasized these points in the Discussion section to strengthen the interpretation of our findings.

"Regional differences: Relative importance of climate versus human activity is expected to differ across regions. Boreal ecosystems are primarily sensitive to climatic factors such as fuel availability, soil moisture, and fire weather conditions, whereas tropical regions are more strongly influenced by human land use change, agricultural expansion, and fire suppression practices (e.g., Andela et al., 2017; Forkel et al., 2019; Wu et al., 2021). This regional heterogeneity highlights the need for caution when interpreting climate-only fire projections, particularly in human-dominated landscapes. Notably, our findings show that the largest projected increase in BA and carbon emissions occur in boreal regions, where human activity is comparatively limited. This reinforces the robustness of our climate-driven projections in these areas. Conversely, the simulated declines in tropical burned area despite constant socioeconomic forcings suggest that climate-induced changes, such as increased precipitation, may independently drive fire suppression in some regions. These contrasting patterns underscore the critical role of regional context in interpreting future wildfire trends." **(Section 4)**

Minor comments

Line 258 "In any case, tropical fires dominate the global landscape for both BA and carbon emissions, compared to boreal fires." – this sentence is quite unclear, could you please rephrase.

We have rephrased the sentence for clarity **(Section 3.1)**:

"Despite the upwards trends in NET fires, the tropics remain the dominant contributor to total global BA and carbon emissions during the 21st century, underscoring a shifting geographic balance of wildfire risks."

Line 342 "In contrast, tropical regions show a decrease in BA as increased precipitation dampens fire activity." – could this not lead to increases in fuel loading, as it does in the northern high latitudes? More detailed discussion as to why decreases are shown in these regions are needed. Furthermore, what causes the large decrease in extra-tropical regions (e.g. eastern United States, United Kingdom and northern Europe, regions of Russia?). More detailed discussion of what is driving decreases in burnt area globally is needed here.

We have now explained the characteristics of BA reduction in extratropical regions (such as the Eastern US and the UK).

"We found important differences at a regional scale. In northern extratropics, particularly near 60°N, where boreal forests dominate alongside alpine forests and shrublands, BA and TC emissions are projected to increase by over 150% in both SSP scenarios (Figure 3a–d and Figure S4). This intensification is most evident in boreal region, where the trend in BA reaches +5237 $km^2\ yr^{-1}$ under SSP1 and +8515 $km^2\ yr^{-1}$ under SSP3. In contrast to the pronounced increases in boreal BA, our simulations project localized decreases in BA across parts of the humid tropics as well as temperate regions such as the UK and eastern US. In tropical rainforest regions, elevated precipitation and humidity under future climate scenarios likely suppress fire activity by maintaining higher fuel moisture levels and shortening the fire season. In temperate zones such as the UK and eastern US, projected climate changes (e.g., increased rainfall or limited warming) may reduce conditions that promote fires. These declines occur despite fixed land use and populations, indicating that purely climatic effects can suppress fire activity in certain fuel-rich or moisture-sensitive systems. Additionally, tropical regions show slight decline in BA under SSP3 (−2429 $km^2\ yr^{-1}$) and SSP1 (−64 $km^2\ yr^{-1}$), both remaining statistically insignificant at 95% level (Figure 3e–h). Despite the upward trends in NET fires, the tropics remain the dominant contributor to total global BA and carbon emissions during the 21st century, underscoring a shifting geographic balance of wildfire risks." **(Section 3.1)"**

Additionally, while precipitation in some regions (e.g., grasslands) could increase fire risk, precipitation in forest regions could reduce the risk of fires. We have now provided a detailed discussion on the meteorological effects on fire activity. While we updated Figure 5 based on Reviewer #3 comment to use annual mean data to avoid seasonal characteristics, we have rephrased the whole discussion in **Section 3.2**, including the stated lines 342 as:

"To identify the main factors influencing climate-driven wildfires, we analyzed the spatial variations (Figure S3) and correlations between BA and meteorological factors, vegetation dynamics, and carbon emissions. To isolate interannual variability and minimize the influence of long-term trends, we performed a Pearson correlation coefficient analysis on detrended annual mean data for each grid cell from 2015 to 2100. We found strong correlations of BA with meteorological variables, total vegetation carbon (TOTVEGC), and TC emissions for both SSP1 (Figure 5) and SSP3 (Figure S6) scenarios. BA is positively correlated with surface temperature across most fire-prone regions ($R > 0.6$), consistent with the role of warming in enhancing fuel flammability and increasing fire risks (e.g., Abatzoglou and Williams, 2016; Wu et al., 2021). A strong positive correlation also appears between BA and total vegetation carbon in Eurasian (Steppe) and tropical grasslands (e.g., African savanna, parts of Australia), where warmer and wetter conditions stimulate plant productivity, thereby increasing the fuel supply and fire risks. This is also likely amplified under future elevated CO_2, which enhances photosynthesis and fuel accumulation via fertilization effects (Lawrence et al., 2019; Walker et al., 2021; Allen et al., 2024). Meanwhile, in forested regions, the correlation between BA and vegetation carbon is often negative, suggesting that dense woody vegetation may suppress fire through improvement in plant water use efficiency, thereby retaining soil moisture and lowering fuel flammability. These findings support the notion that herbaceous fuels respond more rapidly to fire-conducive weather, while forests may buffer such effects due to slower drying and deeper rooting (Jones et al., 2022). Effects of these individual forcing factors, such as climate, CO_2, and land use, on fuel availability and combustibility have also been previously discussed for historical fires using several climate models under FireMIP (Li et al., 2019).

BA shows widespread negative correlations with moisture-related variables (e.g., RH, 10-cm soil moisture, precipitation, and CWA), consistent with their role in suppressing fire through increased fuel moisture and reduced flammability (Jolly et al., 2015). Soil moisture, in particular, has a key indirect control on wildfire activity, influencing both vegetation stress and fuel moisture content. Although the model does not simulate dead fuel moisture explicitly, soil moisture serves as a proxy for fuel combustibility. Drier soil conditions reduce live fuel moisture and increase the likelihood of ignition and fire spread. However, persistently dry conditions may also suppress vegetation growth and thus reduce fuel availability, which can lead to lower fire activity in some cases (Turco et al., 2017).

In tropical forests, high precipitation and soil moisture continue to reduce BA, consistent with fuel combustibility suppression. However, in semiarid savannas, modest precipitation enhancements promote grass growth, boosting fire-prone fine fuel loads. However, upper soil moisture (10 cm) may not fully represent deeper root zones in forests and can vary in flammability (Markewitz et al., 2010; Lawrence et al., 2019). These contrasting relationships demonstrate region-specific climate-fire dynamics, mediated by vegetation types and fuel responses to water availability.

Wind speed shows mixed correlations with BA. In fire-prone regions such as Australia and parts of South America, positive correlations indicate that stronger winds enhance fire spread. In contrast, in some high-latitude northern regions, increased wind is possibly associated with the influx of cooler, moister air masses, leading to a suppression of fire activity.

BA shows a strong spatial correlation with TC emissions ($R > 0.80$) across most regions, highlighting the model-inherent link between area burned and carbon output. Further analysis of the differences in carbonaceous species also corroborates the robust correlation with differences in BA ($0.56 < R < 0.71$, $p < 0.05$; Figure S7), underscoring the synergetic effect of BA on carbon emissions. Although increased BA generally leads to higher emissions, a reduction in grassland BA accompanied by forest fire increases may result in higher emissions despite declining total BA (Zheng et al., 2021)."

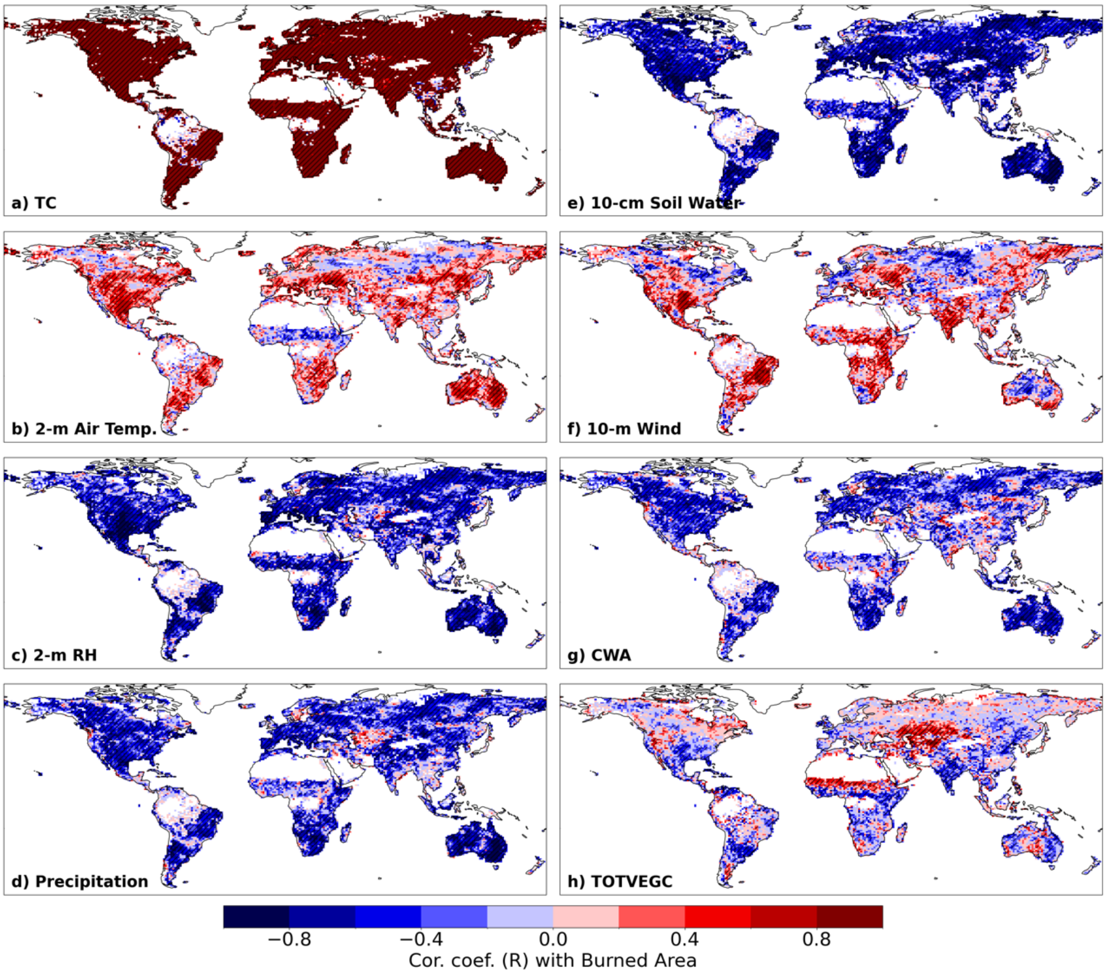

Figure 5. Pearson correlation (R) on annual mean time series data (2015 to 2100). Hatch lines are shown over regions with a 95% significance level.

Response to Reviewer #3

The authors present future simulations under two different scenarios with the fire-enabled DGVM CLM5, and report burnt area and speciated emissions. They examine the drivers of global burnt area using simple univariate linear regression, and further focus on the northern latitudes with three machine learning models. The study is timely, relevant and well-presented. The chosen methods are appropriate. However, I have several scientific concerns with the paper in its current form.

We greatly appreciate and thank the reviewer for their constructive comments and suggestions. We have carefully addressed all the concerns and provided point-by-point responses.

1. I agree strongly with comments from Reviewers 1 and 2 concerning additional benchmarking. Whilst the spatial patterns are indeed reasonable (for a fire-enabled DGVM), both the seasonal patterns and more importantly, the temporal patterns - both interannual variability and trend - should be evaluated over some a reference period. Perhaps 2001 to 2015 which according to the methods was simulated as part of the spinup but not presented here. Regardless of the protocol, when presenting these future simulations, some degree of evidence should be offered that the simulations reliably capture the temporal dynamics and interannual variability. Ideally this should be done regionally as well as globally. Otherwise the future projections are hard to credit.

   It may be that such benchmarking already exists, but it doesn't seem to be in any of the references provided in the manuscript. As part of the FireMIP project, Hantson et al. 2020 found the the CLM fire module, whilst amongst the better performing fire-enabled DGVMs, only managed to better the mean value null model with respect to two of the four burnt area dataset to which it was compared (and even that barely). Can the authors provide evidence that the model has been improved since then?

As also suggested by Reviewer 1 and 2, we have now expanded the benchmarking of the model's temporal dynamics. In addition to the spatial comparison already shown, we now present seasonal and interannual variability in burned area (BA) across global, tropical (20°S–20°N), and northern extratropics (NET: 30°N–70°N) regions using monthly time series from CLM5, GFED4.1, and GFED5 (Figure 1e–g). Additionally, we have also discussed the evaluation by comparing with FireMIP and other relevant studies in further polishing our comparison.

"To further assess the ability of CLM5 to capture temporal fire dynamics, we compared monthly BA across global, tropical (20°S–20°N), and northern extratropical (NET: 30°N–70°N) regions (Figure 1e–g). CLM5 reproduces the observed double-peak seasonal cycle in the tropics, which is also reflected in the global mean due to the dominance of tropical fire activity. This pattern, visible in both GFED4.1 and GFED5, likely reflects distinct early and late dry season burning phases, though with some discrepancies in the timing and magnitudes of the peaks, likely due to known precipitation biases or underrepresentation of early dry season fires and differences in the fuel build-up season (Hantson et al., 2020; Li et al., 2024). In NET regions, CLM5 overestimates BA (1.09 million km^2 vs. 0.37 and 0.81 million km^2 in GFED4.1 and GFED5, respectively), particularly during summer months, potentially due to over-sensitivity to fire weather or fuel availability. Despite these regional biases, CLM5 broadly reproduces key spatiotemporal patterns of global fire regimes. While CLM5 retains the core structure of CLM4.5, key updates to fuel moisture sensitivity and agricultural fire treatment improve fire sensitivity (Lawrence et al., 2019). Comparison of CLM performance with other fire models within the Fire Model Intercomparison Project (FireMIP) also reported that CLM reasonably reproduces the spatiotemporal variability in global fires (Li et al., 2019; Hantson et al., 2020). Importantly, Hantson et al. (2020) reported CLM as the only model to reproduce the double-peak fire season, while all other models produce a single summer peak, indicating its improved ability to simulate fire dynamics. Recent studies have further compared different Earth system models and found CESM estimates closer to observations (e.g., Li et al., 2024).” **(Section 2.4)**

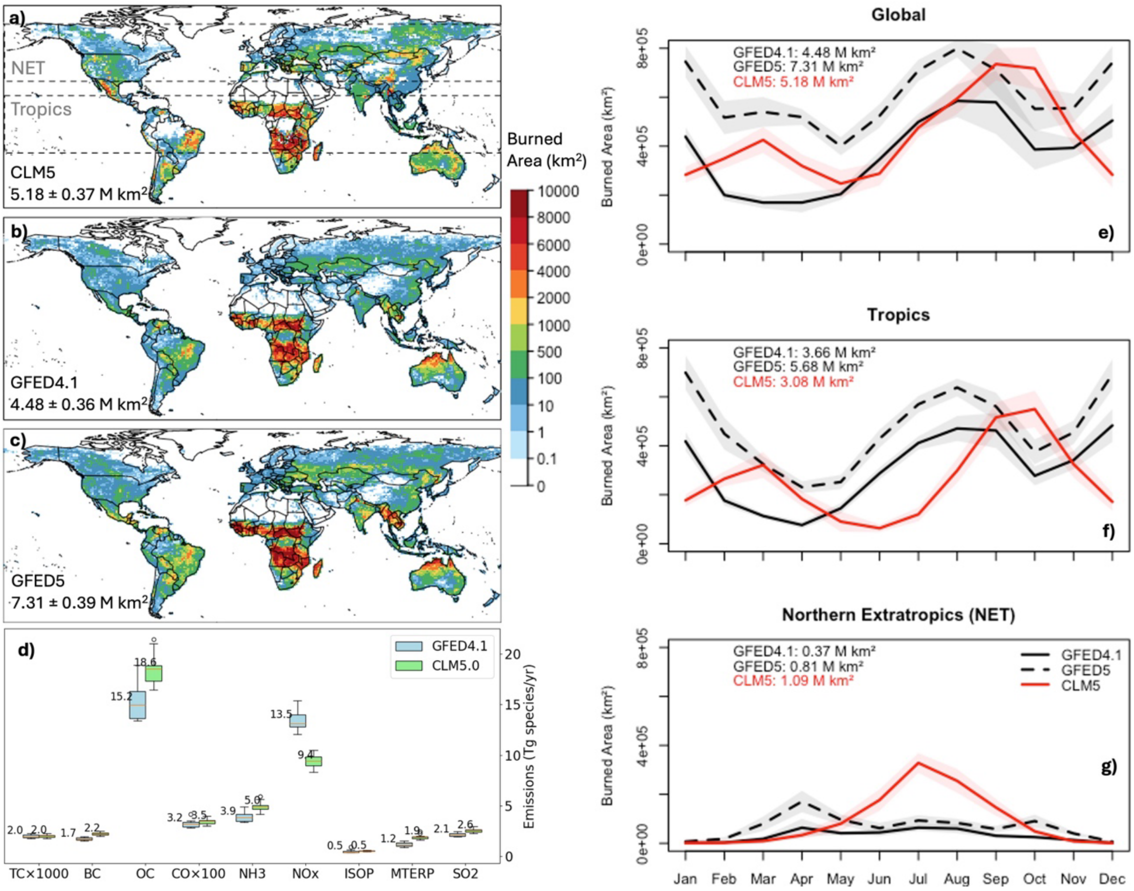

Figure 1. Model validation (added panels e–g and changed ‘boreal’ to ‘northern extratropics (NET)’).

Figure caption is modified adding, “Monthly climatology of BA for (e) global, (f) tropical (20°S–20°N), and (g) northern extratropics (NET: 30°N–70°N) regions are compared for CLM5 with GFED4.1 and GFED5. Shaded areas represent interannual variability (±SD).”

2. I also question the utility of parts of Figure 5, at least as a main manuscript figure. Many of the relationships would entirely expected. Especially because the correlation uses monthly values, and so the seasonal patterns should be expected to dominate the correlation in seasonal areas, this includes of course, soil moisture. I suggest using remaking this figure with annual values, or perhaps better would be fire season months or fire season aggregates, or perhaps deviations from the long term mean. As things stand Fig. 5 is not useful.

   More than this, the discussion should be more nuanced. For example, line 332-33

> "However, in tropical regions, where fuel is already abundant, increased precipitation primarily raises soil moisture, further suppressing fire activity rather than promoting it."
>
> Actually in the arid tropics fuel can often be limiting so this is not a reasonable comment. Furthemore, line 330-332

"Interestingly, in boreal regions, precipitation exhibits a positive correlation with BA, as it enhances vegetation growth, increasing the availability of fuel."

Again, this is against the conventional wisdom here. The boreal zone is not considered to be fuel limited because actually there is a lot of both live and dead biomass available as fuel.

We appreciate the reviewer's suggestion. We have replaced the original correlation maps (previously based on detrended monthly data) with new maps computed from detrended annual mean values, now shown in the revised Figure 5 (for SSP1) and Figure S6 (for SSP3). This approach better isolates interannual variability from dominant seasonal cycles. Importantly, switching to annual means reversed the sign of the BA-precipitation correlation in parts of the boreal region, highlighting the reviewer's valid point that seasonal cycles can obscure ecological drivers. We updated Figure 5 and rephrased the discussion in **Section 3.2**, including the stated lines 330 to 333 as:

"To identify the main factors influencing climate-driven wildfires, we analyzed the spatial variations (Figure S3) and correlations between BA and meteorological factors, vegetation dynamics, and carbon emissions. To isolate interannual variability and minimize the influence of long-term trends, we performed a Pearson correlation coefficient analysis on detrended annual mean data for each grid cell from 2015 to 2100. We found strong correlations of BA with meteorological variables, total vegetation carbon (TOTVEGC), and TC emissions for both SSP1 (Figure 5) and SSP3 (Figure S6) scenarios. BA is positively correlated with surface temperature across most fire-prone regions ($R > 0.6$), consistent with the role of warming in enhancing fuel flammability and increasing fire risks (e.g., Abatzoglou and Williams, 2016; Wu et al., 2021). A strong positive correlation also appears between BA and total vegetation carbon in Eurasian (Steppe) and tropical grasslands (e.g., African savanna, parts of Australia), where warmer and wetter conditions stimulate plant productivity, thereby increasing the fuel supply and fire risks. This is also likely amplified under future elevated CO_2, which enhances photosynthesis and fuel accumulation via fertilization effects (Lawrence et al., 2019; Walker et al., 2021; Allen et al., 2024). Meanwhile, in forested regions, the correlation between BA and vegetation carbon is often negative, suggesting that dense woody vegetation may suppress fire through improvement in plant water use efficiency, thereby retaining soil moisture and lowering fuel flammability. These findings support the notion that herbaceous fuels respond more rapidly to fire-conducive weather, while forests may buffer such effects due to slower drying and deeper rooting (Jones et al., 2022). Effects of these individual forcing factors, such as climate, CO_2, and land use, on fuel availability and combustibility have also been previously discussed for historical fires using several climate models under FireMIP (Li et al., 2019).

BA shows widespread negative correlations with moisture-related variables (e.g., RH, 10-cm soil moisture, precipitation, and CWA), consistent with their role in suppressing fire through increased fuel moisture and reduced flammability (Jolly et al., 2015). Soil moisture, in particular, has a key indirect control on wildfire activity, influencing both vegetation stress and fuel moisture content. Although the model does not simulate dead fuel moisture explicitly, soil moisture serves as a proxy for fuel combustibility. Drier soil conditions reduce live fuel moisture and increase the likelihood of ignition and fire spread. However, persistently dry conditions may also suppress vegetation growth and thus reduce fuel availability, which can lead to lower fire activity in some cases (Turco et al., 2017).

In tropical forests, high precipitation and soil moisture continue to reduce BA, consistent with fuel combustibility suppression. However, in semiarid savannas, modest precipitation enhancements promote grass growth, boosting fire-prone fine fuel loads. However, upper soil moisture (10 cm) may not fully represent deeper root zones in forests and can vary in flammability (Markewitz et al., 2010; Lawrence et al., 2019). These contrasting relationships demonstrate region-specific climate-fire dynamics, mediated by vegetation types and fuel responses to water availability.

Wind speed shows mixed correlations with BA. In fire-prone regions such as Australia and parts of South America, positive correlations indicate that stronger winds enhance fire spread. In contrast, in some high-latitude northern regions, increased wind is possibly associated with the influx of cooler, moister air masses, leading to a suppression of fire activity.

BA shows a strong spatial correlation with TC emissions ($R > 0.80$) across most regions, highlighting the model-inherent link between area burned and carbon output. Further analysis of the differences in carbonaceous species also corroborates the robust correlation with differences in BA ($0.56 < R < 0.71$, $p < 0.05$; Figure S7), underscoring the synergetic effect of BA on carbon emissions. Although increased BA generally leads to higher emissions, a reduction in grassland BA accompanied by forest fire increases may result in higher emissions despite declining total BA (Zheng et al., 2021)."

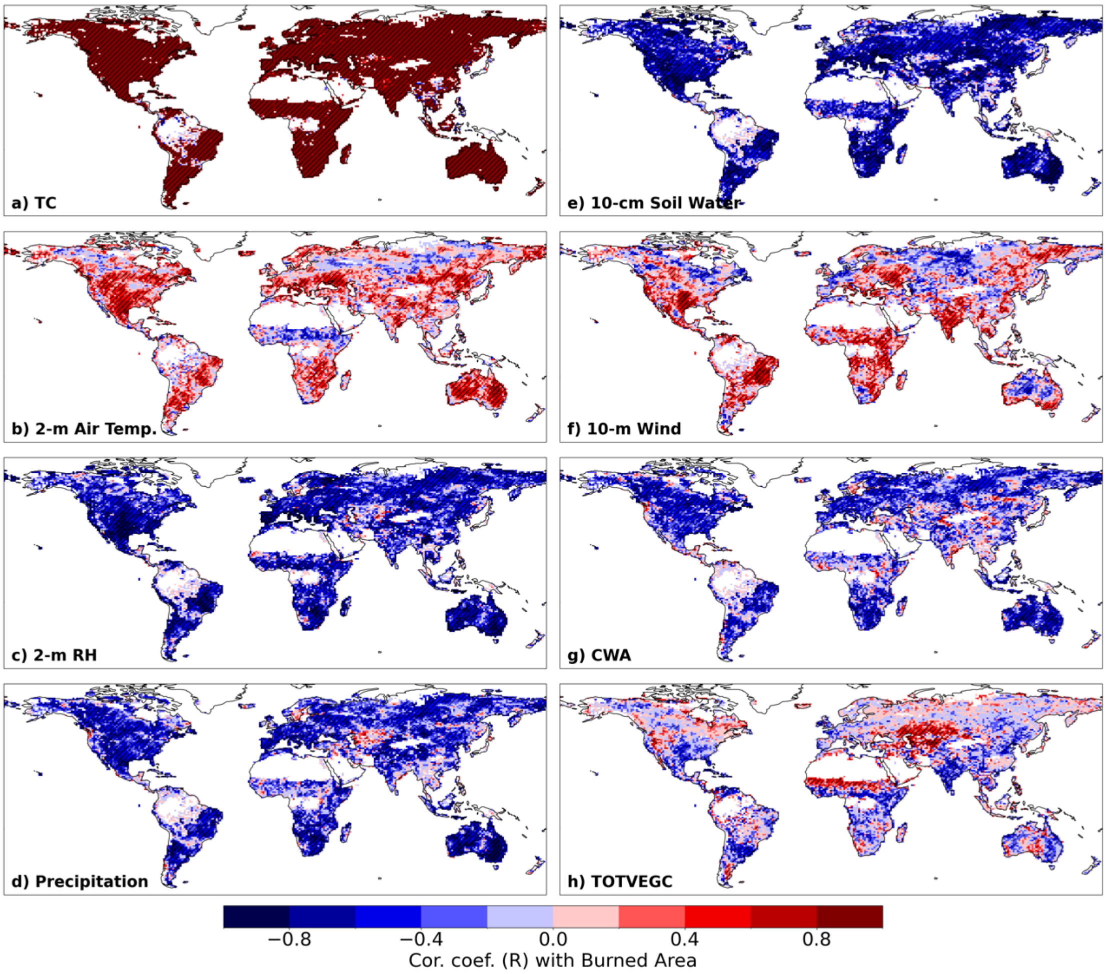

Figure 5. Pearson correlation (*R*) on annual mean time series data (2015 to 2100). Hatch lines are shown over regions with a 95% significance level.

Additionally, we tested fire-season-only means (JJA for the Northern Hemisphere and DJF for the Southern Hemisphere), which yielded broadly similar spatial patterns (Figure R1). Thus, we opted to stay with the annual mean rather than the fire-season mean plot.

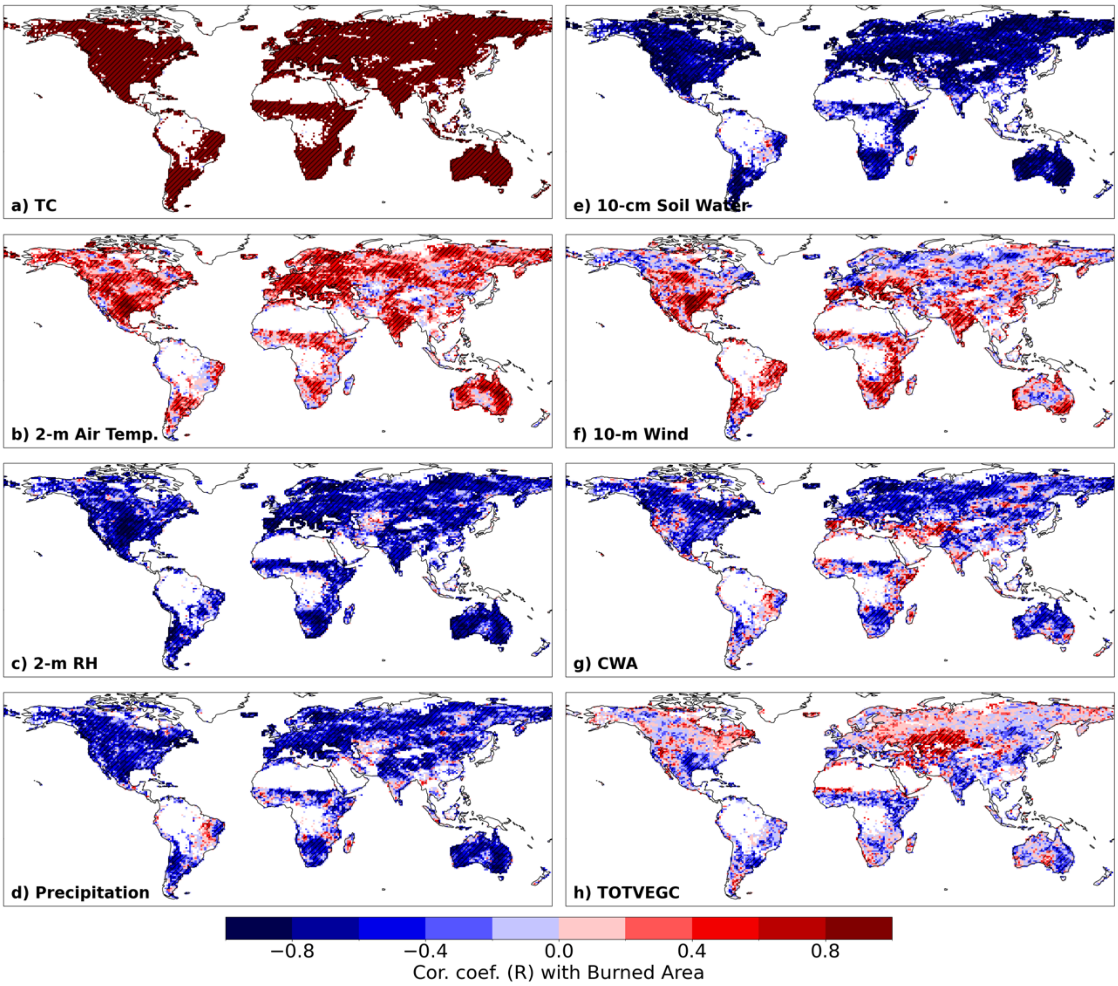

Figure R1. Pearson correlation on fire-season-only means (JJA for the Northern Hemisphere and DJF for the Southern Hemisphere) time series data with hatch lines showing 95% significance level.

3. More detail is needed about the ML methods in Fig 8, but I am also not convinced about their utility. I *guess* they were run on the model outputs and climate inputs as a kind of emulator, and then feature importance was extracted. But emulators should be used to make a short cut to produce results, *not* extract process knowledge. Since they essentially work on correlations, there is no guarantee that they are getting the right result for the right reason, therefore they are truly capturing the model's cause and effect. This is in indeed evidenced by the author's own results which show quite different results between ML methods.

   Having said that, the results are fairly consistent in that they say veg C and soil water content are the most important variables, so perhaps this is all good enough. But since those two things are in themselves very likely to be very correlated (assuming a fuel limited system), I am not so sure what are really learning. More details here please. In fact there are likey to be strong correlations between many of these variables, this should be explored with some pair-wise correlation plots.

We appreciate the reviewer's comment. Our intent was not to infer causality but to complement traditional statistical approaches by identifying dominant covariates within a high-dimensional, nonlinear framework. While we acknowledge that ML models do not explicitly account for causal mechanisms, their application here provides insight into variable importance under complex interactions not easily captured by linear models. Additionally, all of these analyses are based on model outputs.

We have added **Section 2.5** describing the machine learning setup as:

"**2.5 Machine learning models**

To assess the relative contribution of climate and vegetation drivers to high latitudes (≥40°N) summer (JJA) BA, we trained three supervised machine learning models: XGBoost, LightGBM, and Random Forest. These models were trained on monthly grid cell-level data using predictors from CLM5 simulations: 10-cm soil moisture, total vegetation carbon (TOTVEGC), 2-m air temperature, 2-m RH, 10-m wind speed, precipitation, and climate water availability (CWA = precipitation – evapotranspiration).

Each model was trained using an 80/20 train-test split, with Bayesian hyperparameter optimization and 5-fold cross-validation. Predictive performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE) on held-out test sets for both SSP1 and SSP3 scenarios. XGBoost demonstrated the best performance across both scenarios and was selected for further interpretation (Table 1). To interpret the model outputs, we used both gain-based built-in feature importance and SHAP (Shapley Additive exPlanations) values to capture the marginal effects of each feature and their nonlinear interactions with BA.

Table 1. Performance metrics (R^2 and RMSE) for XGBoost, LightGBM, and Random Forest models in predicting boreal summer burned area under SSP1 and SSP3 scenarios.

ML model	SSP1		SSP3	
	R^2	RMSE	R^2	RMSE
XGBoost	0.70	957.48	0.62	1111.06
LightGBM	0.59	1112.72	0.54	1215.03
Random Forest	0.52	1202.24	0.49	1284.20

"

We also updated Figure 8 and the analysis in **Section 3.3**:

"Feature importance results consistently identify 10-cm soil water content (influencing fuel availability and dryness) and vegetation carbon (influencing canopy and surface fuel loads) as primary predictors of wildfire activity (Figure 8). These two factors alone explain over 40–50% of model variance. While CLM5 does not explicitly simulate dead fuel moisture, lower soil moisture is often associated with drier fuels, increasing fire susceptibility.

SHAP analysis further reveals the nonlinear and context-dependent behavior of environmental drivers. Low soil moisture and high vegetation carbon values substantially increase predicted BA, underscoring the critical role of dry and abundant fuels. Surface temperature and RH show moderate yet consistent effects: higher temperatures and lower RH are associated with elevated fire risks. In contrast, precipitation and wind speed exhibit weaker and more variable influences, often depending on local fuel conditions. Moreover, high CWA contributes to elevated BA as it may facilitate vegetation growth and thus indirectly accumulate fuel required for fires, reflecting fuel accumulation during wetter conditions followed by subsequent drying. These insights emphasize both the dominant controls and complex interdependencies shaping wildfire risks in boreal regions. Although these ML results provide useful diagnostic insights into feature importance, they are inherently limited by the underlying correlations in the input variables and model structure. Future work should explore process-level attribution through sensitivity simulations using fixed climate forcings within CLM5."

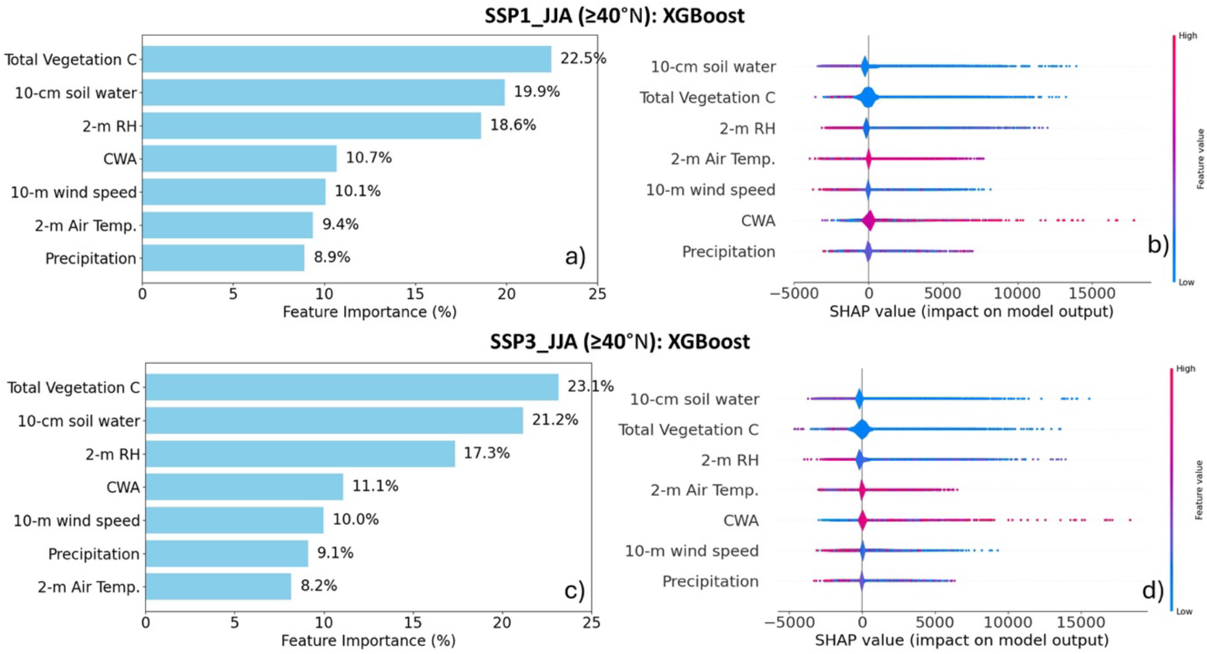

Figure 8. Feature importance and SHAP summary plots showing analysis of environmental drivers of wildfire activity during boreal summer (JJA) over northern latitudes (≥40°N) using XGBoost machine learning model under (a, b) SSP1 and (c, d) SSP3 scenarios."

To address concerns regarding collinearity, we computed pairwise Pearson correlation coefficients using the annual mean of the predictor variables used in ML models (Figure R2). As expected, precipitation and climate water availability (CWA, defined as precipitation minus evapotranspiration) exhibit a strong correlation (R = 0.91). While this redundancy is inherent, we retained both variables in our ML model to capture their potentially distinct nonlinear interactions, as shown in SHAP values. Importantly, the correlation between total vegetation carbon and soil moisture, the two top-ranked features, is relatively low (R = 0.19), indicating that their contributions are not simply redundant. Even moderate correlations (e.g., precipitation–vegetation carbon: R = 0.75) were found to contribute distinct patterns in SHAP results, supporting their retention.

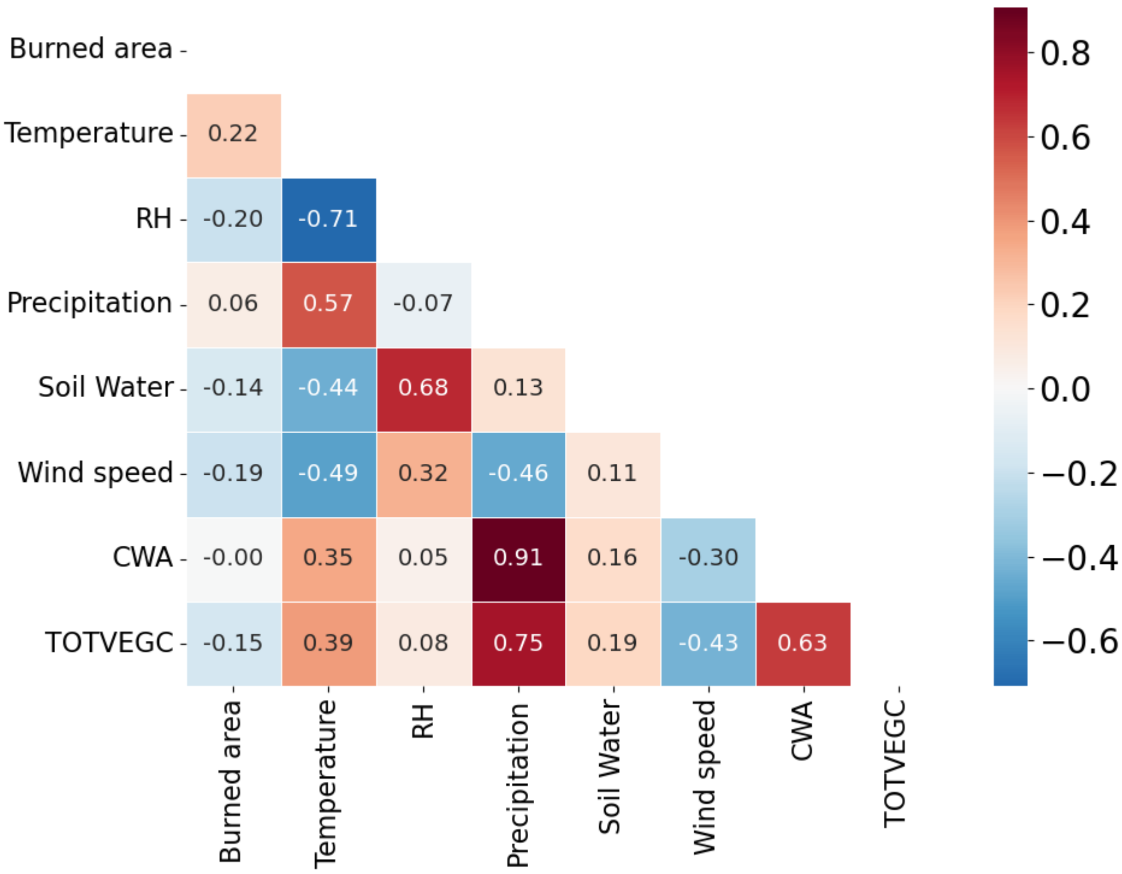

Figure R2: Pairwise correlation of annual mean variables.

4. Instead of running statistical models on model output, I would *strongly recommend* that the authors lean into the strength of a process-based model such as CLM and run sensitivity experiments i.e. fixing temperature, precipitation and CO_2 to present day conditions. This will isolate the effects of the changes to the individual driving variables in a much cleaner way.

We agree that sensitivity experiments would provide cleaner attribution than post hoc statistical methods. Our current study focuses on scenario-based projections using transient simulations, and we recognize the value of targeted sensitivity runs (e.g., holding temperature, precipitation, or CO_2 constant) to isolate the role of individual drivers. However, this is beyond the scope of our current study design. However, similar fire sensitivity studies have been done in the past during FireMIP (Li et al., 2019), and we have added relevant literature highlighting their effect on BA as indicated in response to **comment #5**.

In addition, we have outlined this approach as a key direction for future work in the revised Discussion **(Section 4).**

“Several limitations of this study warrant further investigation and consideration when interpreting our results:

Attribution experiments: Our study isolates the climate effect by holding anthropogenic influence (changes in land use and population density) constant. While this provides a controlled framework for evaluating climate-driven wildfire risks, real-world fire dynamics are shaped by a broader set of factors. Future land use changes – such as agricultural expansion, forest fragmentation, or abandonment – can alter fuel continuity and flammability. For instance, fragmentation may reduce fire spread by breaking fuel connectivity, while deforestation or abandonment could increase fire risk by creating more open, combustible landscapes. Similarly, population growth and urbanization may lead to more frequent human ignitions or enhanced suppression capacity, depending on regional context. These socioeconomic dynamics, which have already contributed to declining BA in recent decades (e.g., Andela et al., 2017; Forkel et al., 2019), are not captured in our simulations. In addition, our interpretation of fire-climate relationships is based on statistical methods, which are inherently correlative. Future research would benefit from targeted sensitivity simulations that systematically vary climate drivers (e.g., CO_2, temperature, precipitation) or land use parameters, either independently or in combination. Such factorial experiments would enable more rigorous causal attribution and improve confidence in regional fire projections under complex future scenarios."

5. In general CO2 effects - both increased water use efficiency which will lead to increased soil moisture and fertilization which will lead to increased biomass – are not adequately discussed. How will these be affecting the results here. How much is the effect here climate change *per se*, and how much is CO2?

CLM5 explicitly represents CO_2 fertilization effects through enhanced photosynthesis and vegetation productivity, as well as increased water use efficiency, which can particularly buffer against drying. These processes contribute to increased fuel availability and modulate soil moisture, and are implicitly reflected in our simulations under both SSP scenarios.

We have now clarified these CO_2-driven mechanisms in the results (Section 3.2). As stated above in comment #4, we also acknowledge that our experimental design does not separate CO_2 effects from concurrent meteorological changes, and emphasized this in the Discussion stating potential future research scope.

"A strong positive correlation also appears between BA and total vegetation carbon in Eurasian (Steppe) and tropical grasslands (e.g., African savanna, parts of Australia), where warmer and wetter conditions stimulate plant productivity, thereby increasing fuel supply and fire risks. This is likely amplified under future elevated CO_2, which enhances photosynthesis and fuel accumulation via fertilization effects (Lawrence et al., 2019; Walker et al., 2021; Allen et al., 2024). Meanwhile, in forested regions, the correlation between BA and vegetation carbon is often negative, suggesting that dense woody vegetation may suppress fire through improvement in plant water use efficiency, thereby retaining soil moisture and lowering fuel flammability. These findings support the notion that herbaceous fuels respond more rapidly to fire-conducive weather, while forests may buffer such effects due to slower drying and deeper rooting (Jones et al., 2022). Effects of these individual forcing factors, such as climate, CO_2, and land use, on fuel availability and combustibility have also been previously discussed for historical fires using several climate models under FireMIP (Li et al., 2019)." **(Section 3.2)**

6. Similarly, soil moisture does not *directly* affect fire (apart from ground fires which maybe included in the peat fire module but isn't clearly discussed). It does affect live

fuel moisture and serve as a proxy for dead fuel moisture, but these are somewhat indirect. The role of soil moisture as a proxy needs to be discussed, particularly how this plays out in the model logic.

The fire module in CLM5 does account for soil moisture indirectly, beyond peatland fires. It uses root zone soil wetness (btran2) to estimate the "combustibility of fuel for fire occurrence" (fire_m) for natural vegetation fires (i.e., non-crop). The root zone soil wetness is in turn linked to soil moisture. We have now added these clarifications:

"BA shows widespread negative correlations with moisture-related variables (e.g., RH, 10-cm soil moisture, precipitation, and climate water availability (CWA = precipitation – evapotranspiration)), consistent with their role in suppressing fire through increased fuel moisture and reduced flammability (Jolly et al., 2015). Soil moisture, in particular, is a key indirect control on wildfire activity, influencing both vegetation stress and fuel moisture content. Although the model does not simulate dead fuel moisture explicitly, soil moisture serves as a proxy for fuel combustibility. Drier soil conditions reduce live fuel moisture and increase the likelihood of ignition and fire spread. However, persistently dry conditions may also suppress vegetation growth and thus reduce fuel availability, which can lead to lower fire activity in some cases (Turco et al., 2017)." **(Section 3.2)**

"Additionally, our analysis relies on 10-cm topsoil moisture as a proxy for assessing fuel dryness, which may not fully reflect water availability for deep-rooted vegetation in forest ecosystems. However, CLM5 fire module internally relies on root-zone soil wetness to estimate fuel combustibility, which captures moisture availability over a deeper soil profile. This distinction introduces some approximation in our interpretation, especially in ecosystems where deeper soil layers better reflect vegetation water access and fire susceptibility." **(Section 4, limitations points)**

7. It would be very interesting (and important) to give some idea of of which fire types are increasing. Presumably it is the peatland and "everything else" category since land use is constant. But the relative proportions of these, given the strong high latitude signal, is important.

As indicated in Section 2.2, CLM5 internally tracks four fire types – natural vegetation, peat, crop, and deforestation fires – but in our model output configuration, these components are not separately archived or post-processed. Given that land use and population are held constant in our simulations, contributions from crop and deforestation fires are expected to remain largely unchanged over time. Therefore, the projected increases in burned area and emissions are primarily driven by natural vegetation and peatland fires. This is consistent with the spatial pattern of high-latitude increases, where peatlands and dense boreal vegetation dominate. We have clarified this point in the revised manuscript:

"Although CLM5 tracks four fire types, our analysis focuses on total BA and aggregated emissions. Since land use and populations were held constant in our simulations, the projected increases in BA are primarily attributable to natural vegetation and peat fires, particularly dominant in high-latitude regions." **(Section 2.2)**

8. The analysis of the "high latitudes"/"Boreal" is rather broad and rather inconsistent. Fig 8 is "northern latitudes" between 30 and 70 North, but this includes all sorts of (seasonally) hot and/or dry ecosystems such as the Mediterranean and the continental

interiors. Figure 7 is stated as the boreal region, but at > 40N this definition also includes a lot of non-Boreal ecosystems. This is not just a semantic issue, there is a big difference in driving dynamics, especially fuel- vs moisture-limited systems across these regions, and it does seem like this is a key issue of this paper. I also don't think it is reasonable to say that tundra dominates at 60N (line 251), there is a lot of forest at that latitude.

We agree that the use of terms such as "boreal" and "tundra" warrants more ecological precision, especially since these zones encompass diverse ecosystems with differing fire-climate controls. We have now reviewed all uses of terms like "boreal", "northern latitudes", and "high latitudes" throughout the manuscript to ensure they are used more consistently and ecologically appropriately. Where applicable, we now refer to "northern extratropics (NET)" for the region explaining 30°N–70°N in the figure and in discussion.

Additionally, in Section 3.3 (Figure 7 and Figure 8), we have clarified that the latitudes ≥40°N are shown/used to explicitly focus on higher northern latitudes. We explicitly state that results reflect fire drivers across NET regions, not boreal forests alone.

Moreover, we have also replaced "tundra" with "boreal", which we believe dominates at around 60°N.

9. Was dynamic vegetation enabled or not? It isn't clear. This needs to be fully detailed, and if not the potential effect on the results discussed.

We used CLM5-BGC mode for our simulation, which simulates vegetation dynamics via prescribed PFTs and carbon-nitrogen cycling, but it does not include dynamic vegetation competition, establishment, or mortality as in a classic DGVM. However, it does simulate dynamic LAI, carbon allocation, and biomass growth in response to climate and CO_2, but PFT composition is fixed in space. So, calling CLM5-BGC a DGVM is not strictly correct unless it is coupled with a DGVM like FATES, which allows for succession and vegetation turnover. We have clarified this in **Section 2.1**:

"… While CLM5 simulates vegetation structure, carbon allocation, and biomass dynamics in response to environmental drivers, it does not include dynamic changes in PFT composition, competition, or succession as in Dynamic Global Vegetation Models. This constraint may limit the representation of biome shifts and their long-term feedbacks on fire regimes. Thus, vegetation types remain fixed in space, although their biomass and productivity evolve, which is important for fire regime responses driven by vegetation."

10. In Fig. 2, why is the SSP1 line much higher than the SSP3 line? The authors report a higher increase in SSP3 (not unexpected), but it is still lower that SS1 at the end of the century. The authors need to to explain what is going on here. Also, I don't find the 25 year moving average to be useful or convincing, especially when it seems not to be centered on the actual year in question (look at about 2080 for example, time series goes up, moving average goes down).

SSP1 initially exhibits a higher absolute value, particularly during the early-to-mid 21st century, potentially due to higher near-term warming in this scenario, which later stabilizes. In contrast, SSP3 begins with lower fire activity but shows a more pronounced increase later in the century as strong warming accelerates. This accelerated rise in BA under SSP3 is especially evident in the northern extratropics, whereas larger reductions occur in the tropics (but increases in SSP1; Figure 2). These tropical declines offset the boreal increases, leading to a slightly lower global BA in SSP3 compared to SSP1 by the end of the century under our simulation settings.

We appreciate the reviewer's observation regarding the moving average in Figure 2. We have updated our analysis to use a 30-year centered moving average, consistent with the World Meteorological Organization climatological baseline (WMO, 2017) and adopted in recent studies (e.g., Bento et al., 2023). This moving average was implemented using a symmetric padding method in convolution, ensuring that each smoothed value is centered on the respective year. We have updated the Methods **(Section 2.3)**:

"To analyze long-term trends, we applied a centered 30-year moving average to the annual values, which was implemented using a symmetric padding method with convolution, ensuring that each smoothed value is centered on the corresponding year. These smoothing highlights decadal variability and long-term trends while minimizing short-term fluctuations."

Figures 2, 3, and S5 have been updated to reflect this change. The revised Figure 2, now based on the 30-year centered moving average, better captures short-term trends and improves interpretability as shown below.

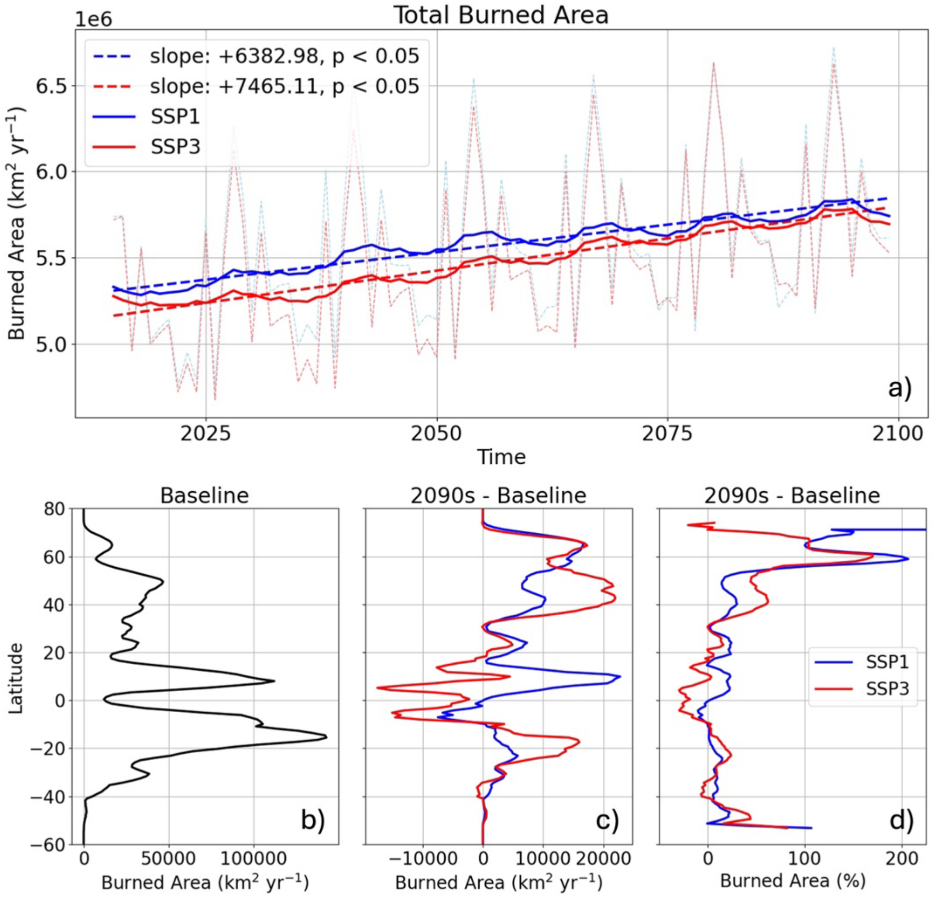

Figure 2. Updated panel (a) in revised Figure 2 with a 30-year centered moving average.

11. Also in Fig. 2 (and others) what is that repeating cycle in results? And why are SSP1 and SSP3 so similar? It doesn't seem like the input climate data was actually two independent GCM runs. Please explain.

The repeated cycles visible in Figure 2 possibly reflect residual interannual variability from the climate forcing data (CESM2). While both SSP1-2.6 and SSP3-7.0 scenarios diverge in terms of greenhouse gas trajectories, they are derived from the same initial condition ensemble member of CESM2, meaning they share natural internal variability in the early part of the simulation. This is a common approach in long-term climate experiments to isolate the effects of external forcing (i.e., SSP pathways) from natural variability. SSP1 and SSP3 look similar for global BA; however, if we track regional variations like in Figure 3 in the manuscript, they differ significantly.

We now clarify this point in the Methods **(Section 2.3)** to avoid misinterpretation.

"Both SSP1 and SSP3 were forced with outputs from the same CESM ensemble member, meaning that they share internal variability in the early part of the simulation."

Concerning the manuscript itself:

12. I think the title should be adjusted. What are "Climate-driven fires"? I think the authors are trying to say that they are only simulate changes in fires due to changes in climate, but the title doesn't express that.

We appreciate the reviewer's suggestion regarding the clarity of the title. For clarity, we have revised the title to:

"Global wildfire patterns and drivers under climate change"

13. The language needs some overhaul for clarity and narrative flow. This applies throughout the Results and Discussion sections, but lines 250-259 really typify this. Whilst the text does kind of describe the results, it is unclear what point we are supposed to take from this formulation.

We have revised the whole Results and Discussion sections, ensuring that each paragraph more explicitly conveys the key message drawn from the results, improving overall readability and interpretation for the reader. In particular, original lines 250-259 have been revised to:

"We found important differences at a regional scale. In northern extratropics, particularly near 60°N, where boreal forests dominate alongside alpine forests and shrublands, BA and TC emissions are projected to increase by over 150% in both SSP scenarios (Figure 3a–d and Figure S4). This intensification is most evident in boreal region, where the trend in BA reaches +5237 km^2 yr^{-1} under SSP1 and +8515 km^2 yr^{-1} under SSP3. In contrast to the pronounced increases in boreal BA, our simulations project localized decreases in BA across parts of the humid tropics as well as temperate regions such as the UK and eastern US. In tropical rainforest regions, elevated precipitation and humidity under future climate scenarios likely suppress fire activity by maintaining higher fuel moisture levels and shortening the fire season. In temperate zones such as the UK and eastern US, projected climate changes (e.g., increased rainfall or limited warming) may reduce fire-conducive conditions. These declines occur despite fixed land use and populations, indicating that purely climatic effects can suppress fire activity in certain fuel-rich or moisture-sensitive systems. Additionally, tropical regions show slight decline in BA under SSP3 (–2429 km^2 yr^{-1}) and SSP1 (–64 km^2 yr^{-1}), both remaining statistically insignificant at 95% level (Figure 3e–h). Despite the upward trends in NET fires, the tropics remain the dominant contributor to total global BA and carbon emissions during the 21^{st} century, underscoring a shifting geographic balance of wildfire risks." **(Section 3.1)**

14. Line 314 – what is "detrained"?

Corrected to "detrended".

15. I don't find that the speciated emission add much value to the paper. They are barely discussed.

While total carbon (TC) emissions is the primary focus of the main text, as it encompasses all carbonaceous fire emissions, we have also analyzed speciated emissions, including black carbon (BC), organic carbon (OC), and carbon monoxide (CO), which are presented in the Supplementary Information (Figures S4, S5, S7, and S8). These species exhibit similar spatial and temporal trends that closely align with those of TC across both scenarios, a point we now clarify explicitly in **Section 3.1**.

Focusing the main discussion on TC helps streamline the narrative and avoid redundancy, while still capturing the broader implications for air quality and radiative forcing. Speciated emissions are primarily used to validate model performance for a broader suite of fire-related species (as discussed in Section 2.4). Since the primary objective of this study is to investigate the influence of climate change on wildfire behavior and associated carbon emissions, we limit our discussion to TC as a representative metric of fire-driven carbon fluxes.

16. There needs to be more discussion of the effects of not including changes to the human aspects, especially as it is now well accepted that global burnt area is going *down* due to anthropogenic effects (Andela et al 2017, Science). This suggests that the simulations presented here (which shown the opposite trend with increasing burnt area) aren't actually capturing the dominant global effect. This needs far more discussion, much beyond the few lines 495-498.

We agree that human factors, especially land use change and fire suppression, have played a major role in the observed global decline in burned area over recent decades (e.g., Andela et al., 2017). Our modeling framework was explicitly designed to isolate the effects of climate change by holding land use and population constant, allowing us to assess fire responses solely to evolving meteorological conditions and CO_2 levels. While this approach helps attribute future fire risks to climate drivers, we fully acknowledge that it omits key anthropogenic influences. To clarify this, we have expanded Section 2.2 and also explained in the limitations section (Section 4), explaining that our setup isolates climate-driven impacts and their possible impacts in BA and carbon emissions, backed up with the relevant studies.

"In this study, to focus on the impacts of future climate change on wildfires, land use and populations were held constant at present-day levels, allowing only climate to evolve over time. This introduces a partial decoupling from the SSP framework but allows us to attribute changes in BA and emissions directly to climate-driven factors, independent of socioeconomic and land use shifts. While fixing land use change directly affects fuel availability, fixing population change is associated with fire management (suppress or ignite), thereby affecting BA and carbon emissions. …" **(Section 2.2)**

We have also discussed this in **Section 4** as indicated in response to **comment #4**.

17. Line 511 – I can't agree with the assertion that "afforestation/reforestation in fire-prone regions can reduce fire risks while enhancing carbon storage." There is no evidence to support that (in fact the author's own results suggest the opposite). Suggesting afforestation or reforestation in fire-prone areas for enhancing C storage seems like a bad idea.

We have revised this final paragraph **(Section 4)** to reflect this more nuanced understanding:

"Our findings have broader implications for sustainable forestry and global climate policies. Balancing biomass harvesting with carbon sequestration goals is crucial for maintaining ecosystem resilience. While afforestation and reforestation can enhance carbon storage, in fire-prone regions these efforts must be carefully evaluated to avoid unintentionally increasing fire risks. Reforestation strategies should prioritize fire-adapted species, ecosystem-appropriate fuel management, and resilience to projected climate extremes. A comprehensive understanding of climate-fire-vegetation feedbacks is essential for developing robust adaptation and mitigation strategies that align with global sustainability objectives."

18. The manuscript structure is somewhat unconventional. The Methods section is rather short, but the Results section is very long and introduces new methods as it goes. As Reviewer 1 points out these aren't fully explained (indeed what exactly is show in Fig 8?) so more detail is required. Additionally, I would suggest moving all methodological details to the methods section.

We have revised the manuscript to move all methodological details, including those related to the machine learning analysis, to the Methods section. This includes expanded descriptions of model training, evaluation metrics, SHAP interpretation, and variable selection. These changes also address related concerns raised by Reviewer 1. We have added Section 2.5 in revised manuscript as also indicated in response to **comment #3**.

19. Abstract line 22 – when you discuss the drivers individually it sounds as if they were tested individually, but they weren't, please rephrase.

We have rephrased and removed the individually named climate parameters.

20. Abstract line 23-25 – this sentence combines both present day evaluation and future projections, please split and rephrase.

Rephrased to separate model evaluation and projection results.

21. Abstract line 28-31 – Please reconsider referring to soil moisture as a "driver" of wild fire (see above) and also reconsider your mention of CO_2 fertilization as a driver in the abstract. This was barely mentioned in the results and wasn't explicitly studied, and increased biomass could also come from warming and wetting.

We have largely rephrased the abstract for smooth flow and clarity. Additionally, effect of CO_2 fertilization and warming and wetting on biomass increase is also discussed in the results section. Together, the changes made for comments 19, 20, and 21 can be seen in the revised **abstract** as:

"Wildfires increasingly threaten human lives, ecosystems, and climate, yet a comprehensive understanding of the factors driving their future dynamics and emissions remains elusive, hampering mitigation efforts. In this study, we assessed how future climate change would influence global burned area (BA) and carbon emissions between 2015 to 2100 using the Community Land Model version 5 (CLM5) with active biogeochemistry and fires. The model reasonably captures observed spatial and seasonal patterns of BA and emissions during the present-day reference period. Under two future scenarios – SSP1-2.6 (low warming) and SSP3-7.0 (high warming) – CLM5 projects global BA increases of +6400 km^2 yr^{-1} and +7500 km^2 yr^{-1}, respectively. Northern extratropics, particularly the boreal regions, emerge as the dominant hotspot with BA increasing by 200% and fire-related carbon emissions by +4 to +7 Tg yr^{-1}, while in tropical regions BA remains comparatively stable or slightly declines. These shifts are associated with warming-induced changes in vegetation productivity and fuel dryness, particularly in boreal ecosystems. Enhanced vegetation carbon contributes to fuel availability, while declines in relative humidity and soil moisture increase flammability. Elevated atmospheric CO_2 also contributes to these effects by enhancing biomass growth through fertilization and increasing water use efficiency, thereby affecting fire risks and carbon emissions. These findings underscore the need to integrate climate-vegetation-fire interactions into global policy frameworks for effective mitigation and adaptation planning of future fire-related threats."

22. Line 256 – no one could say that decline in the tropics under SSP3 is "sharp".

Rephrased it to:

"Conversely, tropical regions (20°S–20°N) show declining BA trends of under SSP3 (−2429 km^2 yr^{-1}) and SSP1 (−64 km^2 yr^{-1}), both remaining statistically insignificant at 95% level (Figure e–h)." **(Section 3.1)**

23. I don't find an adequate reason or discussion for burnt area going down in some regions in the tropics and, for example, the UK and Eastern US.

In the revised manuscript, we have expanded our discussion to reflect the underlying mechanisms in some specific regions, including the UK and the Eastern US. These are already discussed in response to **comment #13**, which includes:

"In contrast to the pronounced increases in boreal BA, our simulations project localized decreases in BA across parts of the humid tropics as well as temperate regions such as the UK and eastern US. In tropical rainforest regions, elevated precipitation and humidity under future climate scenarios likely suppress fire activity by maintaining higher fuel moisture levels and shortening the fire season. In temperate zones such as the UK and eastern US, projected climate changes (e.g., increased rainfall or limited warming) may reduce conditions that promote fires. These declines occur despite fixed land use and populations, indicating that purely climatic effects can suppress fire activity in certain fuel-rich or moisture-sensitive systems." **(Section 3.1)**

I will refrain from making more detailed comments on the manuscript as I believe the comments above may results in some re-writing and re-interpretation. I will be happy to give such comments if reviewing a revised version of the manuscript.

Thank you for all the constructive comments and suggestions.

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