Response to the review comment 2 on gmd-2022-227

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This paper addresses the importance issue of properly representing interspecific variations of plant sensitivity to ozone damage in global ecosystem or Earth system models, by taking advantage of the observed relationships between leaf-based traits (such as leaf mass per area) and ozone sensitivity. The methodology and analysis are scientifically rigorous and valid, and potentially important implications for all future studies of plant-ozone interactions. I recommend the publication of this manuscript as long as the following suggestions have been addressed.

Response: Thank you very much for reviewing this manuscript and offering constructive suggestions for further improvement. We have considered them carefully and revised our manuscript accordingly, especially for the Introduction and Discussion parts. In this version, we have added more explanations and comparisons of previous modeling schemes and fully demonstrated the necessity of this study. Here are point-to-point responses:

Section 1:

Overall, the introduction is too short, thus the motivation and justification for the importance of their work are relatively weak. It is also not as informative as what an introduction section should be like. The authors are thus recommended to lengthen the introduction, especially to:

How exactly are the different kinds of plant sensitivities currently used in models measured/ determined? What are the differences between the different approaches (e.g., Felzer vs. Lombardozzi vs. Sitch)? Based on experimental values or field observations? A discussion on the methodological and theoretical basis of the current approaches should be included. Moreover, a comparative analysis of the numerical results from the different approaches and studies should be included to highlight the uncertainties and justify the need to revise the current approach.

Response: In the revised Introduction, we explained the theoretical basis of different schemes and compared their numerical results for the global estimates on *Lines 84-97* as follows: "Alternatively, more and more mechanistic schemes were developed and implemented in dynamic global vegetation models (DGVMs) to assess the joint effects of environmental factors and O_3 on plants. Felzer et al. (2004) considered both the damaging (through AOT40) and healing (through growth) processes related to O_3 effects within the framework of Terrestrial Ecosystem Model. They further estimated the reduction of 2.6%-6.8% in the net primary productivity by O_3 pollution in U.S. during 1980-1990. Different from Felzer et al. (2004), Sitch et al. (2007) proposed a flux-based scheme linking the instantaneous POD_y with the damaging percentage through the coupling between stomatal conductance and photosynthetic rate. Implementing this scheme into the vegetation model of YIBs, Yue and Unger (2015) predicted a range of 2%-5% reduction in global gross primary productivity (GPP) taking into account the low to high O_3 sensitivities for each vegetation types.

Lombardozzi et al. (2015) collected hundreds of measurements and derived the decoupled responses in stomatal conductance and photosynthesis for the same O_3 uptake fluxes. They further implemented the separate response relationships into the Community Land Model and estimated a reduction of 8%-12% in GPP by O_3 at present day."

The O_3 sensitivities in these schemes are further explained on **lines 101-105** as follows: "Although different schemes considered varied physical processes (Ollinger et al., 1997; Felzer et al., 2004; Sitch et al., 2007; Felzer et al., 2009; Lombardozzi et al., 2015; Oliver et al., 2018), they followed the same principle that different O_3 sensitivities should be applied for varied plant functional types (PFTs), as revealed by many measurements in the past four decades (Buker et al., 2015; Mills et al., 2018) (Table S1)."

In addition to semi-mechanistic representation of sensitivity of photosynthesis to ozone exposure, there have also been other more empirical approaches to quantify plant sensitivity to ozone, including the concentration-based approach (e.g., AOT40) and flux-based approach (e.g., DO$_3$SE, POD). These approaches have been mostly applied to crops but also to some extent to natural vegetation. A paragraph should be devoted to discuss the merits and shortfalls of these various approaches, so as to justify the importance of mechanistically representing photosynthetic responses to ozone exposure. Some references that should be discussed include Tai et al. (2021) and Emberson et al. (2018).

Response: We added the introductions of concentration- and flux-based metrics on **Lines 63-71** as: "To date, O_3 fumigation experiments have been conducted for various plant species. Accordingly, O_3 damaging sensitivities, denoted as the Dose-Response Relationships (DRRs), were derived as the regressions between O_3 exposure metrics and the changes in biotic indicators (Mills et al., 2011). The widely-used O_3 metrics include ambient O_3 concentrations for AOT40 (Accumulated O_3 concertation above the Threshold of 40 ppbv (Fuhrer et al., 1997)), or the stomatal O_3 flux for POD_y (Phytotoxic O_3 Dose above a threshold flux of y (Buker et al., 2015)). The biotic indicators include visual leaf states, photosynthetic rate, biomass, or crop yield. Normally, the DRRs were derived for typical tree/grass species at specific regions, for example, Norway spruce, birch, and beech in Europe (Buker et al., 2015) or poplar (Shang et al., 2017) and crops (Peng et al., 2019) in East Asia."

We added corresponding paragraphs on **Lines 73-82** as "Some assessment studies used DRRs to derive contemporary O_3 plant damage patterns at the large scales. Concentration-based DRRs were widely measured and applied on the homogenized land cover, mostly for estimating crop yield loss (Feng et al., 2022; Tai et al., 2021; Hong et al., 2020). However, such DRRs don't include information about biochemical defense and stomatal regulations. Comparatively, flux-based DRRs reflect a more reasonable consideration in biological processes, but are limited by the application scales in both space and time (Mills et al., 2011; Mills et al., 2018). For example, the estimate of POD_y needs a dry deposition model "DO$_3$SE" (Deposition of Ozone for Stomatal Exchange) (Clrtap, 2017) or an equivalent model to account for environmental constraints on plant stomatal uptake during the whole growing season. Furthermore, the application of DRRs might introduce uncertainties due to the omission of complex interactions among biotic and abiotic factors at varied spatiotemporal scales."

A proper representation of ozone-vegetation interactions is important in Earth system and atmospheric modeling as much as in ecosystem modeling, because ozone damage on plants can subsequently affects land surface fluxes and thus atmospheric chemistry and climate. Some discussion should be done on these aspects, with references to, e.g., Zhou et al. (2018), Gong et al. (2020), and Zhu et al. (2022).

Response: we have added a paragraph to describe such importance, see ***Lines 97-99:*** "Coupling these schemes with earth system models, studies have assessed interactive O_3 impacts on carbon sink (Oliver et al., 2018; Yue and Unger, 2018), global warming (Sitch et al., 2007), and air pollution (Zhou et al., 2018; Gong et al., 2020; Gong et al., 2021; Zhu et al., 2022)."

The possible theoretical basis behind the connection between LMA and ozone sensitivity should be discussed. Possible uses of equations are recommended.

Response: the possible theoretical basis is summarized on ***Lines 319-321*** as "Moreover, it seems plausible that the oxidative stress caused by a given amount of stomatal O_3 flux per unit leaf area would be distributed over a larger leaf mass, and hence diluted, in a leaf with high LMA." We have added brief introduction on ***Lines 122-123*** as "This is likely related to the diluting effect of thicker leaves, which normally have stronger defenses against O_3 in their cross-section." An equation for summarizing such a phenomenon is ***Eqn. 3***, which reveals an inverse relationship between plant O_3 sensitivity and LMA. ***Figs 8 and 9*** also show this message.

Section 2.2:

The authors describe the POD approach here. As mentioned above, a due discussion comparing the various approaches including POD should be given in the introduction section.

Response: as have answered before, a brief introduction of POD has been added ***on Lines 67-69*** as one of the flux-based metrics. Besides, its physiochemical meaning, calculation, and limitation in the direct application have been further demonstrated between ***Lines 76-82***.

Section 2.3:

Since the calibration exercise is so crucial to this study, the authors are recommended to include at least a table or two for the calibration (from Table S3–S7), ideally the most important one or a consolidated one, in the main paper. Details of the calibration method (e.g., Monte Carlo? Or simply varying the value manually until it fits the best?) should be given in the text or table caption.

Response: The original Table S3 has been moved into the main text as ***Table 2***. A more thorough description of calibration has been added in Method in ***Lines 211-218*** as "For all supporting experiments, the parameter a for YIBs-LMA or the eight mean a_{PFT} for YIBs-S2007_adj are derived with the optimal 1:1 fitting between S_S and S_O to minimize the possible biases (Tables 2 and S3-S6). The basic method for calibration is feeding the model with series values of a or a_{PFT} until the

predicted O_3 damage matches observations with the lowest normalized mean biases (NMB). For all LMA-based experiments, S_S from varied PFTs were grouped for the calibration of a, while for a_{PFT} in YIBs-S2007_adj, each a_{PFT} is determined individually by matching simulated S_S with S_O. Since S_O are available only for six out of the eight YIBs PFTs, including EBF, NF, DBF, C_3 grass, C_4 grass, and crop (Table S1), S_O of these PFTs are used for calibration. All runs are summarized in Table 1."

Response: We have moved the original Fig. S1 to ***Fig.1*** in the main context.

Response: We have checked and revised tenses accordingly. Please see the manuscript with tracking changes.

Response: We added some discussion in ***4.3*** on ***Lines 368-378*** to explain why it is an advance in the modeling strategy as follows: "…The similarity between YIBs-S2007 and YIBs-LMA shown in Fig. 5 revealed an advance in the modeling strategy. Simulated O_3 damage in YIBs-S2007 is based on the PFT-level calibrations that tuned sensitivity parameters of each PFT with observed DRRs. Such refinement is a data-driven approach without clear physical reasons. Instead, the YIBs-LMA framework converts the area-based responses to mass-based ones and achieves better unification in

O$_3$ sensitivities among different PFTs. In this algorithm, the O$_3$ damage efficiency is inversely related to plant LMA, which influences both the O$_3$ uptake potential and the detoxification capability of the vegetation. The similarity in the global assessment of O$_3$ vegetation damage between YIBs-S2007 and YIBs-LMA further demonstrated the physical validity of LMA-based scheme in the Earth system modeling, because the independent LMA map was applied in the latter approach."

For other advantages, we have summarized in the previous version, which is now in **4.3** on **Lines 367-395** as: "For the first time, we implemented plant trait LMA into a process-based O$_3$ impact modeling scheme and obtained reasonable interspecific and inter-PFT O$_3$ responses supported by observations.… In addition to the advance in physical mechanisms, the LMA-based approach improves global O$_3$ damage assessments in the following aspects. First, it significantly reduces the number of required key parameters. To account for interspecific sensitivities, many schemes have to define PFT-level parameters to cap the ranges of plant responses (Sitch et al., 2007; Felzer et al., 2009; Lombardozzi et al., 2015). As a result, those schemes rely on dozens of parameters which increases the uncertainties of modeling and the difficulties for model calibration. The LMA-based approach requires the calibration of one single parameter a, largely facilitating its application across different vegetation models. Second, the new approach accounts for the continuous spectrum of O$_3$ sensitivities. Previous studies usually categorized species into groups of low or high O$_3$ sensitivity, depending on very limited data from O$_3$ exposure experiments. As a result, gridcells for a specific PFT share the same sensitivities regardless of their geographic locations and ecosystem characteristics. In reality, there are hundreds and thousands of plant species in each PFT and they usually have large variations in biophysical parameters including LMA and O$_3$ sensitivities. The LMA-based approach takes advantage of the newly revealed unifying concept in O$_3$ sensitivity (Li et al., 2016; Feng et al., 2018; Li et al., 2022) and the recent development in a trait-based LMA global map (Fig. 1a). Such configurations present a spectrum of gridded O$_3$ sensitivities (Fig. 8a) following the variations of LMA distribution."

In **Table S8**, PFT-specific comparisons for different simulations are shown as detailed data. We further plot a picture below. Generally, two schemes show comparative simulation capacity in our global simulation from a PFT-based statistic perspective.
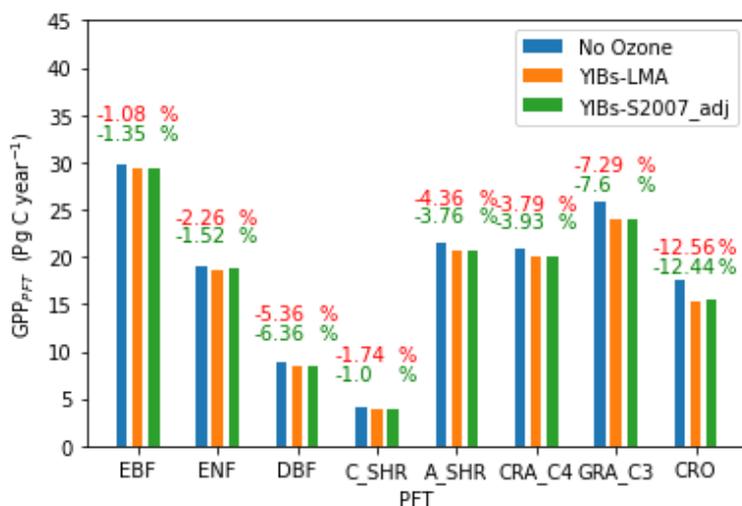
Figure S5. Comparison of PFT-specific GPPs from YIBs-LMA and YIBs-S2007_adj. Data for each PFT are shown as bars with blue, red, and green representing different experiments. Ratio numbers above each group of bars reveal the PFT-specific damage ratios for simulations using two schemes with red and green representing YIBs-LMA and YIBs-S2007_adj, respectively.

A more elaborate discussion should be given to how "the differences in LMA and simulated O3 sensitivities of these PFTs were the main cause of discrepancies in GPP damage at the large scale".

Response: this sentence has been modified to "However, the differences in LMA and simulated O_3 sensitivities of these PFTs also made important contributions to such discrepancies in GPP damages." on ***Lines 290-291***.

Section 4:

The authors have described the possible mechanisms behind the LMA-ozone damage relationships here. As suggested above, some of these should be devoted to the introduction section (at least discussed briefly), and here the authors may discuss how their model development and simulations verify them and allow them to derive a fuller picture.

Response: we have added a brief sentence on ***Lines 122-123*** as "This is likely related to the diluting effect of thicker leaves, which normally have stronger defenses against O_3 in their cross-section." In the discussion part, we explained how we interpreted this idea in our algorithm "Simulated O_3 damage in YIBs-S2007 is based on the PFT-level calibrations that tuned sensitivity parameters of each PFT with observed DRRs. Such refinement is a data-driven approach without clear physical reasons. Instead, the YIBs-LMA framework converts the area-based responses to mass-based ones and achieves better unification in O_3 sensitivities among different PFTs. In this algorithm, the O_3 damage efficiency is inversely related to plant LMA, which influences both the O_3 uptake potential and the detoxification capability of the vegetation." (***Lines 370-375***)

Section 4.3:

The authors well justify the merits of their LMA-based approach. Indeed, this can bring potentially significant unification and simplification of global modeling. I would further recommend an additional merit is that the LMA-based approach can even address the intra-PFT (not just inter-PFT) variations in ozone sensitivity because species in the same PFT can have largely varying LMA. Even though for now each PFT may have a fixed LMA in many models, this LMA-based approach provides a unifying way to model ozone damage as more spatially resolved LMA data become available in the future.

Response: We have strengthened the advantages of the LMA-based approach in ***the Introduction part in Lines 73-115*** and the ***Discussion section 4.3***. Besides, we have also added a ***Section 4.4***

outlook for future modeling to further discuss the prospect of the LMA-based approach "In nature, all aspects of plant physiochemical processes, such as growth, development, reproduction, and defense, are influenced by abiotic factors like water availability, temperature, CO_2 concentration, and light resources (Kochhar and Gujral, 2020). In our modeling, the cumulative O_3 fluxes are based on dynamic plant simulations with well-established DGVM to calculate the effects of these abiotic factors. LMA is considered as a factor representing the vulnerability of each species, by which divergent responses to the same O_3 stomatal dose can be further differentiated. In fact, many other key variables in DGVMs, for example, leaf photosynthetic traits (V_{cmax} and J_{max}), nutrient traits (leaf nitrogen and phosphorus), morphological traits (leaf thickness and size), and phenology-related traits (leaf life span) are all more or less interlinked with LMA (Walker et al., 2014). There are some generic regression relationships between them, which have not yet been fully validated by experimental studies. As a result, considerable improvements can be made in the direction of trait-flexible modeling within the existing DGVM frameworks. Our study demonstrates the validity of LMA-based approach for the O_3 plant damage modeling.

Although we used the most advanced LMA integrated from available observations, this dataset was developed based on static global grids and revealed the mean state for each pixel. In reality, LMA can vary with biotic/abiotic factors like leaf position in the canopy (Keenan and Niinemets, 2017), phenology, plant health, living environment (Fritz et al., 2018), and climate (Wright et al., 2005; Cui et al., 2020). Even long-term exposure to O_3 can alter leaf morphological characteristics and LMA (Li et al., 2017). In future studies, simulations from local to global scales could implement the spatiotemporal variations in LMA taking into account the demographic information and environmental forcings. We expect a breakthrough in the calculation of reliable LMA to achieve fully dynamic predictions of O_3 plant damage in Earth System Modeling, thus facilitating the research of plant response and adaption in changing environments."

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Response: All these references have been cited.

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