# Indirect contributions of global fires to surface ozone through ozone-vegetation feedback

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**Abstract:** Fire is an important source of ozone ($O_3$) precursors. The formation of surface $O_3$ can cause damages to vegetation and reduce stomatal conductance. Such processes can feed back to inhibit dry deposition and indirectly enhance surface $O_3$. Here, we apply a fully coupled chemistry-vegetation model to estimate the indirect contributions of global fires to surface $O_3$ through $O_3$-vegetation feedback during 2005-2012. Fire emissions directly increase the global annual mean $O_3$ by 1.2 ppbv (5.0%) with a maximum of 5.9 ppbv (24.4%) averaged over central Africa by emitting substantial number of precursors. Considering $O_3$-vegetation feedback, fires additionally increase surface $O_3$ by 0.5 ppbv averaged over the Amazon in October, 0.3 ppbv averaged over southern Asia in April, and 0.2 ppbv averaged over central Africa in April. During extreme $O_3$-vegetation interactions, such feedback can rise to >0.6 ppbv in these fire-prone areas. Moreover, large ratios of indirect-to-direct fire $O_3$ are found in eastern China (3.7%) and the eastern U.S. (2.0%), where the high ambient $O_3$ causes strong $O_3$-vegetation interactions. With likelihood of increasing fire risks in a warming climate, fires may promote surface $O_3$ through both direct emissions and indirect chemistry-vegetation feedbacks. Such indirect enhancement will cause additional threats to public health and ecosystem productivity.

**Keywords:** fires, surface ozone, dry deposition, ozone-vegetation feedback, GC-YIBs

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## 1 Introduction

Tropospheric ozone ($O_3$) is a toxic air pollutant with detrimental effects on vegetation (Yue and Unger, 2014; Juráň et al., 2021). Plant stomatal uptake of $O_3$ decreases both chlorophyll and Rubisco contents and increases the deformity rate of chloroplasts (Booker et al., 2007; Akhtar et al., 2010; Inada et al., 2012), which further reduces the leaf area index (LAI) and gross primary productivity (GPP) of ecosystems (Karnosky et al., 2007; Ainsworth et al., 2012). Modeling studies estimated that $O_3$ damage reduces global GPP by 1.5%-3.6% with regional maximum reductions of 8%-20% over eastern U.S., western Europe, and eastern China (Yue and Unger, 2014; Lei et al., 2020; Zhu et al., 2021). In turn, vegetation damage also influences both the sources and sinks of $O_3$ through biogeochemical and biogeophysical feedbacks (Curci et al., 2009; Heald and Geddes, 2016; Fitzky et al., 2019). The damaged vegetation decreases isoprene emissions and stomatal conductance (Wittig et al., 2009; Feng et al., 2019), which influence $O_3$ production and dry deposition. Moreover, weakened leaf-level transpiration following $O_3$ damage modulates meteorological parameters, such as surface air temperature and atmospheric relative humidity, leading to substantial biogeophysical feedbacks on surface $O_3$ (Lombardozzi et al., 2012; Sadiq et al., 2017).

Interactions between air pollution and terrestrial ecosystems remain challenging due to limited process-based knowledge and the separate development of chemistry and vegetation models (He et al., 2020). At present, the feedbacks from $O_3$-damaging

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Tropospheric $O_3$ is a toxic air pollutant with detrimental effects on vegetation (Yue and Unger, 2014).…

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vegetation on $O_3$ have only been examined by four papers (Sadiq et al., 2017; Zhou et al., 2018; Gong et al., 2020; Zhu et al., 2021). Sadiq et al. (2017) implemented a parameterization of $O_3$ vegetation damage into a climate model and quantified online $O_3$-vegetation coupling. Simulations showed that surface $O_3$ could be enhanced by up to 4-6 ppbv over Europe, North America, and China through comparable effects from biogeochemical (decreased dry deposition and increased isoprene emissions) and biogeophysical (changes in meteorological variables following reduced transpiration rate) feedbacks from $O_3$-vegetation interactions. Similar conclusions were achieved by Zhu et al. (2021), who investigated the effects of $O_3$-vegetation interaction in China using a two-way coupled land-atmosphere model. By including $O_3$ damage to isoprene emissions in a fully coupled global chemistry–carbon–climate model, Gong et al. (2020) highlighted that such $O_3$-vegetation positive feedbacks were mainly driven by reduced dry deposition following $O_3$ damage to photosynthesis. Different from above three studies, Zhou et al. (2018) implemented steady-state $O_3$-induced LAI changes into GEOS-Chem and quantified only the influences of $O_3$-vegetation biogeochemical feedbacks because the model is driven with prescribed meteorological fields. Results showed that $O_3$-induced damage to LAI can enhance $O_3$ by up to 3 ppbv in the tropics, eastern North America, and southern China through changes in dry deposition and isoprene emissions. All studies revealed strong positive $O_3$-vegetation feedback to surface $O_3$, though the magnitudes are different due to discrepancies in $O_3$ damaging schemes, as well as differences in the models.

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Fire plays an important role in disturbing the terrestrial carbon budget (Bond-Lamberty et al., 2007; Amiro et al., 2009; Turetsky et al., 2011; Yue and Unger, 2018). Global fires directly emit 2-3 Pg (1 Pg = $10^{15}$ g) carbon into the atmosphere every year (van der Werf et al., 2010). Moreover, fires contribute to the production of tropospheric $O_3$ by emitting substantial number of precursors (Cheng et al., 1998; Kita et al., 2000; Oltmans et al., 2010; Jaffe et al., 2013; Lu et al., 2016). Globally, fires account for 3-5% of the total tropospheric $O_3$ (Bey et al., 2001; Ziemke et al., 2009; Jaffe and Wigder, 2012). Regionally, especially in Amazon and central Africa, fires can enhance surface $O_3$ by 10-30 ppbv through emissions of $NO_x$ and VOCs during fire seasons (Yue and Unger, 2018; Pope et al., 2020). Over these regions, strong $O_3$-vegetation interactions are expected because of high fire $O_3$ concentrations and dense vegetation cover. Previous studies showed that fire $O_3$ causes large GPP reduction of 200-400 Tg C $yr^{-1}$ over Amazon and central Africa (Pacifico et al., 2015; Yue and Unger, 2018). With likely increased wildfire activity due to global warming, surface $O_3$ will be further enhanced by wildfires (Amiro et al., 2009; Balshi et al., 2009; Wang et al., 2016; Yue et al., 2017), leading to more severe $O_3$ damage on vegetation. Although the feedback of vegetation damage on surface $O_3$ have been well explored on global (Sadiq et al., 2017; Zhou et al., 2018; Gong et al., 2020) or regional (Zhu et al., 2021) scales, these studies all focused on $O_3$-vegetation from combined anthropogenic and natural sources. Therefore, quantification of the $O_3$-vegetation interactions associated with fire emissions is very important for a comprehensive understanding of the effects of fires on surface $O_3$.

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Here, we apply a fully coupled chemistry-vegetation model (GEOS-Chem-YIBs, hereafter referred to as GC-YIBs) to examine the indirect contributions of fires to surface $O_3$. Fire-induced $O_3$ affects plant photosynthesis and stomatal conductance. In turn, predicted changes in LAI and canopy stomatal conductance influence both the sources and sinks of tropospheric $O_3$. Such $O_3$-vegetation interactions result in additional enhancement in surface $O_3$ caused by fire emissions (Fig. 1). Section 2 describes the GC-YIBs model and sensitivity experiments conducted in this study. Section 3 quantifies the feedbacks of fire-induced $O_3$ vegetation damage on surface $O_3$ concentrations. The last section summarizes the findings and discusses the uncertainties.

## 2 Materials and Methods

### 2.1 The GC-YIBs model

GC-YIBs is a coupled chemistry-vegetation model developed by implementing the Yale Interactive terrestrial Biosphere (YIBs) model into GEOS-Chem version 12.0.0 (Lei et al., 2020). GEOS-Chem is a widely used global 3-D chemical transport model (CTM) for simulating atmospheric composition and air quality (Yue et al., 2015; Yan et al., 2018; David et al., 2019; Lu et al., 2019). This model uses a detailed $HO_x$-$NO_x$-VOC-$O_3$-halogen-aerosol tropospheric chemistry to simulate tropospheric $O_3$ fluxes (Barret et al., 2016; Gong and Liao, 2019), while a simplified linearized Linoz chemistry mechanism is applied to simulate stratospheric $O_3$ (McLinden et al., 2000). Aerosols simulated in GEOS-Chem include secondary inorganic aerosols, secondary organic aerosols, primary organic aerosols, black carbon, dust, and sea salt (Dang and Liao, 2019; Li et al., 2019). The gas-aerosol partitioning of the sulfate–nitrate–ammonium system is computed by the ISORROPIA v2.0 thermodynamic equilibrium model (Fountoukis and Nenes, 2007). The atmospheric emissions from different sources, regions, and species on a user-defined grid are calculated through the online Harvard NASA Emissions Component (HEMCO) module (Keller et al., 2014). HEMCO is highly customizable in that it can automatically combinate, overlay, and update emission inventories and scale factors specified by the users. In general, the GEOS-Chem model overestimates summer surface $O_3$ concentrations in the eastern U.S. and China (Zhang et al., 2011; Travis et al., 2016; Schiferl and Heald, 2018).

YIBs is a vegetation model designed to dynamically simulate the changes in LAI and tree height based on carbon assimilation, respiration, and allocation processes (Yue and Unger, 2015). The model computes carbon uptake for 9 vegetation types, including evergreen needleleaf forest, deciduous broadleaf forest, evergreen broadleaf forest, shrubland, tundra, $C_3$/$C_4$ grasses, and $C_3$/$C_4$ crops. The canopy is divided into an adaptive number of layers (typically 2-16) for light stratification. The YIBs model applies a well-established Michaelis–Menten enzyme kinetics scheme to compute the leaf photosynthesis (Farquhar et al., 1980; Von Caemmerer and Farquhar, 1981), which is further upscaled to the canopy level by the separation of sunlit and shaded

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leaves (Spitters, 1986). The LAI and carbon allocation schemes are from the TRIFFID model (Clark et al., 2011). Previous studies have shown that the YIBs model has good performance in simulating the spatial pattern and temporal variability of GPP and LAI based on site observations and satellite products (Yue and Unger, 2015, 2018).

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The GC-YIBs model links atmospheric chemistry and vegetation in a two-way coupling. As a result, changes in chemical components or vegetation will simultaneously feed back to influence the other systems. In this study, the GC-YIBs model is driven with the meteorological fields from the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA2) with a horizontal resolution of 4° latitude by 5° longitude, as well as 47 vertical layers from the surface to 0.01 hPa. Within GC-YIBs, the online-simulated surface $O_3$ in GEOS-Chem affects photosynthesis and canopy stomatal conductance; in turn, the online-simulated vegetation parameters, such as LAI and stomatal conductance, in YIBs, affect both the sources and sinks of $O_3$ by altering precursor emissions and dry deposition at the 1-hour integration time step. An earlier study evaluated the GC-YIBs model and showed good performance in simulating surface $O_3$, GPP, LAI, and $O_3$ dry deposition (Lei et al., 2020).

## 2.2 Scheme of $O_3$ vegetation damage

The GC-YIBs model calculates the impacts of $O_3$ exposure on photosynthesis based on a semi-mechanistic scheme (Sitch et al., 2007):

$$A' = \alpha \cdot A \quad (1)$$

where $A'$ and $A$ represent the $O_3$-damaging and original leaf photosynthesis, respectively. The $O_3$ damage factor is represented by $\alpha$; $O_3$ can cause damage to photosynthesis only if $\alpha < 1$. The factor $\alpha$ is calculated as a function of excessive $O_3$ flux and damaging sensitivity coefficient ($\beta$):

$$\alpha = -\beta \cdot max\left(F_{O_3} - T_{O_3}, 0\right) \quad (2)$$

The coefficient $\beta$ can have two values for each vegetation type (Table S1), indicating low to high $O_3$ damaging sensitivities (Sitch et al., 2007). $T_{O_3}$ represents the $O_3$ flux threshold, reflecting the $O_3$ tolerance of different vegetation types. $F_{O_3}$ represents the stomatal $O_3$ flux and is calculated based on ambient $[O_3]$, aerodynamic resistance ($r_a$), boundary layer resistance ($r_b$) and stomatal resistance ($r_s$):

$$F_{O_3} = \frac{[O_3]}{r_a + r_b + k \cdot r_s'} \quad (3)$$

Here $k$ represents the ratio of leaf resistance for $O_3$ to leaf resistance for water vapor. Parameters $r_a$ and $r_b$ are calculated by the GEOS-Chem model. $O_3$-damaging leaf photosynthesis ($A'$) is then integrated over all canopy layers to generate $O_3$-damaging GPP:

$$GPP' = \int_0^{LAI} A' \, dL \quad (4)$$

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The $O_3$-damaging stomatal resistance ($r_s'$) is calculated based on the model of Ball and Berry (Baldocchi et al., 1987):

$$\frac{1}{r_s'} = g_s' = m \frac{A'_{net} \cdot RH}{c_s} + b \quad (5)$$

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where $m$ and $b$ represent the slope and intercept of empirical fitting to the Ball-Berry stomatal conductance equation, respectively. $A'_{net}$ represents

$O_3$-damaging net leaf photosynthesis, $RH$ represents the relative humidity and $c_s$ is the ambient $CO_2$ concentration. Previous studies have shown that this scheme within the framework of YIBs can reasonably capture the response of GPP and stomatal conductance to surface [$O_3$] based on hundreds of global observations (Yue et al., 2016; Yue and Unger, 2018).

**2.3 Fire emissions**

Fire Inventory from NCAR (FINN) version 1.5 is used by GC-YIBs to simulate fire-induced perturbations in $O_3$. FINN provides daily global emissions of many chemical species from open biomass burning at a resolution of 1 $km^2$ (Wiedinmyer et al., 2011). The inventory estimates fire locations and biomass burned using satellite observations of active fires and land cover, together with emission factors and fuel loadings. For each land type, emission factors for different gaseous and particulate species are taken from measurements (Andreae and Merlet, 2001; Andreae and Rosenfeld, 2008; Akagi et al., 2011). Daily fire emissions for 2002-2012 are available at http://bai.acom.ucar.edu/Data/fire/. In GC-YIBs, all biomass burning emissions occur in the atmospheric boundary layer. Such configuration might slightly overestimate regional $O_3$ formation as observations suggested ~20% of fire plumes reached the height above the boundary layer (Val Martin et al., 2010) and consequently enhanced surface $O_3$ level at the downwind regions (Jaffe and Wigder, 2012). The FINN inventory has been widely used in regional and global chemical transport models (e.g., WRF-Chem and GEOS-Chem) to quantify the impacts of fires

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## 2.4 Site-level measurements

Measurements of surface [$O_3$] in the U.S. are provided by Air Quality System (AQS, https://www.epa.gov/aqs), those over Europe are provided by European Monitoring and Evaluation Programme (EMEP, https://emep.int). The observed [$O_3$] at Manaus, Tg Malim, and Welgegund sites are from earlier studies (Ahamad et al., 2014; Laban et al., 2018; Pope et al., 2020).

## 2.5 Model simulations

In this study, eight simulations (Table 1) are performed to examine both the direct and indirect contributions of fires to surface $O_3$. These simulations can be divided into two main groups:

1. CTRL_FIRE and CTRL_NOFIRE are the control runs using the same emissions except that the latter omits fire emissions. These runs calculate and output offline $O_3$ damage, which decreases instantaneous leaf photosynthesis but does not feed back to affect plant growth and $O_3$ dry deposition.
2. O3CPL_FIRE and O3CPL_NOFIRE are the sensitive experiments that consider online coupling between $O_3$ and vegetation. These runs include online $O_3$ damage to plant photosynthesis, which feeds back to affect both vegetation and air pollution. The two simulations apply the same emissions, except that the latter

omits fire emissions.

For each of these four configurations, two runs are conducted with either high (HS) or low (LS) $O_3$ damaging sensitivities. All simulations are performed from 2002-2012 using the GC-YIBs model driven by MERRA2 meteorological fields. The first 3 years are used as spin up, and the results of the last 8 years are analyzed. For the same configurations, the results from low and high $O_3$ damaging sensitivities are averaged. The differences between CTRL_NOFIRE and O3CPL_NOFIRE represent the surface $O_3$ enhancements through $O_3$-vegetation feedback without fire emissions. The differences between CTRL_FIRE and CTRL_NOFIRE, named O3OFF, represent the direct contributions of fires to surface $O_3$. The differences between O3CPL_FIRE and O3CPL_NOFIRE, named O3CPL, represent both direct and indirect contributions of fires to surface $O_3$. The differences between O3CPL and O3OFF represent the indirect contributions of fires to surface $O_3$ through $O_3$-vegetation interactions. It should be noted that only biogeochemical feedbacks from $O_3$ vegetation damage on surface $O_3$ are considered in this study because GC-YIBs uses prescribed meteorology (MERRA2).

## 3 Results

### 3.1 Model validation

Simulated surface daily maximum 8-hour average $O_3$ concentrations (MDA8 [$O_3$], short for [$O_3$] hereafter) are evaluated using measurements from the AQS and EMEP datasets over the period of 2005-2012 (Fig 2). The model well captures the observed spatial distribution of annual [$O_3$] in the U.S. and Europe, with a high correlation coefficient of 0.51 ($p<0.01$). Although GC-YIBs overestimates the [$O_3$] in the eastern U.S. while underestimating it in western Europe, the normalized mean bias (NMB) is only 4.0%, with a root mean square error (RMSE) of 5.4 ppbv. Therefore, the simulated $O_3$ vegetation damage in our study is slightly overestimated in the eastern U.S. but underestimated in western Europe.

### 3.2 Direct contributions of fires to $O_3$

Without fire emissions, the simulated global mean [$O_3$] is 23.9 ppbv, with a grid maximum of 63.7 ppbv over the Beijing–Tianjin–Hebei region averaged for 2005-2012 (Fig. 3a). Most high [$O_3$] is distributed in the Northern Hemisphere, where anthropogenic emissions make the dominant contributions. The inclusion of fire emissions increases global annual [$O_3$] by an average of 1.2 ppbv (5.0%). Regionally, the largest enhancement of [$O_3$] by 5.9 ppbv (24.4%) is averaged over central Africa, with smaller enhancements of 5.7 ppbv (38.2%) averaged over the Amazon, and 3.8 ppbv (10.2%) averaged over southern Asia. Smaller enhancements of 1.1 ppbv (2.2%), 0.9 ppbv (2.1%), and 0.8 ppbv (2.2%) are averaged respectively over eastern China, western Europe, and the eastern U.S. (Fig. 3b). The predicted fire-induced enhancements in [$O_3$] agree well with the simulations using the same model but with fire emissions from the Global Fire Emission Database (GFED) version 3 (Yue and Unger, 2018).

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We further evaluated the model performance in simulating fire-induced $\Delta[O_3]$ at three sites across biomass burning regions (Fig. S1). Without fire emissions, the $[O_3]$ is obviously underestimated, with NMBs of -25.5% at Tg Malim, -53.6% at Manaus, and -21.3% at Welgegund. As a comparison, simulations with fire emissions show NMBs in fire seasons of -8.7% at Tg Malim, -1.4% at Manaus, and -15.1% at Welgegund, suggesting improved $O_3$ simulations by including fire emissions.

## 3.3 Fire-induced $O_3$ damages to GPP

Surface $O_3$ causes strong damage to ecosystem productivity (Fig. 4). Without fire emissions, surface $O_3$ reduces global annual GPP by 1.7% (3899.8 Tg C $yr^{-1}$, Figs. 4a and 4c). Regional maximum reductions of 10.9% (372.0 Tg C $yr^{-1}$), 6.1% (366.1 Tg C $yr^{-1}$), and 4.9% (323.8 Tg C $yr^{-1}$) are averaged respectively over eastern China, the eastern U.S., and western Europe; these reductions are attributed to the high ambient $[O_3]$ level and the large stomatal conductance over these regions. The patterns of $O_3$-induced GPP reductions agree with previous estimates using the same $O_3$ damage schemes (Sitch et al., 2007; Yue and Unger, 2015). However, compared to simulations using another scheme (Lombardozzi et al., 2012; Zhou et al., 2018; Zhu et al., 2021), this study estimates smaller GPP reductions. Such discrepancy indicates there are large uncertainties in $O_3$ vegetation damage schemes, and more observations should be developed to evaluate different schemes in future studies.

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The inclusion of fire emissions causes additional GPP reductions. Globally, fire-induced $\Delta O_3$ decreases annual GPP by 0.4% (1312.0 Tg C $yr^{-1}$, Figs. 4b and 4d). Regionally, the largest GPP reduction of 1.4% (370.3 Tg C $yr^{-1}$) is averaged over the Amazon due to the largest enhancement of [$O_3$] caused by fires. Furthermore, fire $\Delta$[$O_3$] causes additional annual GPP reductions of 1.3% (358.0 Tg C $yr^{-1}$), averaged over central Africa, and 1.0% (77.1 Tg C $yr^{-1}$), averaged over southern Asia. In contrast, limited damage is found in eastern China, western Europe, and the eastern U.S. due to low fire $\Delta$[$O_3$]. Following the changes in GPP, fire-induced $O_3$ damage to LAI shows a regional maximum of 0.3-0.7% in central Africa and a global reduction of 0.02-0.5% (Fig. S2).

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### 3.4 Indirect contributions of fires to $O_3$

Vegetation parameters such as LAI and stomatal conductance play important roles in modulating surface [$O_3$]. The $O_3$-induced changes in these variables interactively feed back to alter local [$O_3$] (Fig. 5). Without fire emissions, the annual $\Delta$[$O_3$] from $O_3$-vegetation interactions is limited to eastern China by 0.5 ppbv, the eastern U.S. by 0.3 ppbv, and western Europe by 0.2 ppbv. The largest grid positive feedback of up to 0.8 ppbv is found in the eastern U.S. (Figs. 5a and 5c). Sensitivity experiments further show that such enhancement of surface [$O_3$] mainly results from the inhibition of stomatal conductance following reduced photosynthesis by $O_3$ damage (Fig. S3a). Consequently, large $\Delta$[$O_3$] (Figs. 5a and 5c) are collocated with areas enduring high levels of $O_3$ vegetation damage (Figs. 4a and 4c). As a comparison, the feedback of

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LAI changes is generally small (Fig. S3b), which is mainly attributed to limited $O_3$ damage on LAI (Fig. S2). The enhancement of [$O_3$] from fires causes additional feedback to the surface [$O_3$]. The largest annual $\Delta$[$O_3$] of 0.13 ppbv due to $O_3$-vegetation feedback is averaged on over the Amazon (Figs. 5b and 5d), where the highest GPP reductions by fire-induced $O_3$ are predicted (Figs. 4b and 4d). Such feedback additionally enhances local [$O_3$] by 0.12 ppbv, averaged over central Africa, and 0.09 ppbv, averaged over southern Asia. However, limited $O_3$-vegetation feedback is found in the eastern U.S., eastern China, and western Europe, either because of low fire-induced $\Delta$[$O_3$] (Fig. 3b) or low $\Delta$GPP (Figs. 4b and 4d). The changes in $O_3$ dry deposition velocity broadly match the pattern of $O_3$-vegetation feedback (Fig. S4), suggesting that reduced dry deposition velocity due to $O_3$-induced inhibition of stomatal conductance is the dominant driver for the enhanced surface [$O_3$].

Fig. 6 shows seasonal variations in $O_3$-vegetation feedback. Without fire emissions, $O_3$-vegetation feedback in eastern China, the eastern U.S., and western Europe shows similar seasonal variations, increasing from January to July and then decreasing (Fig. 6a). For these regions, surface [$O_3$] and stomatal conductance reach maximums during the growth season (May-October), resulting in instantaneous $O_3$ uptake. Therefore, $O_3$-vegetation interactions are expected to be stronger during the growth season in the Northern Hemisphere. However, $O_3$-vegetation feedback driven by fires in the Amazon and Southern Asia reaches a maximum during August-December and February-June, respectively. Moreover, double peaks are shown in central Africa, with maximums during February-April and July-September (Fig. 6b). The distinct seasonal variations in biomass burning regions are attributed to fire emissions. At low latitudes, stomatal conductance shows limited seasonal variations. Therefore, $O_3$-vegetation feedback driven by fires is mainly dependent on fire-induced $\Delta[O_3]$.

Fire-induced $O_3$ shows stronger interactions with vegetation under favorable meteorological conditions. We sort daily $\Delta[O_3]$ from $O_3$-vegetation feedback and calculate the average of $\Delta[O_3]$ above the $95^{th}$ percentile (Fig. S5). The spatial pattern of $\Delta[O_3]$ during extreme $O_3$-vegetation feedback is broadly consistent with that of the annual average, albeit with much stronger $O_3$-vegetation feedback. Without fire emissions, $O_3$-vegetation feedback enhances $[O_3]$ by 2.0 ppbv averaged over eastern China, 1.8 ppbv averaged over the eastern U.S., and 1.1 ppbv averaged over western Europe (Figs. S5a and S5c). Fire emissions alone enhance $[O_3]$ through $O_3$-vegetation interactions by 1.1 ppbv averaged over the Amazon, 0.8 ppbv averaged over southern Asia, and 0.6 ppbv averaged over central Africa during extreme $O_3$-vegetation feedback (Figs. S5b and S5d).

### 3.5 Indirect vs. direct contributions of fires to $O_3$

We further compare the indirect and direct contributions of fire emissions to surface $[O_3]$. Here, the direct contributions indicate $\Delta[O_3]$ caused by fire emissions of chemical precursors, while the indirect contributions represent additional $\Delta[O_3]$ from $O_3$-vegetation interactions caused by fire-induced $O_3$. Without fire emissions,

$O_3$-vegetation interactions cause enhancement of [$O_3$] by 1.0% averaged over eastern China, 0.8% averaged over the eastern U.S., and 0.5% averaged over western Europe (Figs. 7a and 7c). Compared to nonfire sources, fire emissions cause larger relative perturbations in surface [$O_3$] through $O_3$-vegetation interactions (Figs. 7b and 7d). The ratios of indirect to direct annual $\Delta$[$O_3$] are 3.7% averaged over eastern China, 2.0% averaged over the eastern U.S., and 1.6% averaged over western Europe. For these regions, the absolute $\Delta$[$O_3$] from direct fire emissions is usually lower than 1 ppbv (Fig. 3b). However, the high level of background [$O_3$] (all sources except fire emissions, Fig. 3a) provides such a sensitive environment that the moderate increases of [$O_3$] from fires can cause large feedback to regional surface [$O_3$] through vegetation damage. For fire-prone regions, the ratios of indirect to direct annual $\Delta$[$O_3$] are 2.6% averaged over southern Asia, 1.9% averaged over the eastern U.S., and 1.4% averaged over central Africa.

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### 3.6 Aggravated $O_3$ damage to GPP through $O_3$-vegetation feedback

The additional $O_3$ enhancement can exacerbate the damaging effects on vegetation. Without fire emissions, online $O_3$ causes a global annual GPP reduction of 0.2% (299.6 Tg C $yr^{-1}$, Figs. S6a and S6c) from the offline $O_3$. Regionally, additional reductions are mainly found in eastern China, the eastern U.S., and western Europe, where GPP is further decreased by 27.1 Tg C $yr^{-1}$, 40.8 Tg C $yr^{-1}$ and 28.4 Tg C $yr^{-1}$, respectively. For fire emissions, the online fire-induced $\Delta O_3$ results in a higher GPP reduction by 25.0 Tg C $yr^{-1}$ averaged over the Amazon, and 24.3 Tg C $yr^{-1}$ averaged over central Africa, and 7.1 Tg C $yr^{-1}$ averaged over southern Asia compared to the offline fire-induced $\Delta O_3$ (Figs. S6b and S6d). Such spatial patterns are broadly consistent with $\Delta[O_3]$ induced by $O_3$-vegetation feedback (Fig. 5).

## 4 Conclusions and discussion

Many studies have explored the direct contributions to surface $O_3$ by fire emissions. However, the feedback of fire-induced $O_3$ vegetation damage to surface $[O_3]$ remains unquantified. In this study, we find that fire-induced $O_3$ causes a positive feedback to surface $[O_3]$ mainly because of the inhibition effects on stomatal conductance. Regionally, $O_3$-vegetation feedback driven by fires enhances surface annual $[O_3]$ by 0.13 ppbv averaged over the Amazon, 0.12 ppbv averaged over central Africa, and 0.09 ppbv averaged over southern Asia. Such feedback exhibit large seasonal variations, with the maximums of 0.5 ppbv averaged over the Amazon in October, 0.3 ppbv averaged over southern Asia in April, and 0.2 ppbv averaged over central Africa in April. During extreme $O_3$-vegetation interactions, the feedback can rise to >0.6 ppbv in these fire-prone areas. Although direct formations of $O_3$ from fires are limited in eastern China and the eastern U.S., the feedback of $O_3$-vegetation coupling results in additional enhancement of surface $[O_3]$ by 3.7% and 2.0% upon the fire-induced $\Delta[O_3]$. Such large ratios in these regions are attributed to the high level of ambient $[O_3]$ that provides a sensitive environment in which moderate increases in $[O_3]$ from fires can cause large indirect contributions to regional $[O_3]$ through vegetation damage.

Some uncertainties may affect the conclusions of this study. (i) The GC-YIBs simulations do not consider the direct fire damages to vegetation and the consequent long-term recovery of forests. In our study, we focus only on the feedbacks of fire-induced $O_3$-vegetation interactions to surface $O_3$. (ii) Fires can decrease VOC emissions from biogenic sources by damaging vegetation directly. However, compared to the VOCs emitted by fires, the VOC loss from burned vegetation is generally smaller (Fig. S7). Therefore, the influence of reduced VOCs from vegetation loss on surface [$O_3$] can be ignored. (iii) There is evidence that $O_3$ exposure may cause "sluggishness" that delays the stomatal responses to $O_3$ damage (Huntingford et al., 2018). However, we do not include "sluggishness" in our scheme because its net impacts on stomatal conductance remain uncertain. For example, observations found that the increased short-term water loss (delayed stomatal responses) may be offset by the decreased long-term water loss (lower steady-state stomatal conductance) with the stomatal "sluggishness" (Paoletti et al., 2019). (iv) We employed a model resolution of 4°×5° due to the limitations in computational resources. We performed a one-year sensitivity simulation at a 2°×2.5° resolution. The comparisons show that fire-induced direct $O_3$ enhancement is very similar between the simulations with low and high resolutions, although the former runs predict slightly higher changes in [$O_3$] than the latter (Fig. S8). (v) different biomass burning datasets may affect the estimated $O_3$-vegetation feedback in our study. At present, the FINNv1.5 and GFEDv4.1 inventories are available in the public-release of GEOS-Chem v12.0.0. Compared with the FINNv1.5 inventory, simulations using

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the GFEDv4.1 inventory predict a lower $O_3$-vegetation feedback in the Amazon (Fig. S9a) and southern Asia (Fig. S9c) but a higher $O_3$-vegetation feedback in central Africa (Fig. S9b).

Despite these uncertainties, we present the first estimate of $O_3$ enhancement by fire emissions through $O_3$-vegetation interactions. Such enhancement is not limited to fire-prone regions, but is also significant over downwind areas with high ambient [$O_3$] levels. Although the absolute perturbations may be moderate for the whole fire season, $O_3$-vegetation interactions can largely increase surface $O_3$ during extreme $O_3$-vegetation interactions, leading to additional threats to public health and ecosystem productivity.

## Data availability

The site-level [$O_3$] in the U.S. can be download from AQS (https://www.epa.gov/aqs). The site-level [$O_3$] in the Europe can be download from EMEP (https://emep.int). The observed [$O_3$] at Manaus, Tg Malim, and Welgegund sites are from earlier studies (Ahamad et al., 2014; Laban et al., 2018; Pope et al., 2020). The GC-YIBs simulation results are available from the corresponding authors on request.

**Competing interests.** The authors declare no competing financial interests.

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**Author Contributions.** XY conceived the study. YL conducted the model simulations. YL and XY were responsible for results analysis. HL, LZ, and YY revised and improved the manuscript. HZ, CT, and CG helped prepare model input. YM, LG, and YC helped prepare observation dataset.

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**Table 1** Summary of simulations using the GC-YIBs model

| Name | Emissions | $O_3$ damaging | $O_3$ sensitivities |
|---|---|---|---|
| CTRL_FIRE_HS | All including fires | Offline | High |
| CTRL_FIRE_LS | All including fires | Offline | Low |
| CTRL_NOFIRE_HS | All but without fires | Offline | High |
| CTRL_NOFIRE_LS | All but without fires | Offline | Low |
| O3CPL_FIRE_HS | All including fires | Online | High |
| O3CPL_FIRE_LS | All including fires | Online | Low |
| O3CPL_NOFIRE_HS | All but without fires | Online | High |
| O3CPL_NOFIRE_LS | All but without fires | Online | Low |

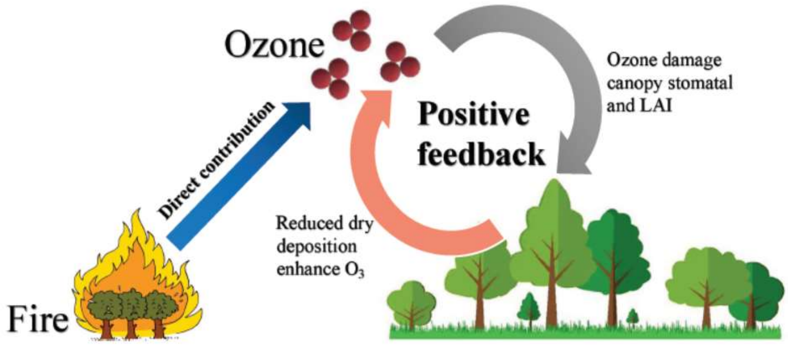


**Figure 1** Diagram of the impacts of fires on surface $O_3$ through direct emissions and $O_3$-vegetation feedback.

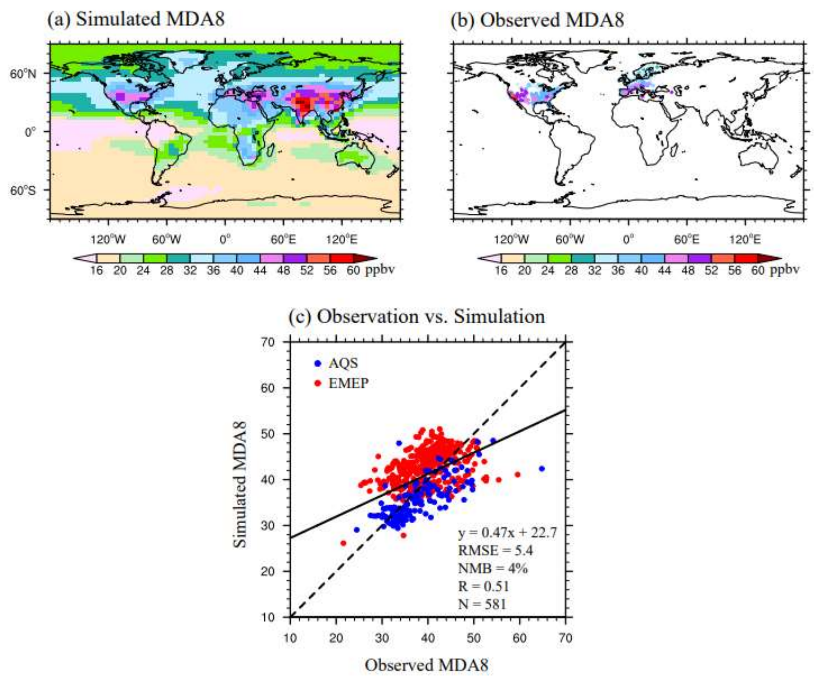


**Figure 2** Spatial pattern of (a) simulated and (b) observed surface [$O_3$]. (c) Scatter plot of surface [$O_3$] over measurements in two regions. The black line shows the linear regression between the observed and simulated [$O_3$]. The regression fit, correlation coefficient (R), root mean square error (RMSE), and normalized mean bias (NMB) are shown in the bottom panel with an indication of site numbers (N) used for statistics.

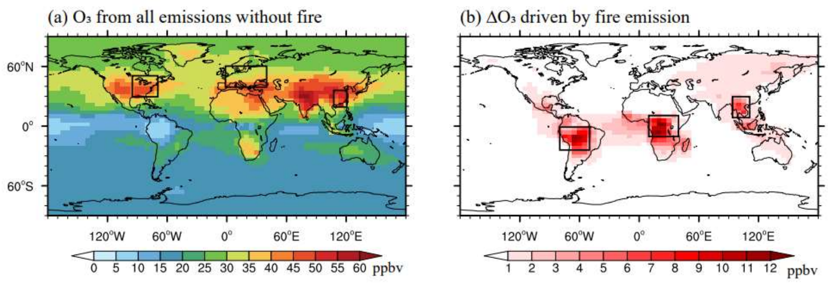


**Figure 3** Annual surface [$O_3$] from (a) nonfire and (b) fire-alone sources. The six subregions are marked with black boxes: Eastern U.S. (EUS, 30°N-50°N, 95°W-70°W), Western Europe (WEU, 40°N-60°N, 0°-40°E), Eastern China (ECH, 20°N-35°N, 108°E-120°E), Amazon (AMZ, 25°S-0°, 80°W-50°W), Central Africa (CAF, 10°S-10°N, 10°E-40°E), and Southern Asia (SAS, 10°N-30°N, 95°E-110°E).

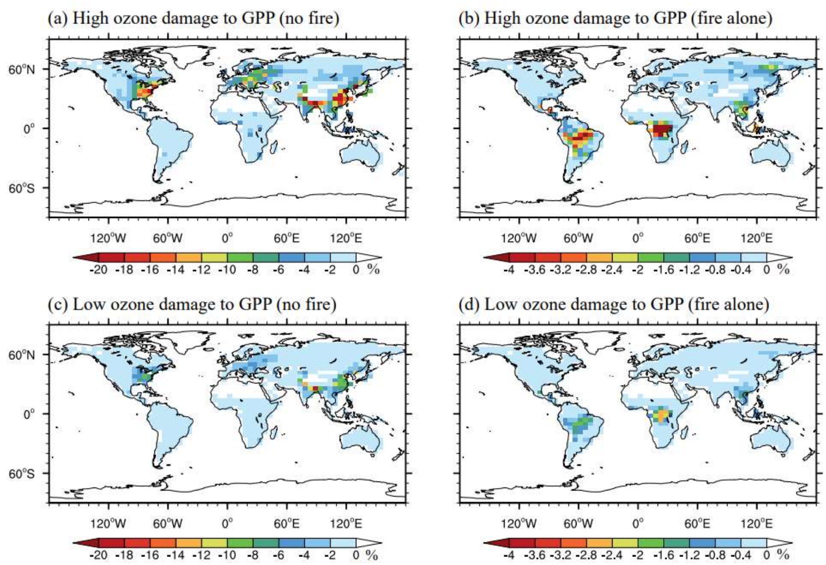


**Figure 4** Annual percentage of reductions in GPP caused by $O_3$ from (a, c) nonfire and (b, d) fire alone sources with (a, b) high and (c, d) low $O_3$ sensitivities. Please note the differences in color scales.

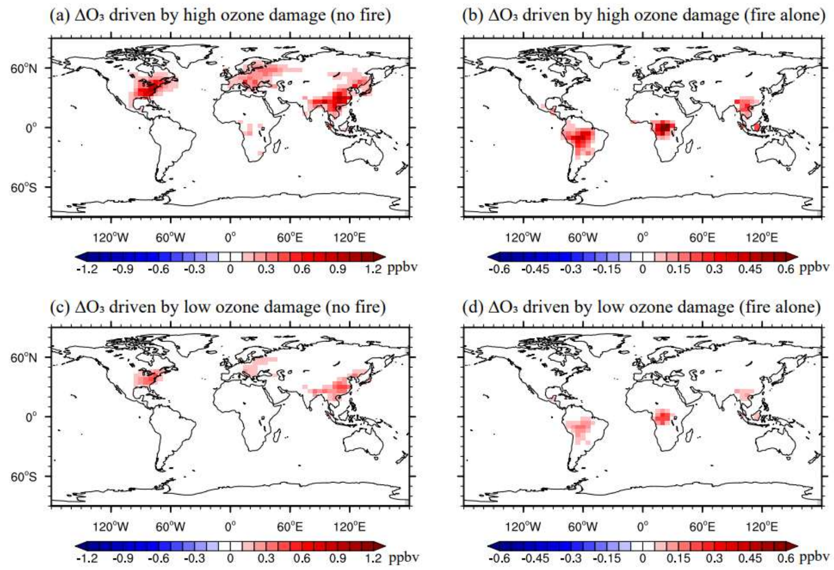


**Figure 5** Annual feedback to surface $O_3$ caused by $O_3$ vegetation damage with (a, b) high and (c, d) low $O_3$ sensitivities. (a) and (c) represent feedback by $O_3$ from nonfire sources; (b) and (d) represent feedback by $O_3$ from fire emissions alone. Please note the differences in color scales.

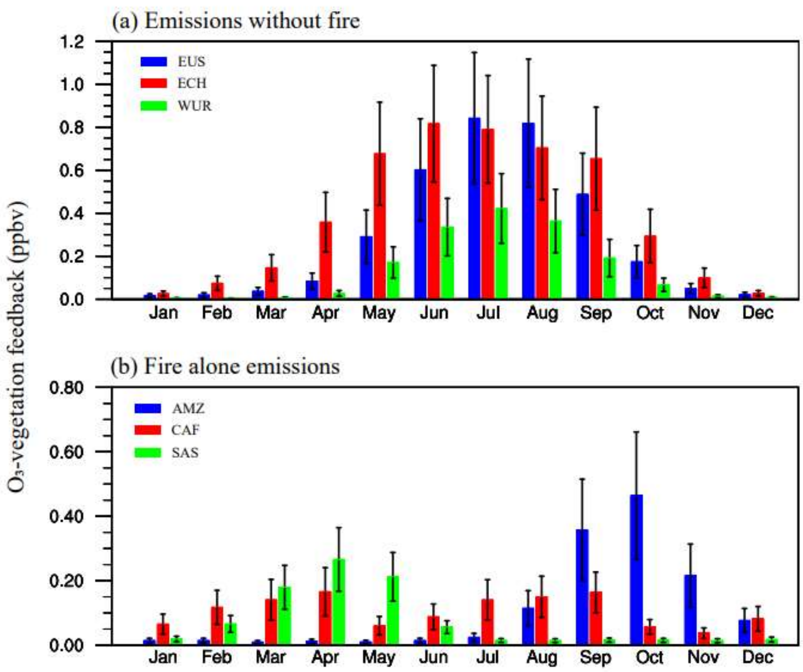


**Figure 6** Seasonal variations in $O_3$-vegetation feedback driven by (a) nonfire and (b) fire-alone sources. The blue, red, and green bars in (a) represent the $O_3$-vegetation feedback in Eastern U.S. (EUS), Eastern China (ECH), Western Europe (WUR), respectively. The blue, red, and green bars in (b) represent the $O_3$-vegetation feedback in Amazon (AMZ), Central Africa (CAF), and Southern Asia (SAS), respectively. The error bars represent low to high $O_3$ damaging sensitivities.

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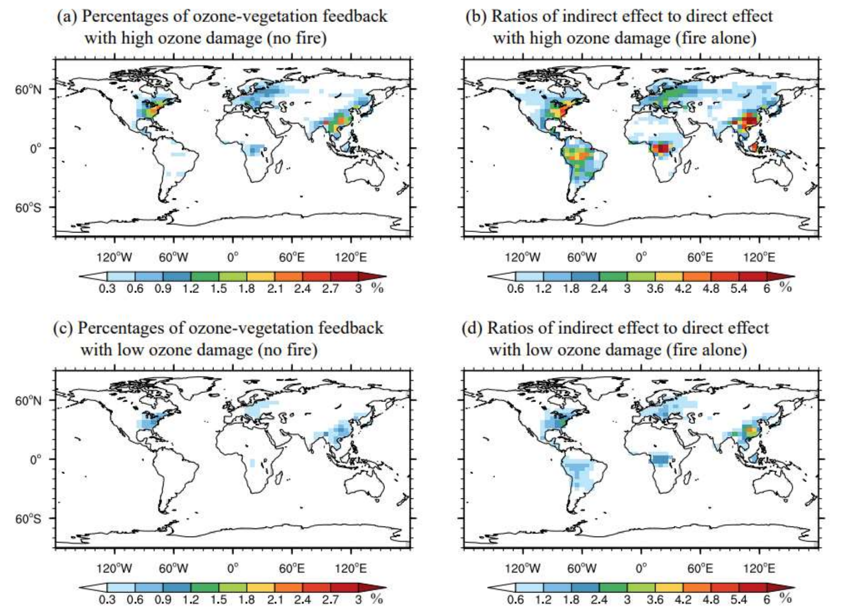


**Figure 7** Annal ratios of indirect $\Delta[O_3]$ to ambient $[O_3]$ from (a, c) nonfire emissions and the ratios of indirect to direct $\Delta[O_3]$ from (b, d) fire emissions alone with (a, b) high and (c, d) low $O_3$ damaging sensitivities. Please note the differences in color scales.