Dear editor,

Thank for giving us a chance to revise the manuscript. We have significantly revised the manuscript based on editor's and reviewer's suggestions. The detailed responses are as follows. Besides, we also changed the rank of the authors to list Yumeng Shao as the second author instead of the third author in the original version. It was attributable to her important contribution in the revisions of manuscript and modelling performance evaluation.

Reviewer #1

This manuscript proposes a three-stage modeling framework to estimate the current and future global distributions of wildfire-sourced ozone under various SSP scenarios. By combining GEOS-Chem simulations with XGBoost, the authors (1) calibrate modeled ozone using historical observations, (2) project future ozone using CMIP6 data, and (3) estimate fire-sourced ozone through a ratio-based approach. The methodology is rigorous and the study addresses an important but underexplored topic, namely the future concentrations of wildfire-induced ozone and their impacts on crop yields. However, several methodological assumptions and data consistency issues require further clarification or revision.

Response: Thank for reviewer's suggestions. We have significantly revised the manuscript based on reviewer's suggestions. The detailed responses are as follows:

Major Comments

Comment 1:

Data Consistency Between Model Stages

While the authors avoid using GEOS-Chem for future total ozone due to uncertainties in emission inventories, they still apply the fire-to-total ozone ratio derived from GEOS-Chem to CMIP6-based projections. This raises two issues: (1) the manuscript does not evaluate whether this ratio is stable across different models or emission scenarios, and whether it can be reliably transferred from GEOS-Chem outputs to CMIP6-driven ozone fields; and (2) it does not explain why GEOS-Chem total ozone is considered unreliable, while the fire contribution ratio, derived from the same emission inputs, is assumed to be trustworthy.

Response: We sincerely appreciate the reviewer's insightful comments, which have helped us improve the manuscript. Your question, while challenging, is certainly worthy of in-depth consideration. For the instability in wildfire O_3 contribution ratios across different models, we optimized both total O_3 and wildfire-induced O_3 concentrations through observation-constrained data assimilation during the historical period. For future scenario projections, we input the output from 16 Earth System Models (ESMs) as independent variables into a machine learning model to derive more reliable future total O_3 concentrations. At this stage, rather than applying individual wildfire-to-total-O_3 ratios for each ESM, we first obtained optimized total O_3 concentrations and then estimated future wildfire O_3 contributions based solely on GEOS-Chem's projected wildfire-to-total-O_3 ratio. Since this approach consistently uses GEOS-Chem as the single reference model for ratio derivation throughout the entire process, the issue of inter-model ratio instability is inherently avoided. The same approach applies to different scenarios: we likewise utilize GEOS-Chem-quantified future wildfire-to-total-O_3 ratios to calculate optimized future wildfire O_3 concentrations in different scenarios. Throughout this process, we maintain the fundamental assumption that the bias between wildfire O_3 concentrations and their true values remains proportional to the bias between total O_3 concentrations and observations.

For whether it can be reliably transferred from GEOS-Chem outputs to CMIP6-driven ozone

fields. In the future scenarios, we cannot validate directly. However, for the historical period (during 2015-2019), we have validated it. As shown in Figure S3, we have confirmed the optimized total O_3 and fire-sourced O_3 concentrations were robust based on the ground-level K^+ and levoglucosan observations.

GEOS-Chem total ozone concentrations are considered unreliable because they largely biased from the ground-level observations. Thus, we employed the machine-learning model to assimilate the observations to construct the improved ozone dataset. For the optimization fire-sourced ozone concentration, we cannot directly validate the accuracy because the contribution of single source is difficult to assess based on observations. We can only assume that the bias in the model-simulated wildfire ozone concentrations is proportional to the bias in the model-simulated total ozone concentrations relative to the true total ozone concentrations. This method was also employed by previous studies (McDuffie et al. 2021). Besides, some studies about the top-down emission inversion also used similar method to allocate the emission in each sector. It should be noted that this method is not universally applicable. It must be validated before the application. In our study, we have confirmed that this model could improve the total ozone and fire-sourced concentrations (Figure S3) compared with the direct estimates using GEOS-Chem model. Therefore, we could believe the fire contribution ratio was relatively robust.

Comment 2:

Estimation of Fire-Induced Ozone in GEOS-Chem

The manuscript states that fire-related ozone was estimated by comparing GEOS-Chem simulations with and without fire emissions. However, key details of this implementation are missing. The authors should provide more information on how the simulations were configured in order to ensure transparency and reproducibility.

Response: Thank for reviewer's suggestions. (Line 113-119) We have added detailed implementation plan in the revised version. The whole simulation processes included four steps. Firstly, we run the GEOS-Chem model with all emissions (including wildfires) to establish reference O_3 concentrations (Baseline simulation). Second, we repeated the simulation while excluding wildfire emissions with the same meteorological conditions (MERRA2 and GCAP2_CMIP6) and anthropogenic emission inventory (CEDS). Third, we computed the wildfire-induced O_3 by subtracting zero-out results from the baseline. At last, we compare modeled O_3 concentrations with observational data (e.g., ground-based measurements) to assess uncertainty.

Comment 3:

Attribution without internal evidence

The manuscript attributes regional ozone differences to known processes by citing external literature. For example, it attributes high wildfire-induced ozone in the SS region to higher fuel consumption and burned area, yet presents no corresponding model outputs. Similarly, the discussion of low ozone enhancement over the US refers to temperature and NO_x concentrations but does not show any temperature or NO_x fields from the model. The authors are encouraged to support such interpretations using variables directly derived from their simulation.

Response: I agree with reviewer's suggestions. (Line 227-266) We have used model outputs to explain the spatiotemporal differences in ozone concentrations generated by wildfires. The detailed revisions are shown in section 3.2.

"Global variations of fire-sourced MDA8 O_3 concentrations in historical and future scenarios are shown in Figure 1 and 2. From 2015 to 2019, the fire-sourced MDA8 O_3 level was in the order

of Sub-Saharan Africa (SS) (14.9 ± 8.4 μg/m^3) > South Asia (SA) (4.0 ± 2.5 μg/m^3) > China (1.6 ± 0.7 μg/m^3) > United States (US) (1.3 ± 0.9 μg/m^3) > Europe (1.2 ± 0.4 μg/m^3). In future scenarios, fire-sourced MDA8 O_3 levels display marked spatial variability across different Shared Socioeconomic Pathways (SSPs). MDA8 O_3 showed the higher concentrations in some regions such as SS, SA, and US. Among all of the scenarios, fire-sourced O_3 levels displayed the highest concentrations in SS. It was assumed that this region possessed extensive burned area (52%) and higher biomass fuel consumption (5200 g C m^{-2}) compared with other regions (van Wees et al. 2022). Following SS, SA also exhibited the higher wildfire-related MDA8 O_3 concentrations. The elevated concentrations of fire-sourced O_3 levels in SA were closely associated with exceptionally high fuel consumption (8600 g C m^{-2}) (Chen et al. 2023, van Wees et al. 2022) though the burned areas were not very high among all of the regions. In addition, it should be noted that many previous studies have confirmed US showed the higher wildfire-induced $PM_{2.5}$ or other aerosol components compared with many other regions (e.g., East Asia and South America) (Park et al. 2024, Xu et al. 2023). However, it did not show the higher O_3 concentrations in nearly all of the scenarios in our study. It was assumed that the MDA8 O_3 concentration exhibited significant latitudinal distribution (decreasing with the increase of latitude) globally. Both of China and Europe showed very low burned areas (0.2%) and fuel consumption (950 g C m^{-2}), and thus the fire-sourced MDA8 O_3 concentrations were relatively lower compared with SS and SA.

Besides, the fire-sourced MDA8 O_3 levels exhibited significant inter-annual trends and large discrepancy between different scenarios. The global average fire-sourced MDA8 O_3 concentrations showed overall increase from 2010s (1.3 ± 0.7 μg/m^3) to 2090s (SSP1-2.6, SSP3-7.0, and SSP5-8.5: 1.9 ± 0.9, 1.6 ± 0.8, and 1.4 ± 0.7 μg/m^3) for nearly all of the scenarios. The global average wildfire-related MDA8 O_3 concentrations (the average of 2040s and 2090s) followed the order of SSP3-7.0 (1.6 ± 0.9 μg/m^3) > SSP5-8.5 (1.5 ± 0.8 μg/m^3) > SSP1-2.6 (1.4 ± 0.8 μg/m^3). The highest wildfire-related MDA8 O_3 levels in SSP3-7.0 (air temperature: about 1.8°C higher than SSP1-2.6) and SSP5-8.5 (air temperature: about 2.3°C higher than SSP1-2.6) scenarios were contributed by the increased fuel consumption and the warmer condition because O_3 level was more sensitive to air temperature increase (Wang et al. 2021, Wu et al. 2021).

Nevertheless, different regions showed distinct long-term trends. Wildfire-related MDA8 O_3 levels in nearly all of the regions in SSP3-7.0 scenario (air temperature: about 1.1°C higher than historical period) showed remarkable increases compared with the historical period because the warmer condition facilitated the rapid increase of O_3 level (Zhao et al. 2020). For low-carbon scenario (SSP1-2.6), the wildfire-related MDA8 O_3 concentrations in China, Europe, and US showed the relatively lower O_3 levels, whereas SA and SS still increased by 40% and 64%, respectively. The results suggested that the low-carbon pathway cannot effectively reduce the wildfire-induced O_3 pollution in both of SA and SS" has been added in the revised version.

Minor Comments

Comment 4: Figures 1 and 2 show wildfire-induced MDA8 O_3 for the 2010s and 2040s, but the temporal averaging method is unclear. Please specify whether values represent multi-year means, seasonal averages, or other metrics.

Response: Thank for reviewer's suggestions. The wildfire-induced MDA8 O_3 for the 2010s and 2040s were calculated based on the concentrations during 2015-2019 and 2045-2049, respectively. The temporal averaging method is the arithmetic mean. It reflects the multi-year means.

Comment 5: The AOT40 formula is provided, but key details are missing, such as the daily 8-hour

window used, how growing seasons were defined, and whether values were averaged annually or over multiple years.

Response: Thank for reviewer's suggestions. The growing season was determined by the University of Wisconsin Center for Sustainability and the Global Environment (UW SAGE) global crop calendar containing the planting and harvest dates by crop species and variety (Sacks et al., 2010; Schiferl et al., 2018). The AOT40 used to assess the adverse impact on crop yields were averaged annually. Then, the RY in each year was quantified based on the equation of RY and AOT40. At last, we could calculate the CPL values in each year for all of the crops. The CPL during 2015-2019 and 2045-2049 reflect the annual average values during this period.

Comment 6: Line 77: The text refers to Figure S1 as showing the monitoring site distribution, but it only presents the modeling workflow.

Response: Thank for reviewer's suggestions. It is our fault, we have added the new Figure S1 to show the monitoring site distribution of ground-level O_3 observations at the global scale.

Reviewer #2

This study aims to explore the future impact that fires will have on ozone, and how that fire-sourced ozone will change future crop yields across different emissions scenarios. This is an important and scientifically relevant question, particularly as wildfires have been shown to increase during the hotter and drier fire seasons brought about by climate change. The authors use a "multi-stage model" to answer this question, combining output from GEOS-Chem and CMIP models with reanalysis data and ground (MDA8 O_3) observations. I appreciate the effort it took to combine disparate data sources and attempt to extract meaningful results. The topic of the study is increasingly relevant, but some of the methods need clarification, and a few conclusions require additional evidence.

Response: Thank for reviewer's suggestions. We have significantly revised the manuscript based on reviewer's suggestions. The detailed responses are as follows:

Major Comments

Comment 1:

Estimation of fire-induced ozone in GEOS-Chem (bumping this from initial evaluation)

The GEOS-Chem chemical transport model (CTM) is used to simulate total ozone concentrations and wildfire-induced ozone concentrations. It is unclear to me exactly how the wildfire-induced ozone concentrations are calculated. Is this done by subtracting the output of simulations which include wildfire emissions from those which don't? If so, this introduces some uncertainty to the issue: ozone chemistry is highly nonlinear and hence regionally specific. Shutting off wildfire emissions entirely will change the chemical environment (i.e. global oxidative potential) and makes a direct comparison to the base case more complex. In your response, you mention the "air pollutant tracing method" as another option, but it is unclear how this would be implemented. This discussion would benefit from another sentence for clarification or an illustrative reference.

Response: Thank for reviewer's suggestions. We firstly simulated ozone concentrations under scenarios with and without wildfires using the GEOS-Chem model. Then, we assimilated ground-based observational data from numerous global sites to adjust the total ozone concentrations, which include contributions from wildfires and other emission sources, ultimately obtaining an optimized global ozone concentration dataset. Using this dataset as a benchmark, we further refined the wildfire-generated ozone concentrations. We assumed that the errors in wildfire-generated ozone concentrations were entirely due to uncertainties in the wildfire emission inventory. The ratio of

wildfire-generated ozone to total ozone concentration in the GEOS-Chem model was set equal to the corresponding ratio in the optimized dataset. Based on this, we inversely calculated the optimized wildfire-generated ozone concentrations. In this process, we employed the zeroing-out method to estimate wildfire-generated ozone concentrations. While this approach has been widely used by many researchers, it does carry inherent uncertainties. Therefore, we addressed these uncertainties in the final section of the paper as part of our discussion on limitations.

In the last paragraph, we mentioned the air pollutant tracing method. In the GEOS-Chem model, wildfire-emitted precursors (e.g., NO_x, VOCs) are assigned unique "tags" as separate tracers. These tagged species undergo the same transport, chemistry, and deposition processes as regular emissions but are tracked independently. For ozone (O_3) attribution, the model calculates the fraction of O_3 produced from wildfire-tagged NO_x/VOCs oxidation pathways. The tagged O_3 concentrations are then extracted to quantify the wildfire contribution, while accounting for nonlinear chemical interactions (e.g., NO_x saturation effects). We have introduced the modelling method in the last paragraph. Although this method could decrease the uncertainties derived from nonlinear O_3 chemistry, this method still suffers from some limitations such as high computational costs due to the tracking of multiple tagged species and potential inaccuracies from nonlinear chemical interactions (e.g., ozone production sensitivity to NO_x-VOC ratios), which cannot be fully resolved by simple tracer separation.

Comment 2: Since the model is not evaluated against observations, also be clear that this conclusion is based off the results of a single model – using different CTMs could potentially lead to different conclusions. What are the implications if the surface ozone background is high in GEOS-Chem, as reported over the U.S. in Guo et al 2018?

Response: Thank for reviewer's suggestions. In fact, our study has collected the ground-level observation to constrain our model estimates. We firstly used the global ground-level O_3 observations to improve the GEOS-Chem output to obtain the high-accuracy global O_3 (from all of the sources) concentrations. Then, we used the improved global O_3 dataset to optimize the fire-sourced O_3 concentrations. In this stage, we cannot assess the accuracy of O_3 pollution contributed by fire alone. We only used indirect method such as the relationship of some fingerprints (e.g., K^+ and levoglucosan) and O_3 concentrations to validate its accuracy. Figure S3 also confirms the robustness of our study. Indeed, the use of only one model could increase the uncertainties, and thus we introduced the limitations of our study in section 3.4 (Line 327-350). For the simulations in the future scenarios, we used the outputs from 16 earth system models coupled with the optimized historical dataset (including ground-level observations) to improve the future estimates. The future modelling might decrease the uncertainty derived from only one model.

Comment 3:

Fire attribution with K^+

I appreciate the authors efforts to address my earlier comments, and I am sympathetic to the challenge of limited data. However, I am still skeptical of the fit shown in Fig. S2b. Would it be possible to include levoglucosan measurements, like you mentioned in your response, from the same observational sites for validation of the fire influence? Are there anthropogenic tracers that are also observed from those sites, so that the possibility anthropogenic K^+ could be counted out?

Response: Thank for reviewer's suggestions. In our study, it was not possible to exclude K^+ contributions from anthropogenic sources and dust resuspension because auxiliary ions such as Na^+ and Ca^{2+} were not measured in some areas during data collection. Therefore, we only used the total

K^+ concentrations to validate it. To overcome this defect, we have collected global ground-level levoglucosan measurements to validate the predictive accuracy of fire-sourced O_3. (Figure S3) The strong fire fingerprint (levoglucosan) was employed to construct the relationship with fire-sourced MDA8 O_3 concentrations. The results suggested that the R value (R = 0.73) was even higher than that between observed K^+ levels and fire-sourced MDA8 O_3 concentrations (R = 0.67). Therefore, we believe the fire-sourced MDA8 O_3 estimate is robust.

Comment 4: One thing that adds to my skepticism is that the predicted fire O_3 enhancements seem very small (1-2 μg/m^3) in Figure S2b compared to the complete distribution shown in Figure S2a. Even if the potassium is fire-derived, do the authors feel that these enhancements are convincing enough to say that fires are contributing excess ozone?

Response: Thank for reviewer's suggestions. Figure S3a and S3b represent the total O_3 concentrations (from all of the sources) and the fire-sourced O_3 concentrations, respectively. The latter was much lower than the former. In our study, we cannot directly demonstrate the accuracy of predicted fire-sourced O_3 concentrations. We only firstly assessed the predictive accuracy of total O_3 concentrations globally based on ground-level observations. Then, we used some fingerprints of wildfire (e.g., K^+ and levoglucosan) to assess the relationship of fire-sourced O_3 concentrations and K^+ level. Fortunately, the results suggested our model showed the better performance in fire-sourced ozone estimate. Therefore, we believe fires certainly contributed excess ozone pollution.

Comment 5:

XGBoost model training and evaluation

It is unclear what predictors are used. Li et al. 2024b, which is mentioned in L121 seems to incorporate satellite data, which doesn't align with this study.

Response: Thank for reviewer's suggestions. In the first stage, the ground-level MDA8 O_3 levels (dependent variable), meteorological factors (independent variables), land use types (independent variables), and simulated O_3 levels (independent variables) derived from GEOS-Chem model were integrated into XGBoost model to simulate the full-coverage MDA8 O_3 levels during 2015-2019. In the second stage, the simulated O_3 concentrations (independent variables) and meteorological parameters (independent variables) in four scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) during 2015-2019, 2045-2049, and 2095-2099 were collected from CMIP6 dataset including 16 earth system models. Then, the data in the future scenarios were integrated into the XGBoost model to further calibrate the CMIP6 modeling results based on historical dataset (2015-2019) (dependent variable) derived from the first stage model.

Comment 6: In the author's evaluation of their model, they cite the R^2 but do not comment on the slope of predicted vs observed, which is 0.67 (Figure S2a). Does this indicate an underestimate in predicted ozone of about 33%?

Response: Thank for reviewer's suggestions. (Line 199-210) In our study, the slope of predictive and observed values reached 0.67, indicating the simulated O_3 concentrations were underestimated compared with observed values. However, we cannot conclude that the underestimate degree was 33% because the intercept should be considered in the model.

Comment 7:

Questionable attribution

The link to temperature is mentioned multiple times but there is not adequate evidence that this plays a role in governing wildfire-ozone production. Do the temperature fields reflect the conclusions that the study presents, such as in L224?

Response: Thank for reviewer's suggestions. We have removed the sentence in Line 234 because the proof might be not very convincible. Besides, we also mentioned the relationship between O_3 pollution and air temperature (e.g., Line 255). I think the proof is convincible because the global average air temperatures in SSP3-7.0 and SSP5-8.5 were around 1.8℃ and 2.3℃ higher than that in SSP1-2.6. It was well known that the O_3 concentration was very sensitive to the air temperature, and thus the warmer climate conditions were beneficial to the O_3 elevation (Bloomer et al., 2009; Wang et al., 2024).

Minor Comments

Comment 8: L54 MDA8our typo

Response: Thank for reviewer's suggestions. (Line 54) We have corrected this error.

Comment 9: L56: Provide more details on this method, and be clear that this is a modeling study -- I believe Xu 2023 also uses GEOS-Chem.

Response: Thank for reviewer's suggestions. (Line 57) We have added "using the GEOS-Chem model".

Comment 10: L58: I wouldn't say the focus is historical, but instead that observational studies have sought to understand the exact impact of wildfires on ozone production, while modeling studies have sought to evaluate the performance of models against observations. There is a lot of uncertainty here that should be mentioned.

Response: I agree with reviewer's suggestions. (Line 57-61) We have added the introduction of uncertainties of fire-sourced O_3 estimates in this part. "Unfortunately, most of the current studies assessed the contribution of historical wildfire to ambient O_3 level, and the estimates showed large uncertainties associated with the burned areas, fuel consumption, and fuel types. Moreover, most of these studies only focused on the historical estimates, while only two studies explored the wildfire contribution to O_3 pollution in the future scenarios" has been added in this paragraph.

Comment 11: L71: What sort of control measures? To comment on this would need to know how ozone formation regime is changing and what anthropogenic emissions could be controlled to move in the right direction.

Response: I agree with reviewer's suggestions. The ozone pollution was strongly dependent on the VOC/NO_x ratio, and thus the ozone pollution control must consider the region was dependent on VOC or NO_x. In our study, we focused on fire-sourced O_3 pollution and tried to propose some control measures to mitigate O_3 pollution. Some prevention policy should be proposed to reduce agricultural waste incineration and some prescribed fires. Some wildlands could be also changed into agricultural or commercial lands to reduce the occurrence frequency of forest wildfire. Moreover, our study revealed carbon neutrality policy could largely decrease O_3 concentrations and CPL in China. For some regions (e.g., SS and SA) not sensitive to carbon neutrality policy, some anthropogenic emission control measures should be implemented. For instance, most of regions in SS were NO_x-limited regions, and thus the priority for NO_x emission reduction could effectively decrease O_3 concentrations.

Comment 12: L90: It would be nice to see the spatial distribution of these observations.

Response: Thank for reviewer's suggestions. We have added the spatial distribution of these observations in Figure S1.

Comment 13: L167: Does the crop growing season differ by region? How is it defined across the world?

Response: Thank for reviewer's suggestions. Different regions have their local growing seasons.

The growing season was determined by the University of Wisconsin Center for Sustainability and the Global Environment (UW SAGE) global crop calendar containing the planting and harvest dates by crop species and variety (Sacks et al., 2010; Schiferl et al., 2018).

Comment 14: L182: Would be interesting to see how much variance there is between different crop yield models, and how that impacts the spread of CPL estimated with your model.

Response: Thank for reviewer's suggestions. (Section 3.3) The standard deviations of total products for maize, rice, spring wheat, and winter wheat based on multiple crop models during historical period were 1.4, 0.4, 15, and 22 t/km^2. The standard deviations of total products for maize, rice, spring wheat, and winter wheat based on multiple crop models in SSP1-2.6 scenario were 0.5, 0.1, 0.8, and 1.1 t/km^2. The standard deviations of total products for maize, rice, spring wheat, and winter wheat based on multiple crop models in SSP3-7.0 scenario were 1.1, 0.4, 154, and 48 t/km^2. The standard deviations of total products for maize, rice, spring wheat, and winter wheat based on multiple crop models in SSP5-8.5 scenario were 1.1, 0.5, 20, and 6.5 t/km^2.

Due to the uncertainties of simulate crop yields, we added the CPL ranges in the revised version to make the readers know the uncertainties of CPL.

"As shown in Figure 4, the global crop yield losses caused by fire-sourced O_3 exposure have been quantified based on the equations 3-5. During historical period, the global fire-sourced O_3 caused 3.1 (2.4-3.8), 1.7 (1.5-1.9), 24 (21-27), and 43 (39-47) t/km^2 crop losses for maize, rice, spring wheat, and winter wheat, respectively. Compared with the historical period, CPL values in different future scenarios displayed large discrepancy. In SSP1-2.6 scenario, CPL of maize, rice, spring wheat, and winter wheat associated with fire-sourced O_3 exposure were 1.1 (0.9-1.3), 0.5 (0.4-0.6), 4.6 (4.1-5.4), and 4.6 (3.5-5.2) t/km^2, respectively (Figure S4-S11). However, CPL for maize (2.1 (1.9-2.3) and 2.4 (2.1-3.0) t/km^2), rice (1.1 (0.9-1.3) and 1.3 (1.1-1.5) t/km^2), spring wheat (557 (486-628) and 184 (154-218) t/km^2), and winter wheat (258 (208-308) and 19 (14-22) t/km^2) caused by fire-sourced O_3 exposure experienced dramatic increases in SSP3-7.0 and SSP5-8.5 scenarios (Figure S4-S11). There are two reasons accounting for the fact. First of all, the wildfire-related O_3 exposures showed marked increase in high-emission scenarios (Yang et al. 2022, Yue et al. 2017). Moreover, the crop yields also displayed substantial increases in both of these scenarios because rapid increase of fertilizer consumption (Brunelle et al. 2015, Randive et al. 2021).

In addition, CPL caused by fire-sourced O_3 exposure also suffered significant spatial difference. During the historical period, the total CPL for four major foods caused by fire-sourced O_3 exposure in China, Europe, US, SA, and SS were 1451 (1302-1650), 65 (54-82), 61 (48-70), 56 (52-59), and 404 (372-425) t/km^2, respectively. In the future scenario (SSP1-2.6, SSP3-7.0, and SSP5-8.5), the total CPL for four major foods caused by fire-sourced O_3 exposure in China, Europe, US, SA, and SS were 23 (19-28) (711 (630-802) and 339 (299-375)), 14 (12-16) (684 (596-768) and 32 (28-34)), 11 (8-12) (19 (17-22) and 21 (18-23)), 14 (12-15) (35 (30-39) and 21 (18-24)), 298 (272-320) (160 (145-179) and 745 (641-840) t/km^2, respectively. In both of historical and future scenarios, SS, SA, and China showed the higher CPL compared with other regions. The higher CPL in SS and SA might be attributable to the higher fire-sourced O_3 concentrations and crop yields. The higher CPL in China might be associated with exceptionally high crop yields though the wildfire-induced O_3 level was not very high. For most regions, CPL showed the higher values in high-emission scenarios (SSP3-7.0 and SSP5-8.5). Although SS and SA also showed the higher CPL in high-emission scenarios (SSP5-8.5), the CPL values of SS and SA in SSP1-2.6 scenario were still very high. The results suggested that the low-carbon policy still cannot effectively weaken local agricultural

damage of fire-sourced O_3 exposure" has been added in the revised version.

Comment 15: L221: U.S. showed higher PM than the other regions discussed above? Or higher PM than reported in previous studies? Language is a bit unclear.

Response: Thank for reviewer's suggestions. (Line 239-242) In our study, we did not analyze the spatiotemporal variations of $PM_{2.5}$ in the United States compared with other regions. We only introduced the conclusion reported in previous studies. In this part, we only confirmed the United States showed the lower fire-sourced O_3 concentrations though the wildfire-induced $PM_{2.5}$ concentrations were not low. We have corrected this sentence.

Comment 16: L224: "The lower air temperature…" This is an unsubstantiated hypothesis. The latitudinal distribution is driven by many factors and most of them are likely fire-related, not meteorological. This is even mentioned in the next sentence.

Response: I agree with reviewer's suggestions. We have removed this sentence in the revised version.