



**Global fire emissions impact on tropospheric chemistry and radiation in the Energy
Exascale Earth System Model (E3SM)**

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24 **Abstract**

25 Wildfires release large amounts of trace gases and aerosols into the atmosphere, thereby
26 playing a significant role in structuring tropospheric composition. Understanding and quantifying
27 the interactions between fire, atmospheric chemistry, and climate has become increasingly
28 important as wildfire activity has intensified in many regions over the past several decades. Here,
29 we applied the Energy Exascale Earth System Model (E3SM) version 3, coupled with an
30 interactive chemistry module as its default configuration and GFED5 fire emissions, to assess how
31 contemporary wildfires influence atmospheric composition and radiation. We find that wildfires
32 increase global annual average CO and O₃ column concentrations by $16 \pm 2\%$ and $6 \pm 1\%$ (reported
33 as mean $\pm$ standard deviation hereafter), respectively, during 1997-2022, with the largest increases
34 occurring in wildfire-prone regions of the southern Amazon, central Africa, and tropical Asia. We
35 also find that wildfires strongly promote interannual variations in CO and O₃ at tropical sites,
36 thereby improving consistency with in situ observations. Fire emissions increase global aerosol
37 optical depth (AOD) by $7 \pm 2\%$, resulting in a reduction in net radiation at the surface by about 1.1
38 W m^{-2} , primarily due to the direct attenuation of incoming solar radiation and indirect cloud effects
39 associated with fire-emitted aerosols. These cooling effects are only partially offset by a small fire-
40 induced ozone radiative warming at surface ($+0.07 \text{ W m}^{-2}$). Our analysis provides insight into the
41 spatiotemporal influence of wildfires on global tropospheric trace gas and aerosol abundances and
42 establishes several new diagnostics for evaluating coupled climate-wildfire models.

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44



45 **1. Introduction**

46 Wildfires significantly impact tropospheric composition, affecting the abundances of a
47 wide range of trace gases and aerosol constituents (Akagi et al., 2011; Andreae, 2019; Shahid et
48 al., 2024). Wildfires have long been recognized as playing an important role in shaping
49 tropospheric chemistry (Crutzen and Andreae, 1990) and influencing regional and global climate
50 (Ramanathan et al., 1987) through radiative forcing from changes in methane, ozone, and aerosols
51 (Penner et al., 1992). At a global scale, annual burned area has been estimated to be 774 ± 63 Mha
52 y^{-1} (i.e., 5.9 ± 0.5 % y^{-1} of the global ice-free land surface) over the past three decades, with open
53 savanna ecosystems experiencing a long-term decline as a consequence of agricultural expansion
54 (Andela et al., 2017; Chen et al., 2023). Apart from carbon dioxide (CO_2), other key constituents
55 emitted by wildfires include carbon monoxide (CO), methane (CH_4), nitrogen oxides (NO_x), non-
56 methane volatile organic compounds (VOCs), and primary aerosols of black carbon (BC) and
57 organic carbon (OC). As important sources, fire emissions are responsible for roughly 40% of the
58 global carbon monoxide direct emissions (Olivier et al., 2005; Wiedinmyer et al., 2011; Zheng et
59 al., 2019; Horowitz et al., 2020), 10% to 25% for nitrogen oxides (Oliveira et al., 2007; Horowitz
60 et al., 2020; Jin et al., 2021), 50 to 70% for primary OC aerosol (Bond et al., 2013), and roughly
61 35-45% for BC (Bond et al., 2013; Feng et al., 2013). Mostly due to VOC and NO_x emissions,
62 wildfires are an important contributor to the formation of tropospheric ozone and secondary
63 organic aerosols through a set of complex photochemical reactions.

64 Trace gases such as CO_2 and CH_4 are directly emitted from wildfires, and tropospheric
65 ozone is secondarily produced from fire emissions of ozone precursors; together, these gases
66 influence climate as greenhouse gases that absorb the longwave radiation, while tropospheric
67 ozone can also absorb the shortwave solar radiation and alter the heating profile throughout the



68 atmosphere. Surface ozone damages leaves, thereby reducing photosynthesis and impairing plant
69 productivity (Lombardozzi et al., 2013). Particulate matter and ozone from fire emissions also
70 adversely affect human health by increasing the risk of respiratory problems, cardiovascular
71 diseases, and premature mortality. Johnston et al. (2012) reported that wildfires contribute to as
72 many as 600,000 premature deaths annually worldwide. Recent regional analyses have quantified
73 substantial health burdens associated with extreme wildfire smoke episodes. For example, Zhang
74 et al. (2025) attributed increases in population exposure to hazardous air pollution and a large
75 mortality burden to the 2023 Canadian wildfires; Johnston et al. (2021) estimated hundreds of
76 excess deaths and thousands of smoke-related cardiorespiratory hospitalizations and asthma
77 presentations during the 2019–2020 Australian megafires; and Connolly et al. (2024) reported
78 significant excess mortality and morbidity associated with repeated wildfire smoke events from
79 major California fires between 2008 and 2018.

80 Wildfire aerosol emissions shape climate through a number of distinct pathways. Key
81 drivers of surface cooling include direct emissions of highly scattering organic aerosol (Penner et
82 al., 1992; Penner et al., 1998; Palm et al., 2020; Szopa et al., 2021; Kelesidis et al., 2025),
83 secondary organic aerosols formed through the condensation of fire-emitted volatile organic
84 compounds (Jimenez et al., 2009; Zhu et al., 2017; Thornhill et al., 2021), and the influence of
85 these aerosols on cloud microphysical properties (Bellouin et al., 2020; Chen et al., 2022). In
86 contrast, fire-emitted black carbon (Ramanathan and Carmichael, 2008; Bond et al., 2013; Coppola
87 et al., 2022) along with large quantities of wildfire-derived brown carbon (Feng et al., 2013; Xu et
88 al., 2026) behave in the opposite manner, strongly absorbing incoming solar radiation and warming
89 the atmospheric layers in which they reside. When black carbon deposits onto snow and ice, it
90 lowers surface albedo and accelerates melting, adding a further warming influence (Flanner et al.,



91 2007; Skiles et al., 2018; Kang et al., 2020; Réveillet et al., 2022). In Arctic and boreal regions,
92 expected increases in fire aerosols might act as a negative feedback on climate warming, as a
93 consequence of regional decreases in surface solar radiation and surface air temperature, further
94 amplified by decreases in sea ice loss (Blanchard-Wrigglesworth et al., 2025). Beyond the balance
95 between aerosol absorption and scattering, post-fire increases in surface albedo within fire
96 perimeters may further offset warming caused by fire emissions of greenhouse gases (van
97 Gerrevink et al., 2026).

98 Investigating the impacts of fire emissions on chemistry-climate interactions typically
99 relies on an Earth System Model (ESM) or a chemistry-climate model. Examples of ESMs with
100 comprehensive atmospheric chemistry, including interactive ozone in both the troposphere and
101 stratosphere, are UKESM1 (Archibald et al., 2020), GFDL-AM4.1 (Horowitz et al., 2020),
102 CESM2 (Gettelman et al., 2019; Emmons et al., 2020). In particular, ESMs that include interactive
103 chemistry mechanisms provide a more comprehensive representation of atmospheric composition
104 and its spatial and temporal variability. For instance, Mao et al. (2013) investigated the sensitivity
105 of tropospheric oxidant concentrations to fire emissions using the GFDL-AM3 chemistry-climate
106 model. Gaubert et al. (2016) used the CESM1.2 chemistry-climate model to evaluate CO emissions
107 and their impact on tropospheric composition. Xie et al. (2022) studied western US surface fine
108 particle concentration (i.e., PM_{2.5}) changes from wildfires in a warming climate using the GFDL
109 ESM4.1 global model with interactive stratosphere-troposphere chemistry.

110 In addition to better representing the spatial distribution and temporal variability of
111 atmospheric constituents, ESMs with chemistry-climate coupling can capture feedbacks among
112 atmospheric chemistry, atmospheric dynamics, and other components of the Earth system such as
113 atmosphere-land interactions. For example, using CESM2, Fasullo et al. (2023) showed that



114 aerosol emissions from the Australian wildfires during the 2019-2020 dry season contributed to
115 decreases in absorbed shortwave radiation across the Southern Hemisphere, which, in turn, through
116 atmosphere-ocean teleconnections, likely intensified surface cooling and the concurrent La Niña
117 state across the tropical Pacific.

118 Here, we explore the impacts of fire emissions on tropospheric chemistry and radiation
119 using the Energy Exascale Earth System Model version 3 (E3SMv3). E3SMv3 includes interactive
120 chemistry in its default configuration (Tang et al., 2025). We performed two global simulations
121 using E3SMv3 with and without fire emissions prescribed from the Global Fire Emissions
122 Database version 5 during 1997-2022. The data and methods are described in Section 2, along with
123 satellite and in situ observations used for model evaluation. We report the influence of wildfires
124 on OH, CO, and O₃ concentrations; aerosol optical depth; and atmospheric radiation in Section 3,
125 and compare these results with available observations. We discuss the indirect effect of wildfires
126 on the CH₄ lifetime through changes in OH in Section 4, along with implications from our analysis
127 for the evaluation of prognostic wildfire simulations. We provide a brief summary and conclusions
128 in Section 5.

129

130 **2. Data and Methods**

131 **2.1 Energy Exascale Earth System Model**

132 We used the Energy Exascale Earth System Model version 3 (E3SMv3) (Xie et al., 2025)
133 and its default interactive chemistry (Tang et al., 2025) to simulate the influence of wildfires on
134 atmospheric chemistry constituents. The new chemistry submodel includes the chemUCI
135 interactive tropospheric package (Prather and Zhu, 2024b) and the Linoz version 3 interactive
136 stratospheric package (Hsu and Prather, 2010). The chemUCI submodel in the troposphere



137 implements 28 advected tropospheric tracers and solves for more than 80 chemical reactions of
138 the O₃-CH₄-HO_x-NO_x-NMVOCs chemistry. In the stratosphere, the Linoz v3 module calculates
139 four prognostic gas tracers (O₃, CH₄, N₂O and NO_y) with a first-order Taylor expansion around a
140 monthly zonal mean climatology of ozone column and local values of O₃, CH₄, N₂O, NO_y, and
141 temperature (Hsu and Prather, 2010). The chemistry module alters the radiative forcing of the E3SM
142 model by calculating 3-D fields of stratospheric and tropospheric O₃ and stratospheric H₂O, CH₄
143 and N₂O every time step. The radiative transfer calculations have been evaluated for both their
144 chemistry and climate response in Tang et al. (2025).

145 In our analysis, we used the default configuration of E3SMv3 (Xie et al., 2025), which has
146 a horizontal resolution of about 1° × 1° and 80 vertical layers extending from the Earth's surface
147 to about 0.1 hPa. The E3SM atmospheric model (EAM) uses a spectral element dynamical core
148 (Taylor and Fournier, 2010; Dennis et al., 2012) on a cubed-sphere computational grid. The aerosol
149 module used in E3SM is an updated 5-mode version of the modal aerosol module (MAM5) with
150 prognostic stratospheric sulfate (Hu et al., 2025). In E3SM version 3, the atmospheric chemistry
151 and aerosol modules are implemented as separate components, with chemistry calculations
152 performed independently of the aerosol module.

153 We performed two E3SM simulations to examine the impacts of wildfires on trace gases
154 and aerosols (Table 1): (1) we included the history of GFED5 fire emissions of trace gases and
155 aerosols during 1997-2022 (i.e., the control simulation) and (2) we excluded all GFED5 emissions
156 (i.e., the no-fire simulation). In both simulations, we used the same non-fire emissions of trace
157 gases and aerosols from anthropogenic (Hoesly et al., 2018) and biogenic sources (Sindelarova et
158 al., 2014). Sea surface temperatures (SSTs) were prescribed as the ocean surface boundary
159 condition in all of the simulations using the Hadley Center monthly mean sea surface temperature



dataset merged with version 2 of the National Oceanic and Atmospheric Administration (NOAA) weekly optimum interpolation sea surface temperature analysis (Hurrell et al., 2008). The monthly and annual variations in SSTs over the 1997-2022 period enable the model to partially capture the influence of El Niño and other climate modes on large-scale atmospheric dynamics.

2.2 Fire emission inventory

We used emissions of trace gases, primary carbonaceous (i.e., black carbon and organic matter) and sulfate aerosols, and precursor gases for secondary organic aerosols and SO₂ from the Global Fire Emissions Database, version 5 (GFED5) (van der Werf et al., 2025). The GFED5 emissions inventory covers 1997-2022 at a spatial resolution of 0.25°×0.25° and a monthly temporal resolution.

Global annual mean fire emissions for the 1997-2022 period, along with standard deviations computed from year-to-year variability, are reported in Table 2. Averaged over this period, wildfires emitted 529.7 Tg y⁻¹ of CO, 41.0 Tg y⁻¹ of non-methane hydrocarbons (NMHCs), 24.3 Tg y⁻¹ of NO, and 5.9 Tg y⁻¹ of SO₂. The wildfire relative contribution to the direct emissions of non-methane hydrocarbon gases ranged from 0.2% for isoprene to 60% for CH₂O. Over the study period, the GFED5 inventory emitted 19 Tg CH₄ y⁻¹. This source was not used because in our simulations, CH₄ is interactively diagnosed in the stratosphere and reacts with OH in the troposphere, relaxing towards observations at the surface (Tang et al., 2025). Mean wildfire aerosol emissions during this period were estimated to be 38 Tg y⁻¹ for POM (73% of total emissions) and 2.5 Tg y⁻¹ for BC (37% of the total). We assumed that all primary sulfate aerosol emissions were in the form of ammonium bisulfate, with a total mass estimated at 2.5% of fire SO₂ emissions (Liu et al., 2012). The new GFED5 emissions are substantially greater than earlier versions of the GFED inventory for most species, reflecting markedly increased burning in savanna, grassland, and



183 agricultural ecosystems, driven by improved burned-area mapping using higher-resolution satellite
184 imagery. The improved burned area estimates provide a renewed opportunity to reassess the
185 influence of fires on atmospheric chemistry and radiative forcing. Within the E3SMv3 emissions
186 framework, wildfires account for approximately 47% of global CO emissions, 22% of NO
187 emissions, and 5% of SO₂ emissions (Table 2). Following the standard configuration of E3SMv3,
188 fire-emitted aerosols are injected into the atmosphere using a mean injection profile derived for
189 each of the 14 continental regions using MISR observations (val Martin et al., 2018) described in
190 Xu et al. (2021).

191 In E3SM version 3, secondary organic aerosols (SOAs) are represented using a modified
192 Volatility Basis Set (VBS) approach that applies to both SOA precursor gases and particulate
193 SOAs (Shrivastava et al., 2015; Lou et al., 2020). The semi-volatile and intermediate volatility
194 SOA precursor gases (S/IVOC) emitted from wildfire, biofuel, and fossil fuel sources are scaled
195 with the traditional primary organic aerosol (POA) inventory co-emitted from the same sources,
196 which has been widely adopted in the SOA modeling community. The IVOC-to-POA mass ratio
197 is a critical parameter in regional and global atmospheric models, used to account for unspciated
198 gas-phase IVOCs co-emitted with POA but missed by traditional emission inventories. For
199 instance, the most widely adopted value is 1.5 in regional (Koo et al., 2014) and global models
200 (Hodzic et al., 2010; Jathar et al., 2011), a convention derived from observations from diesel-
201 exhaust smog-chamber studies by Robinson et al. (2007) and Grieshop et al. (2009). This ratio can
202 vary widely, with some studies reporting IVOC-to-POA ratios exceeding 1.5. For example,
203 Shrivastava et al. (2015) assume that S/IVOC emissions were 6.5 times those of POA from
204 biomass burning and fossil fuels. Lou et al. (2020) assumed that IVOC emissions were 4 times
205 POA emissions because the simulated organic aerosol concentrations and aerosol optical depth



206 yielded a better agreement with available observations for the E3SMv1 model. Tsimpidi et al.
207 (2010) adopted a factor of 3.0 for anthropogenic sources in a three-dimensional chemical transport
208 model (i.e., PMCAMx). The wide range of this ratio highlights a key uncertainty in the SOA
209 modeling. Here we adopted 1.5, recommended by Robinson et al. (2007) and Grieshop et al. (2009),
210 as a baseline to maintain consistency with the mass budget of non-methane hydrocarbon trace gas
211 emissions. With this assumption, emissions of the initial secondary organic aerosol precursor gas
212 (i.e., SOAG0 in Table 2) are estimated to be 57 Tg y⁻¹ for wildfires, about 53% of the 107 Tg y⁻¹
213 of non-methane hydrocarbon emissions reported in GFED5 (van der Werf et al., 2025). This allows
214 for consistency with observations that direct oxidation (to CO and CO₂) of many non-methane
215 hydrocarbon species with lower SOA-forming potential is also an important loss pathway (Hatch
216 et al., 2017). Compared with anthropogenic sources of SOAG0, wildfires contribute about 68% of
217 the total global emissions.

218 **2.3 Anthropogenic emission inventory**

219 We applied an updated global anthropogenic emission inventory of reactive gases and
220 aerosols from the v2025_04_18 version of Community Emission Data System (CEDS) (Hoesly et
221 al., 2018), which covers the period 1750-2023. This CEDS dataset includes monthly anthropogenic
222 emissions of primary organic matter, black carbon, sulfate, and SO₂ with updated seasonality
223 including sub-annual variations during COVID. The detailed description of the up-to-date CEDS
224 data is accessible at <https://github.com/JGCRI/CEDS>. Other greenhouse gas mole fractions,
225 including CO₂, N₂O, CFC11, and CFC12, were prescribed annually and evolved with time.
226 Emissions of dust and sea salt aerosols were calculated online as a function of wind speed and
227 temperature.

228 **2.4 Observations for model evaluation**



229 To evaluate the tropospheric CO column from model simulations, we used the
230 Measurement of Pollution in the Troposphere (MOPITT) v9 gridded monthly mean product
231 (Deeter et al., 2021). We used the MOPITT monthly mean averaging kernels with our modeled
232 data for this comparison, following the MOPITT Version 9 Product User's Guide. We also
233 compared model-simulated surface CO with measurements from four representative stations
234 across different latitude belts in the Carbon Cycle Greenhouse Gases (CCGG) Cooperative Air
235 Sampling Network maintained by the Global Monitoring Laboratory (GML) of the National
236 Oceanic and Atmospheric Administration (NOAA) (<https://gml.noaa.gov/ccgg/data/co.html>). The
237 four selected sites were: 1) Utqiagvik (formerly Point Barrow), AK, USA; 2) Mauna Loa, Hawaii,
238 USA; 3) Ascension Island, UK; and 4) South Pole, Antarctica, USA. Monthly mean surface CO
239 mole fractions from 1997 through 2022 were used to evaluate model performance.

240 To evaluate modeled tropospheric O₃, we use the monthly gridded troposphere column
241 ozone derived for 60°S-60°N from the Aura Ozone Monitoring Instrument/Microwave Limb
242 Sounder (OMI/MLS) (Ziemke et al., 2006) for the January 2005-December 2020 period. The
243 modeled monthly mean total column ozone values were compared directly with the OMI/MLS
244 product; no adjustments were applied to account for differences in clear-sky and cloudy-sky
245 sampling that have the potential to influence the satellite retrievals. In E3SM, total column ozone
246 was diagnosed at each model time step for every atmospheric column using a tropopause height
247 determined from the e90 tracer following Prather (2025).

248 To evaluate surface ozone, we selected several stations in the Tropospheric Ozone
249 Assessment Report (TOAR) database (<https://toar-data.org/surface-data/>) where wildfires were
250 major sources of air pollution and the observed time series had sufficient duration to enable
251 comparisons on seasonal and interannual timescales. The six representative sites were a) Utqiagvik,



252 AK, USA (formerly Point Barrow), b) Cape Verde, Africa, c) Huancayo, Peru, d) American Samoa,
 253 USA, e) Cape Grim, Australia, f) South Pole, Antarctica, USA. We computed the monthly mean
 254 ozone using the 24-hour mean data for each site.

255 To evaluate aerosol optical depth (AOD), we compared the monthly-averaged AOD from
 256 E3SM with satellite retrievals from the monthly Level-3 MODIS-Terra product MOD08_M3,
 257 Collection 6.1 (Sayer et al., 2014).

258

259 **3. Results**

260 **3.1 The influence of fires on atmospheric composition**

261 **3.1.1 OH**

262 Tropospheric hydroxyl radical, OH, determines the oxidizing potential of the troposphere
 263 and controls the lifetime of CH₄, CO, NO_x, and various other non-methane hydrocarbon gases
 264 relevant for climate and air quality. Figure 1a shows the geographic distribution of column-
 265 averaged annual-mean OH concentration over the years 1997 through 2022. Our E3SM-simulated
 266 tropospheric mean OH concentration of 11.1×10^5 molecules cm⁻³ is slightly greater than the value
 267 of 10.7×10^5 molecules cm⁻³ reported by Tang et al. (2025), but our simulation includes updated
 268 anthropogenic and wildfire emissions. Our value falls within the multi-model range of 8.7×10^5
 269 to 12.8×10^5 molecules cm⁻³ reported by Zhao et al. (2019) and is consistent with their geographic
 270 pattern.

271 The influence of wildfires on tropospheric column-mean OH concentrations is complex.
 272 Wildfires increase OH by 10–20% in high-fire regions of South America, central Africa, and
 273 tropical Asia, where elevated NO_x emissions from fires, together with abundant sunlight and water
 274 vapor, favor the OH formation. In contrast, fires decrease OH concentrations in remote oceanic



275 and polar regions (Fig. 1b). This spatial pattern reflects a short-lived enhancement of OH near
 276 source regions driven by wildfire-emitted NO_x, alongside a more widespread reduction in the
 277 remote troposphere due to OH loss by fire-emitted CO. The resulting $3.7 \pm 1.7\%$ global decline in
 278 OH implies a modest lengthening of the atmospheric CH₄ lifetime, an effect examined further in
 279 Section 4.2. The mean reported here is for the 1997-2022 period, and the standard deviation is
 280 estimated from the year-to-year variability given in Table 2. The direction of the mean global OH
 281 change is consistent with simulations from the fully coupled Earth system model GFDL-AM3,
 282 which report an approximately 6% decline attributable to fire emissions (Mao et al., 2013).

283 **3.1.2 CO**

284 To explore the influence of wildfire on the column CO abundance, we compared our model
 285 simulations with MOPITT retrievals (Figure 2). The simulated spatial pattern of the tropospheric
 286 CO column from the control simulation with fire emissions included agrees reasonably well with
 287 the MOPITT retrievals in terms of magnitude and spatial distribution. The simulated global mean
 288 CO column of $15.3 \pm 1.3 \times 10^{17}$ molecules cm⁻² for 2000-2022 is approximately 5% lower than
 289 the MOPITT estimate. However, the control simulation underestimates CO in mid- and high-
 290 latitude regions of the Northern Hemisphere and slightly overestimates CO in the Southern
 291 Hemisphere (Figure 3a), thereby improving the column CO underestimates over the whole globe
 292 relative to the no-fire simulation (Figure 3b). A similar hemispheric model bias in simulating the
 293 tropospheric CO column is reported by Horowitz et al. (2020) for the GFDL-AM4.1 fully coupled
 294 ESM. The relative influence of wildfires on the column CO is greater in tropical and boreal forest
 295 areas, whereas it is lower in Northern Hemisphere temperate regions, because the background CO
 296 column is typically higher owing to larger anthropogenic emissions there (Figure 2c). Wildfires
 297 contribute to a $16 \pm 2\%$ increase in global mean column CO, with the largest relative increases of



298 over 30% centered in wildfire-prone regimes, including central Africa and boreal forest
299 ecosystems across North America and Eurasia (Figure 2d).

300 In the historical record, large but infrequent wildfire complexes have generated extensive
301 CO plumes that persist for weeks to months and disperse across downwind continental regions and
302 adjacent ocean basins. The long atmospheric lifetime of CO, together with observations of fire-
303 specific emission factors, has enabled atmospheric inversion studies to estimate carbon emissions
304 from major wildfire events (Byrne et al., 2024; Zheng et al., 2023; van der Velde et al., 2021; Liu
305 et al., 2017; van der Werf et al., 2004). Here, we examine the influence of the timing and magnitude
306 of wildfire-driven CO anomalies on CO column observation as an independent benchmark for
307 model evaluation (Figure 4). Including fire emissions considerably improves both the correlation
308 (Figures 4a and 4b; Table 3) and the ratio of standard deviations of interannual CO anomalies from
309 the model relative to the MOPITT observations (Figures 4c and 4d), highlighting the widespread
310 and persistent influence of wildfire emissions on tropospheric CO in remote regions far away from
311 high-fire source regions. This comparison tests the model's ability to represent the transport,
312 dispersion, and chemical evolution of large fire-emission plumes. In addition to the interannual
313 variability signal captured by the MOPITT CO column anomalies, fire emissions substantially
314 improve the spatial agreement between the simulated and observed annual mean column CO from
315 MOPITT, increasing the spatial correlation from 0.75 in the no-fire simulation to 0.88 in the
316 control simulation, and yielding even greater improvements when considering the mean annual
317 cycle and the full time series (Table 3).

318 In the tropics, fire emissions are critical for explaining seasonal and interannual variability
319 of column CO over continental regions (Figure 5). The simulated column CO time series during
320 2000-2022 from the control simulation for all three tropical regions shows much better agreement



321 with the MOPITT observations than the no-fire simulation, with correlations of 0.93, 0.83, and
 322 0.84 for the control simulation and 0.46, -0.07, and -0.02 for the no-fire simulations in the southern
 323 Amazon, central Africa, and tropical Asia, respectively (Figures 5a-5c, Table 4). In the southern
 324 Amazon and tropical Asia, E3SM captures both the magnitude and seasonal timing of monthly
 325 peaks in MOPITT column CO, as well as interannual variability over the 23-year period. In central
 326 Africa, the simulation that includes fire emissions significantly improves the representation of
 327 seasonal and interannual variation in column CO, whereas the no-fire simulation misses the
 328 observed semiannual cycle (Figure 5b, Table 4). In tropical Asia, including fire emissions
 329 improves the model's ability to capture El Niño-driven positive emissions anomalies associated
 330 with peat burning, as observed by MOPITT in 2002, 2006, 2015, and 2019.

331 Comparisons between simulated surface CO concentrations and observations from NOAA
 332 GML monitoring sites further reveal a persistent underestimation of CO concentrations in the
 333 Northern Hemisphere. At Utqiagvik in Alaska (formerly Point Barrow), inclusion of fire emissions
 334 brings E3SM's annual mean CO concentrations into closer agreement with observations but
 335 degrades the model's ability to reproduce the magnitude and phase of the seasonal cycle (Fig 6a).
 336 In contrast, at Mauna Loa, Ascension Island, and the South Pole, the control simulation improves
 337 the simulation of both the annual mean and the seasonal cycle of CO (Figs. 6b–6d). At Ascension
 338 Island in particular, the seasonal variability in CO is dominated by fire emissions, indicating that
 339 this site—located in the outflow from southern Africa—may provide a strong constraint on long-
 340 term trends in burned area and fire emissions from the region. Similarly, nearly half of the annual
 341 mean CO cycle at the South Pole originates from fire emissions, suggesting that this station may
 342 be valuable for constraining interannual variability and trends in the integrated sum of fire
 343 emissions across the Southern Hemisphere.



3.1.3 O₃

Tropospheric ozone, which is secondarily produced from fire emissions of NO_x and hydrocarbons, is a key atmospheric constituent that influences radiative forcing of the climate (Szopa et al., 2021). We evaluated simulated annual mean tropospheric ozone columns against satellite-based estimates from the OMI/MLS instruments (Ziemke et al., 2019). Over 2005–2020, the global mean simulated tropospheric ozone column within 60°S–60°N is approximately 30.3 ± 0.4 Dobson Units (DU), about 3% lower than the OMI/MLS mean value of 31.4 ± 0.9 DU and likely within the combined observational and modeling uncertainties (Figs. 7a and 7b). The model exhibits localized overestimations in high-fire areas such as the southern Amazon and central Africa. Fire emissions substantially increase tropospheric ozone, enhancing global mean columns by approximately $6 \pm 1\%$ (Figs. 7c and 7d). This response is consistent with prior estimates that attribute about 3.5% of global tropospheric ozone to fire emissions (Jaffe and Wigder, 2012). Including fire emissions slightly reduces correlations with OMI/MLS observations in spatial, climatological mean annual cycle, and full time series comparisons (Table 3). However, when considering monthly anomalies and the influence of fires on interannual variability of ozone, the inclusion of fire emissions slightly improves model agreement, suggesting systematic bias in the annual mean climatology. The largest relative increase in tropospheric ozone columns—exceeding 20% (i.e., 8 DU in absolute difference terms in Fig. 7c)—occurs in central Africa, highlighting the strong influence of wildfire activity in Africa on regional ozone burdens and a possible high bias in NO_x or non-methane hydrocarbon emissions from savanna ecosystems.

Time-series comparisons with OMI/MLS observations indicate that the positive biases in the model O₃ tropospheric column in high fire regions are persistent on annual and interannual timescales, and that fire emissions exacerbate these biases across all three tropical continents



367 (Figure 8). For the southern Amazon, including fire emissions increases the positive bias, but
368 considerably improves the representation of the column O_3 annual cycle, shifting the phase to
369 match the observed peak in October, near the end of the dry season. In central Africa and tropical
370 Asia, improvements in the phasing of the annual cycle from the inclusion of fire emissions were
371 modest, and over central Africa, fire emissions contributed to an annual cycle approximately a
372 factor of two larger than the observations.

373 Comparison of model-simulated O_3 mole fractions with observations from the NOAA
374 Global Monitoring Laboratory (GML) and the Tropospheric Ozone Assessment Report (TOAR)
375 networks indicates that fire emissions exert only a weak influence on surface O_3 in remote regions
376 (Figure 9). At Utqiagvik, Cape Verde, American Samoa, Cape Grim, and the South Pole (Figs. 9a-
377 9b, 9d-9f), the E3SM control and no-fire simulations are nearly indistinguishable. In contrast, at
378 Huancayo, Peru—located on the eastern flank of the Andes—fire emissions substantially improve
379 the simulated O_3 magnitude and seasonal cycle (Figure 9c). The influence of fire on the annual
380 cycle at this Amazon basin site is consistent with its impact on tropospheric column O_3 over the
381 southern Amazon (Figure 8a). At Utqiagvik, the model substantially overestimates surface O_3
382 during late winter and spring (Figure 9a). Although this bias shows little sensitivity to fire
383 emissions, it may reflect the absence of halogen chemistry in the current E3SM chemical
384 mechanism or biases in simulated stratosphere–troposphere exchange.

385 **3.2 The influence of wildfires on aerosol optical depth and atmospheric radiation**

386 To assess the influence of wildfires on the atmospheric radiation budget, we first examined
387 the simulated global mean total AOD and compared it with observations from MODIS. The global
388 annual mean AOD in the control simulation is 0.10 for 2000–2022, comparable to the value of
389 0.11 reported for 2000–2014 by Xie et al. (2025), but substantially lower than the MODIS-derived



mean of 0.17 (Figures 10a and 10b). The control simulation exhibits a systematic low bias over eastern Asia, northern Africa, South America, and across many remote ocean regions. Both the sign and magnitude of this bias are broadly consistent with the low AOD biases reported by Xie et al. (2025) for E3SMv3 when evaluated against AERONET AOD and surface observations of sulfate (SO_4) and black carbon (BC).

The influence of fire aerosols on AOD is strongest in tropical and boreal regions. Annual mean AOD regional enhancements attributable to fire emissions exceed 0.05—corresponding to relative increases of more than 30%—across central and southern Africa, the southern Amazon, Southeast Asia, and extensive boreal regions of North America and Eurasia (Figures 10c and 10d). Globally, fire aerosol emissions increase mean AOD by approximately $7 \pm 2\%$ (Figure 10d). Including fire emissions in the model substantially improves both the spatial and temporal correlations with MODIS AOD observations (Table 3).

Time-series comparisons between E3SMv3 and MODIS AOD over tropical continental regions demonstrate that fire emissions are essential for reproducing both the seasonal cycle and the interannual variability of AOD. Across tropical Asia, the southern Amazon, and central Africa, the control simulation consistently exhibits higher temporal correlations and lower root-mean-square errors (RMSE) than the no-fire simulation (Figure 11, Table 4). In tropical Asia, the model captures observed AOD maxima in 2002, 2006, 2015, and 2019, with corresponding peaks in the southern Amazon occurring approximately one year later. This phasing is consistent with previous studies showing that El Niño events initiate a cascading sequence of enhanced wildfire activity across tropical regions (Chen et al., 2017). In central Africa, inclusion of fire emissions is particularly important for reproducing the observed semiannual AOD cycle, which is largely absent in the no-fire simulation.



413 The direct and indirect radiative effects of carbonaceous aerosols, particularly those
 414 emitted by landscape fires, interact in complex ways with Earth's radiation balance. Primary
 415 organic matter and secondary organic aerosols generated from wildfires primarily act as scattering
 416 aerosols, increasing the reflectance of shortwave radiation at the top of the atmosphere and thereby
 417 reducing the downward shortwave radiation flux reaching the surface. In contrast, black carbon
 418 plays an important role in atmospheric warming but can also attenuate surface solar radiation
 419 through absorption and scattering. Figure 12 shows the spatial distribution of wildfire-induced
 420 aerosol direct and indirect effects on radiation at the surface and the top of the atmosphere. The
 421 global average net aerosol direct effect from fire emissions at the surface is about $-0.8 \pm 0.1 \text{ W m}^{-2}$
 422 (Figure 12a), contributing to a net cooling effect at the surface (Xu et al., 2021). Wildfire aerosols
 423 exert nearly zero change in net radiation at the top of the atmosphere (Figure 12b). Moreover, the
 424 fire aerosol indirect effect, stemming from the influence of fire aerosols on cloud properties, leads
 425 to an additional small negative change in both surface and top-of-atmosphere radiative fluxes ($-$
 426 $0.4 \pm 0.3 \text{ W m}^{-2}$) shown in Figure 12c and 12d. Notably, the regional impact of this indirect effect
 427 is most pronounced in central and western Africa, coinciding with the influence of the direct effect
 428 in these areas (Figures 12c and 12d).

429 In addition to the radiative perturbation from fire-emitted aerosols, the fire-enhanced
 430 tropospheric O_3 (shown in Figure 5) absorbs more incoming solar radiation, resulting in a small
 431 warming radiative effect of $+0.02 \pm 0.01 \text{ W m}^{-2}$ at the surface and at TOA, with the largest increase
 432 of more than $+0.3 \text{ W m}^{-2}$ in central Africa shown in Figure 13a and 13b. At the same time,
 433 tropospheric O_3 serves as a potent greenhouse gas that efficiently absorbs infrared radiation,
 434 leading to a positive longwave radiative effect of $+0.05 \pm 0.04 \text{ W m}^{-2}$ at the surface with the
 435 maximum increases over $+0.3 \text{ W m}^{-2}$ in central Africa (Figure 13c). The longwave radiative effects



display a relatively smaller magnitude of $+0.03 \pm 0.02 \text{ W m}^{-2}$ at the TOA (Figure 13d) because the fire-enhanced O_3 layer mainly resides in the warm lower troposphere close to the surface. Together, the global mean net radiative effect at TOA from fire-induced ozone increases, including both shortwave and longwave components, is $+0.05 \pm 0.04 \text{ W m}^{-2}$, consistent with the approximately $+0.03 \text{ W m}^{-2}$ effect attributable to fire emissions from the fully coupled Earth system model GFDL-AM3 (Mao et al., 2013).

In response to both aerosol direct and indirect effects, surface solar radiation over land decreases by 1.2 W m^{-2} (1.6%) in the control simulation relative to the no-fire simulation. The overall fire aerosol direct and indirect effect is smaller than those reported in Xu et al. (2021), likely as a consequence of the negative aerosol bias in E3SMv3, even though fire emissions of particulate matter in GFED5 are about 60% higher (van der Werf et al., 2025). With the additional fire-enhanced tropospheric O_3 positive radiative effects in both shortwave and longwave spectra, fire emissions contribute a net radiative effect (shortwave and longwave) of about -1.12 W m^{-2} at the surface. At TOA, the decreases in shortwave radiative effects due to fire aerosols are partially offset by the warming effects due to fire-enhanced tropospheric O_3 , resulting in a net radiative effect of -0.35 W m^{-2} at TOA.

4. Discussion

4.1 Indirect effect of fires on the CH_4 lifetime

Interactions between atmospheric OH and CH_4 significantly amplify the impacts of fire emissions on CH_4 interannual variability and trends. Specifically, increases in fire-emitted CO and CH_4 reduce tropospheric OH, thereby extending the CH_4 lifetime and enhancing its overall atmospheric abundance, which has been identified as a positive climate-carbon cycle feedback in



past work (Chen et al., 2026). As reported in Section 3.1 above, wildfires overall reduce global OH concentrations by 3.7%. Assuming a background mean CH₄ concentration of 1805 ppb during 1997-2022 (Dlugokencky et al., 1994) and assuming a CH₄ tropospheric chemical lifetime with respect to OH of 11.2 years constrained by methyl chloroform surface observations (Prather et al., 2012), global fire emissions generate about 16.5 Tg CH₄ y⁻¹ assuming a conversion factor of 2.748 Tg CH₄ ppb⁻¹ (Prather et al., 2012), through fire emission impacts on OH. This indirect effect is comparable to the direct annual mean fire CH₄ emissions of 18.7 ± 3.4 Tg CH₄ y⁻¹ estimated by GFED5 (Table 2).

4.2 Steps toward reducing uncertainties in future ESM assessments of fire impacts

Our analysis highlights several priorities for model improvement, spanning both the fire emissions inventory and the representation of atmospheric chemistry and aerosols in the Earth system model. The persistent high biases in CO and O₃ column abundances over central Africa (Figures 5 and 8) suggest that GFED5 may overestimate savanna fire emissions in northern and southern Africa. Emissions from this biome increased by approximately 70% from GFED4 to GFED5, primarily due to the incorporation of 20 m Sentinel-2 burned-area estimates to correct omission and commission errors in the 500 m MODIS burned-area product that serves as the primary reference dataset for the time series. As burned area estimation from Sentinel-2 and Landsat time series continues to improve in quality and expand in scope, further refinements in burned-area mapping and associated emission estimates are expected. Evidence for a positive emission bias also emerges in boreal forests of North America and Eurasia. At Utqiagvik, the coupled simulation shows a weaker annual CO cycle than observations, implying that simulated summer fire emissions may be too large. In this region, enhanced summertime emissions offset CO losses from faster chemical removal, and the model–observation mismatch suggests this



482 compensating effect is overestimated. A key remaining uncertainty in boreal emission estimates
483 concerns how low-severity burns are treated and how well GFED5 represents fuel consumption in
484 these areas.

485 Within E3SM, the pervasive negative bias in AOD in the control simulation indicates that
486 aerosol removal processes—particularly dry and wet deposition—and other aspects of aerosol
487 parameterization require further evaluation and optimization. The magnitude and spatial structure
488 of the negative AOD bias are consistent with AERONET and surface network comparisons
489 reported for E3SMv3 by Xie et al. (2025). Notably, this bias persists across regions and time
490 periods characterized by both active and minimal fire influence. For example, in tropical Asia,
491 simulated AOD during La Niña conditions—when elevated precipitation suppresses fire activity—
492 is more than a factor of two lower than MODIS observations, as shown in Figure 11c. This pattern
493 suggests that processes unrelated to fire emissions contribute substantially to the model–
494 observation discrepancies. It is also important to apply more advanced algorithms to dynamically
495 account for the injection height of fire aerosol emissions in the atmospheric model. Recent extreme
496 wildfire events in Australia, California, and Canada have produced pyrocumulonimbus (pyroCb)
497 convection, lofting aerosols into the upper troposphere and lower stratosphere and thereby
498 substantially increasing aerosol lifetimes and radiative impacts (Peterson et al., 2021). Although
499 individual pyroCb events have been simulated in E3SM using regionally refined grids and a
500 multiscale modeling framework (Ke et al., 2025), a critical next step is to develop a systematic
501 capability to identify and represent these events in multi-year global simulations.

502 The underestimation of surface CO concentrations in E3SM relative to observations over
503 the boreal northern hemisphere is a persistent bias reported in multiple global modeling studies
504 (Alvarado et al., 2010; Hooghiemstra et al., 2012; Mao et al., 2013; Tang et al., 2025). This model–



505 observation discrepancy likely reflects biases in atmospheric chemistry and transport, uncertainties
506 in anthropogenic emissions, or limitations in surface station data used for evaluation (Bian et al.,
507 2007). Mao et al. (2013) demonstrated that excessive tropospheric OH in models can lead to
508 systematic CO underestimation. Hooghiemstra et al. (2012) suggested that anthropogenic
509 emissions from Asia may be too low to reproduce observed Northern Hemisphere CO levels, while
510 Alvarado et al. (2010) identified chemical and transport adjustments needed to reduce high-latitude
511 CO biases. van Leeuwen et al. (2013) reported that model–observation discrepancies in surface
512 CO exceeded differences among wildfire emission inventories, underscoring the dominant role of
513 chemical and transport processes. Tang et al. (2025) also found a systematic CO underestimation
514 in E3SM-chem over the Northern Hemisphere and attributed it to underestimated CO and VOC
515 precursor emissions.

516 Taken together, these studies indicate that CO biases in northern high latitudes likely arise
517 from a combination of emissions biases and errors in chemical processing. A systematic negative
518 bias in boreal wildfire emission inventories appears unlikely to be the dominant factor, particularly
519 given the remaining challenges in accurately reproducing the observed seasonal cycle shown in
520 Figure 6. Instead, low biases in CO emitted by fossil fuel sources or uncertainties in OH chemistry
521 may play a more central role. Refinements in the representation of OH—such as improved
522 treatment of radiation absorption by water vapor (Prather and Zhu, 2024a) and reductions in
523 background aerosol biases described above—could decrease simulated OH concentrations and
524 thereby increase CO lifetimes.

525 **4.3 Toward a wildfire emissions benchmark**

526 Our analysis provides a first step toward developing a systematic framework for
527 benchmarking fire emissions and their atmospheric impacts in Earth system models. By comparing



528 simulations with and without fire emissions while prescribing observed sea surface temperatures,
529 our experimental design allowed us to isolate the contribution of fires to seasonal and interannual
530 variability in carbon monoxide, ozone, and aerosol optical depth. These model–observation
531 comparisons demonstrate the important role of fire emissions in regulating atmospheric
532 composition, particularly in column observations over tropical continents and at surface stations
533 downwind of major fire regions.

534 Several extensions will be needed to develop a more comprehensive benchmarking
535 framework. First, the analysis could incorporate a broader suite of observational constraints,
536 including column measurements of carbon monoxide and NO_x from Tropospheric Monitoring
537 Instrument (TROPOMI) (van der Velde et al., 2021; Jin et al., 2021), column carbon dioxide from
538 Orbiting Carbon Observatory-2 (OCO-2) (Liu et al., 2017), and surface PM_{2.5} observations
539 (Zhang et al., 2023). Second, automating model–observation comparisons across a larger and more
540 representative set of locations and stations would enable systematic evaluation across fire regimes,
541 chemical environments, and downwind regions. Third, complementary benchmarks are needed for
542 fully coupled Earth system model simulations, in which the timing of individual climate extremes
543 and fire events is not expected to coincide with the observed record. Such benchmarks could
544 instead evaluate whether models reproduce observed relationships between fire emissions,
545 atmospheric composition, and large-scale modes of climate variability, including the El Niño–
546 Southern Oscillation. An important next step is to apply this framework to the fully coupled fire
547 model in E3SMv3. Comparing simulated fire emissions and their atmospheric impacts against
548 these observational benchmarks will provide a quantitative assessment of model performance and
549 help identify biases in fire activity, emissions, and atmospheric responses before using E3SMv3
550 to investigate coupled fire–climate interactions.



551 **5. Conclusions**

552 Here, we used E3SMv3 with interactive atmospheric chemistry to quantify the influence
553 of fire emissions on tropospheric composition and radiation during 1997–2022. In the control
554 simulation, fires emitted 530 ± 74 Tg CO yr⁻¹, accounting for $47 \pm 3\%$ of annual CO emissions
555 from all sources. This contribution is larger than in many previous assessments, primarily because
556 GFED5 includes substantially higher emissions from savanna, grassland, and agricultural fires as
557 a result of improved burned-area mapping. Comparing simulations with and without fire emissions
558 allowed us to isolate their effects on atmospheric chemistry, aerosols, and radiation over the 26-
559 year study period. Fire emissions increased the global mean tropospheric CO column by $16 \pm 2\%$
560 and strongly influenced its seasonal and interannual variability, particularly over tropical
561 continents and adjacent ocean regions. Their influence on the atmosphere's oxidative capacity was
562 more complex. Fires increased OH by approximately 10–20% in the southern Amazon, central
563 Africa, and tropical Asia, where emissions of NO_x and other reactive species interact with abundant
564 sunlight and water vapor to promote OH formation. In contrast, fire-emitted CO consumes OH
565 over broader and more remote regions, resulting in a net decrease in global mean tropospheric OH
566 of approximately 4%. Fire emissions also increased the global mean tropospheric O₃ column by 6
567 $\pm 1\%$, with enhancements exceeding 20% over central Africa. Together, these results demonstrate
568 that fires substantially alter tropospheric oxidation chemistry and that their effects on OH can differ
569 in sign between source regions and the global atmosphere.

570 Fire emissions also substantially influenced atmospheric aerosols and radiation. They
571 accounted for approximately 37% of global BC emissions, 73% of primary organic matter
572 emissions, and 68% of secondary organic aerosol precursor emissions in the E3SM emissions
573 framework. Consequently, fires increased global annual mean AOD by $7 \pm 2\%$ and substantially



574 improved the representation of seasonal and interannual AOD variability observed by MODIS in
575 major tropical fire regions. Fire aerosols reduced surface shortwave radiation through direct and
576 indirect effects, producing a net cooling influence. Fire-enhanced tropospheric O₃ produced
577 shortwave and longwave warming that partially offset this aerosol cooling. Thus, the net radiative
578 response to fire emissions emerges from interactions among chemically and radiatively active
579 constituents with contrasting effects.

580 Our estimates are broadly consistent with previous modeling studies while highlighting the
581 consequences of the larger fire emissions represented in GFED5. The approximately 4% reduction
582 in global mean OH and +0.05 W m⁻² O₃ radiative effect at the top of the atmosphere are similar to
583 the 6% reduction and +0.03 W m⁻² effect, respectively, simulated with GFDL-AM3 by Mao et al.
584 (2013). In contrast, the $6 \pm 1\%$ fire contribution to the global tropospheric O₃ column is larger than
585 the approximately 3.5% estimated by Jaffe and Wigder (2012). Similarly, the 47% contribution of
586 fires to global CO emissions exceeds the approximately 40% reported in many previous studies.
587 These differences are consistent with the higher savanna, grassland, and agricultural fire emissions
588 in GFED5.

589 Model–observation comparisons provide additional evidence for the importance of these
590 revised emissions, although they also reveal important regional biases. Including fires substantially
591 improves the representation of the spatial distribution and seasonal and interannual variability of
592 CO and AOD, particularly across tropical fire regions. For example, the model reproduces major
593 CO and AOD anomalies associated with El Niño-related fire activity in tropical Asia and better
594 represents the semiannual cycles of CO and AOD over central Africa. At the same time, positive
595 O₃ biases over central Africa and remaining CO biases at northern high latitudes demonstrate that
596 increasing fire emissions does not uniformly improve model performance. These contrasting



597 responses provide useful constraints on both the emissions inventory and atmospheric chemistry.

598 Relative to our earlier E3SMv1 analysis, which focused on aerosols without interactive
599 atmospheric chemistry (Xu et al., 2021), the present E3SMv3 framework enables the effects of
600 fires on OH, CO, and O₃ to be simulated together with aerosol and O₃ radiative effects. This
601 coupled framework therefore provides a more complete representation of the chemical and
602 radiative pathways through which fires influence atmospheric composition and climate. However,
603 several uncertainties remain in both the fire emissions inventory and E3SM's representation of
604 atmospheric processes. Fire emissions depend on uncertainties in burned area, fuel consumption,
605 combustion completeness, land-cover classification, and emission factors. Although GFED5
606 improves the representation of burned area relative to earlier inventories, important uncertainties
607 remain for small fires, peat combustion, and fuel consumption in boreal ecosystems. The high
608 simulated CO and O₃ abundances over central Africa suggest that emissions from savanna fires
609 may be overestimated or that their chemical speciation requires further refinement.

610 Other model–observation discrepancies point to uncertainties in atmospheric processing
611 rather than fire emissions alone. The systematic negative AOD bias in E3SMv3 indicates a need
612 to further evaluate aerosol production and removal processes, including wet and dry deposition.
613 The fixed representation of fire injection heights also does not capture extreme pyrocumulonimbus
614 events that transport smoke into the upper troposphere and lower stratosphere, increasing aerosol
615 lifetimes and radiative impacts. Meanwhile, persistent CO underestimation at northern high
616 latitudes likely reflects a combination of uncertainties in anthropogenic precursor emissions,
617 atmospheric transport, and OH chemistry rather than a simple underestimate of boreal fire
618 emissions. These regional model–observation mismatches provide useful constraints for
619 improving future fire inventories and prognostic fire–chemistry models.



620 Taken together, our results demonstrate that fire emissions are an important component of
621 the global atmospheric system, influencing air quality, oxidative capacity, aerosols, radiation, and
622 climate from regional to global scales. Their atmospheric effects cannot be inferred from emissions
623 alone because nonlinear chemistry and atmospheric processing determine both the magnitude and,
624 in some cases, the sign of responses. This is particularly evident for OH, which increases in several
625 major tropical fire regions but decreases globally, and for radiation, where aerosol cooling is
626 partially offset by warming from fire-enhanced O₃. Accurately representing these coupled
627 processes is therefore important for simulating contemporary atmospheric composition and for
628 projecting how changes in fire regimes will influence climate and air quality. By combining paired
629 fire and no-fire E3SMv3 simulations with satellite and surface observations, our analysis
630 establishes diagnostics for evaluating the atmospheric consequences of fire emissions. Extending
631 these diagnostics across additional observational datasets and applying them to prognostic fire
632 simulations offers a pathway toward a systematic benchmark for evaluating coupled fire–
633 chemistry–climate interactions in Earth system models.

634

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649

650 **Code and Data Availability**

651 Model code may be accessed at the GitHub repository <https://github.com/E3SM-Project/E3SM>.
652 The fire emission data are publicly available from the Global Fire Emission Database version 5
653 (<https://www.globalfiredata.org/>). The level-3 monthly Terra-MODIS product (Collection 6.1) is
654 publicly available at [https://ladsweb.modaps.eosdis.nasa.gov/missions-and-](https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MOD08_M3)
655 [measurements/products/MOD08_M3](https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MOD08_M3). The level 3 monthly MOPITT version 9 gridded data is
656 available at <https://terra.nasa.gov/about/terra-instruments/mopitt>. The monthly gridded
657 troposphere column ozone derived from the Aura Ozone Monitoring Instrument/Microwave Limb
658 Sounder (OMI/MLS) is available at <https://acd-ext.gsfc.nasa.gov/index.html>. The monthly in-situ
659 surface CO measurement are obtained from the Global Monitoring Laboratory (GML) of the
660 National Oceanic and Atmospheric Administration (NOAA)
661 (<https://gml.noaa.gov/ccgg/data/co.html>). The surface O₃ measurements are obtained from the
662 Tropospheric Ozone Assessment Report (TOAR) database (<https://toar-data.org/surface-data/>).
663 The E3SM simulations are available on request from the corresponding author.

664

665 **Author Contributions**



666 LX, QT, QZ, WJR and JTR designed the study. LX performed the model simulations and analyzed
667 the model outputs. YC and GRvdW developed the GFED5 emission inventory. All authors
668 contributed to data interpretation and the writing of the paper.

669

670 **Competing Interests**

671 The authors declare that they have no conflict of interest.
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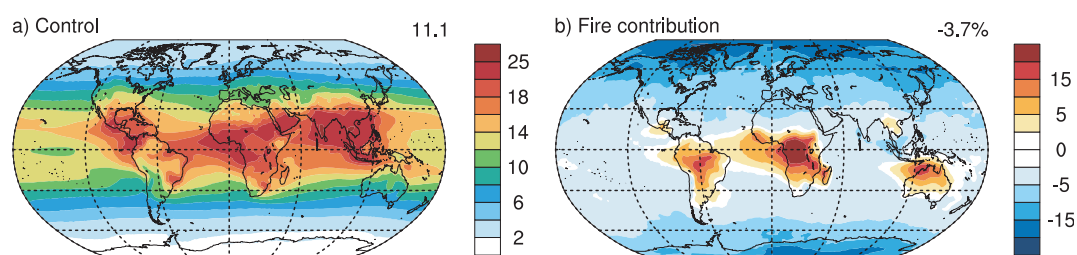


Figure 1: Annual average tropospheric OH concentration (unit: 10^5 molecules cm^{-3}) during 1997-2022 for a) the control run, and b) fire contribution (unit: %) computed as the absolute difference between the control and no-fire simulations relative to the control simulation. The tropospheric average OH concentration is calculated from the surface to 200 hPa. The global area-weighted mean values are given in the upper right corner of each panel.



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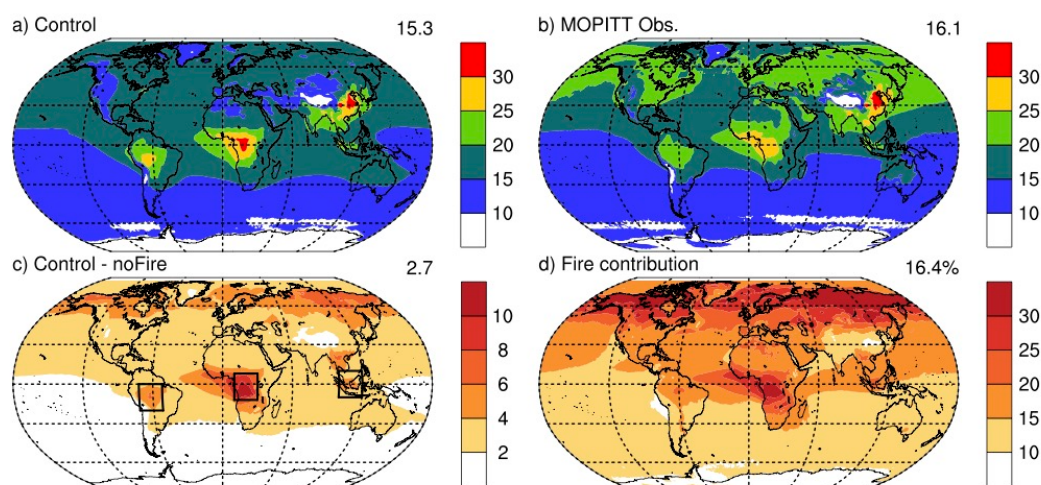


Figure 2: Annual average CO column (unit: 10^{17} molecules cm^{-2}) during 2000-2022 for a) the control run, b) the MOPITT satellite observations, c) the difference (10^{17} molecules cm^{-2}) between the control and no-fire runs and d) the fire contribution (unit: %) computed as the difference between the control and no-fire simulations relative to the control simulation. The global area weighted mean values are displayed in the upper right corner of each panel. The three selected $20^\circ \times 20^\circ$ tropical regions in the southern Amazon, central Africa, and tropical Asia that characterized by strong fire influence are marked with black squares in Figure 2c. We report time series from these regions in subsequent analyses.

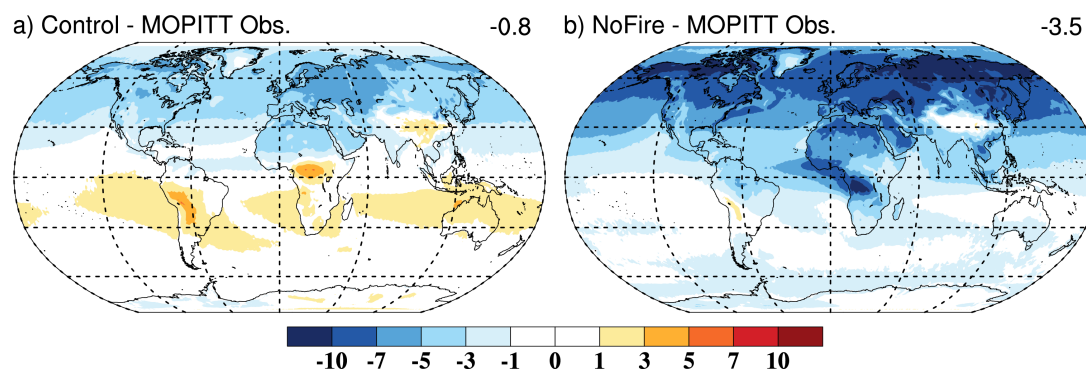


Figure 3: Mean annual average CO column differences (unit: 10^{17} molecules cm^{-2}) during 2000-2022 between MOPITT satellite observations and a) the control run and b) the no-fire run. The global area-weighted mean values are shown in upper right corner of each panel.

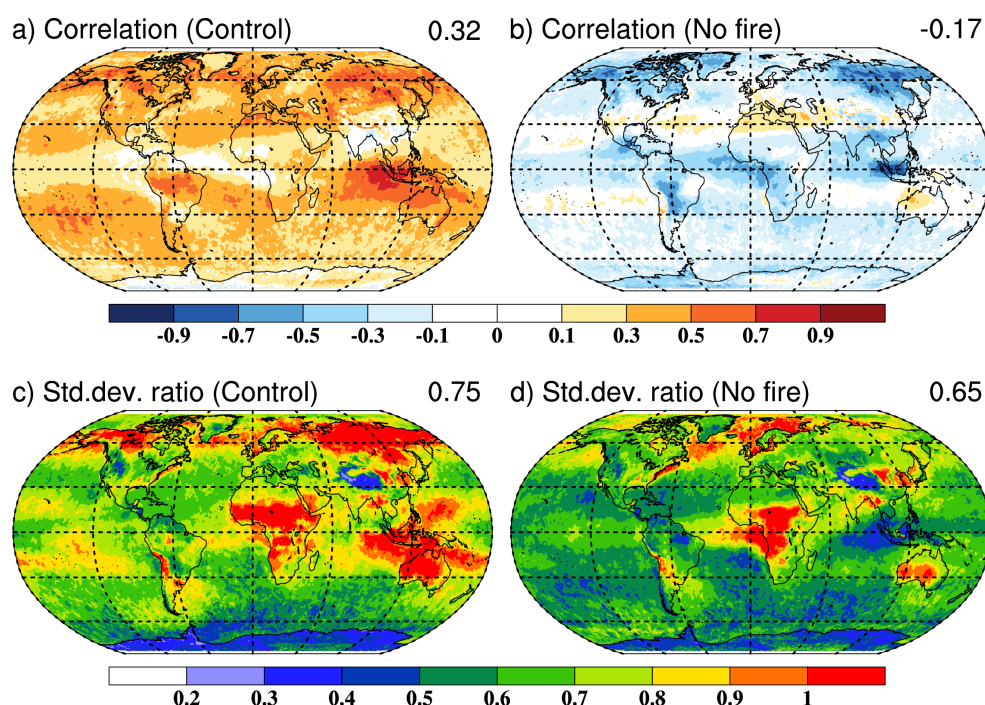


Figure 4: The correlation and ratio of standard deviations between E3SM simulations and MOPITT column CO observations for CO anomalies. The first row shows the correlation between monthly column CO anomalies from the control simulation, including fire emissions, and the observation in panel a), and the same for the no-fire simulation in panel b). The anomalies were computed by removing a mean annual cycle of column CO from the original data at each grid cell separately for the model and MOPITT satellite observations. The second row shows the ratio of the standard deviations of the anomalies for the model simulation and the MOPITT observations for the control simulation (panel c) and the no-fire simulation (panel d). The global area-weighted mean values are shown in the upper right corner of each panel.



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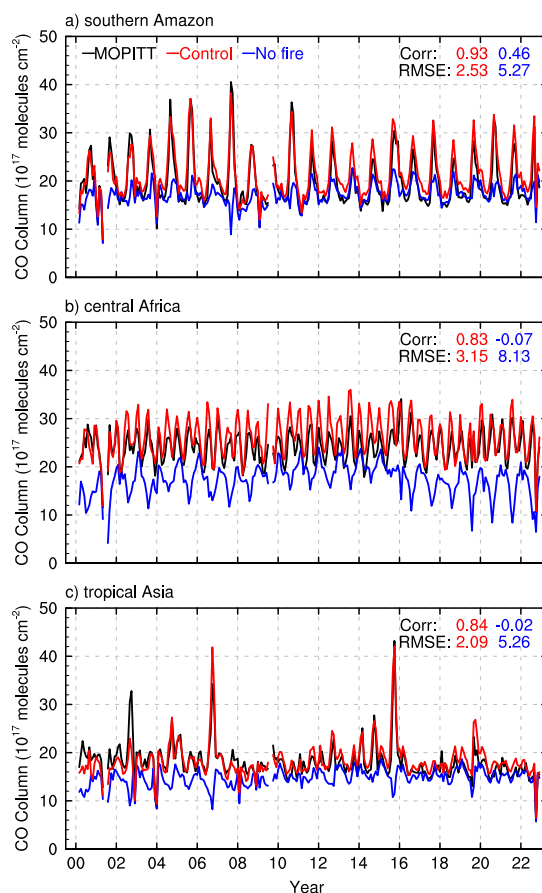


Figure 5: Time series of the MOPITT observed and modeled CO column (10^{17} molecules cm^{-2}) from the control (red line) and no-fire (blue line) simulations during 2000-2022 in a) southern Amazon, b) central Africa, and c) tropical Asia. The Pearson correlation and root mean square error (i.e., RMSE) between the modeled and observed values are given in each panel. The red and blue values represent the computed values for the control and no-fire simulations, respectively.

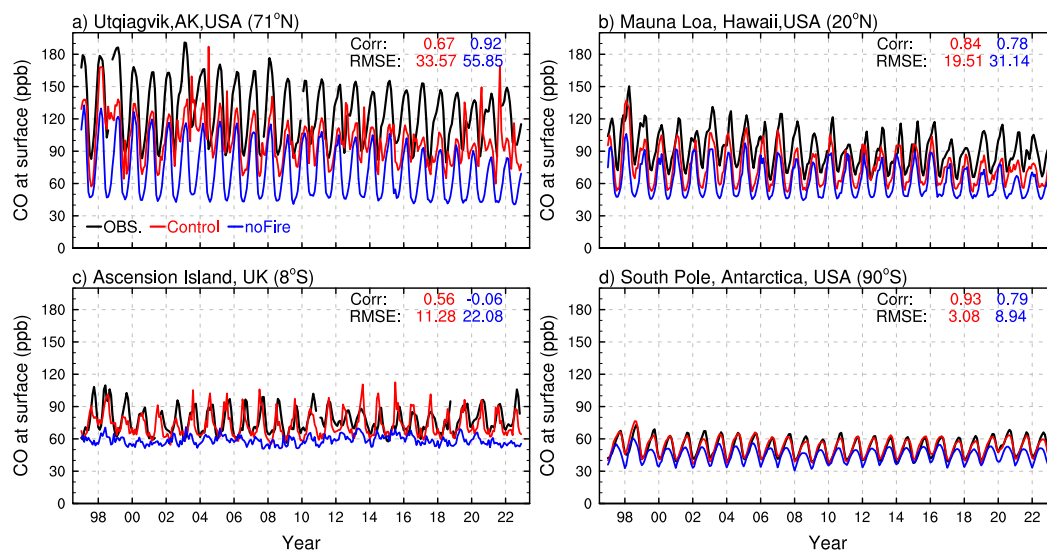


Figure 6: Surface CO mixing ratio (ppb) derived during 1997-2022 for the control run, no-fire run and observations in a) Utqiagvik, AK, USA (formerly Point Barrow), b) Mauna Loa, USA, c) Ascension Island, UK, and d) South Pole, Antarctica, USA. The Pearson correlation and root mean square error (i.e., RMSE) between the modeled and observed values are given in each panel. The red and blue values represent the computed values for the control and no-fire simulations, respectively.



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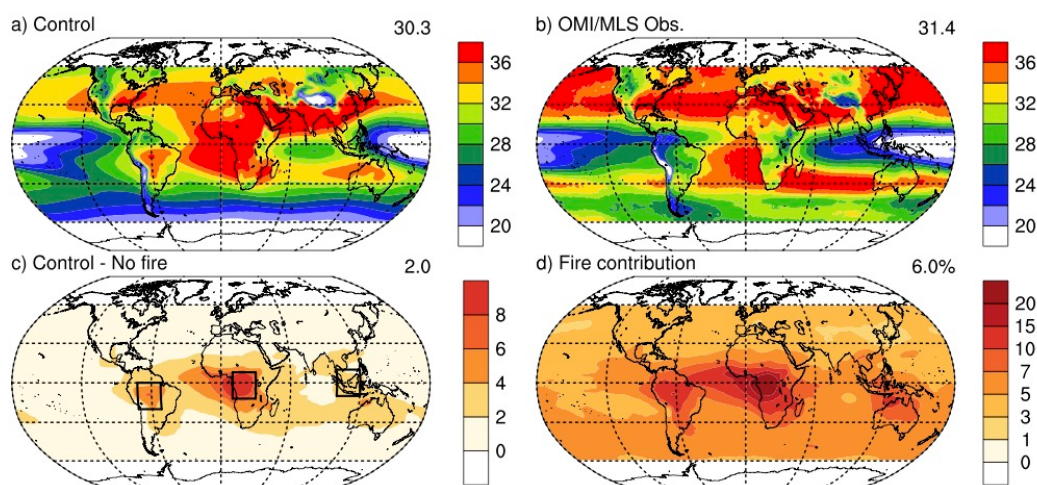


Figure 7: Annual average tropospheric column O₃ (DU) for a) the control run, b) the OMI/MLS satellite climatology observations during 2005-2020, c) the difference (DU) between the control and no-fire runs, and d) fire contribution in terms of the relative percentage difference (%) between the control and no-fire runs. The selected 20°×20° three tropical regions in Southern Amazon, Central Africa and Tropical Asia are marked with black squares. The global area-weighted mean values are shown in the upper right corner of each panel.

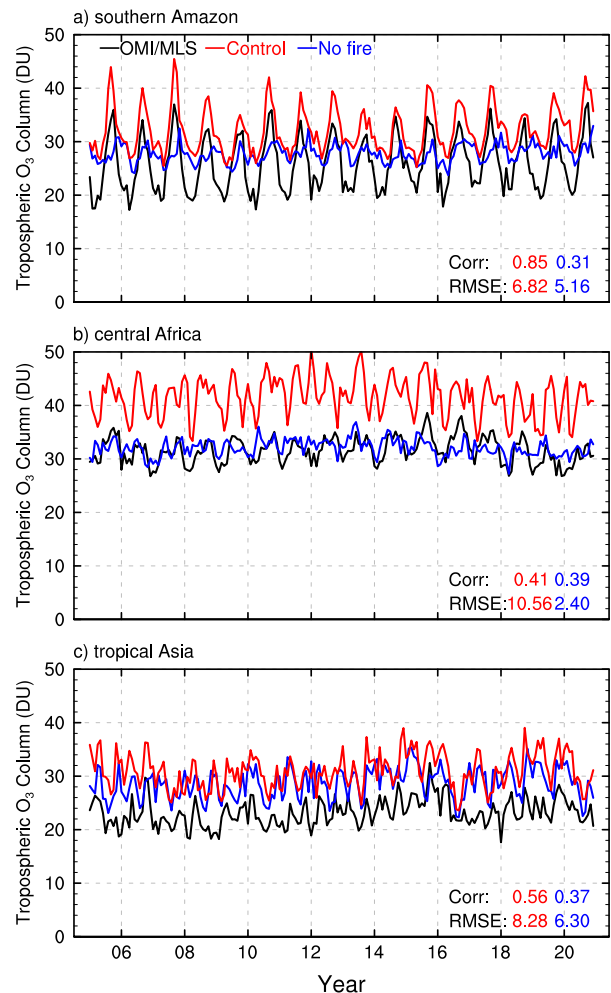


Figure 8: Time series of the OMI/MLS observed and modeled tropospheric O₃ column (DU) from the control (red line) and no-fire (blue line) simulations during 2005-2020 in a) southern Amazon, b) central Africa, and c) tropical Asia. The Pearson correlation and root mean square error (i.e., RMSE) between the modeled and observed values are given in each panel. The red and blue texts represent the computed values for the control and no-fire simulations, respectively.

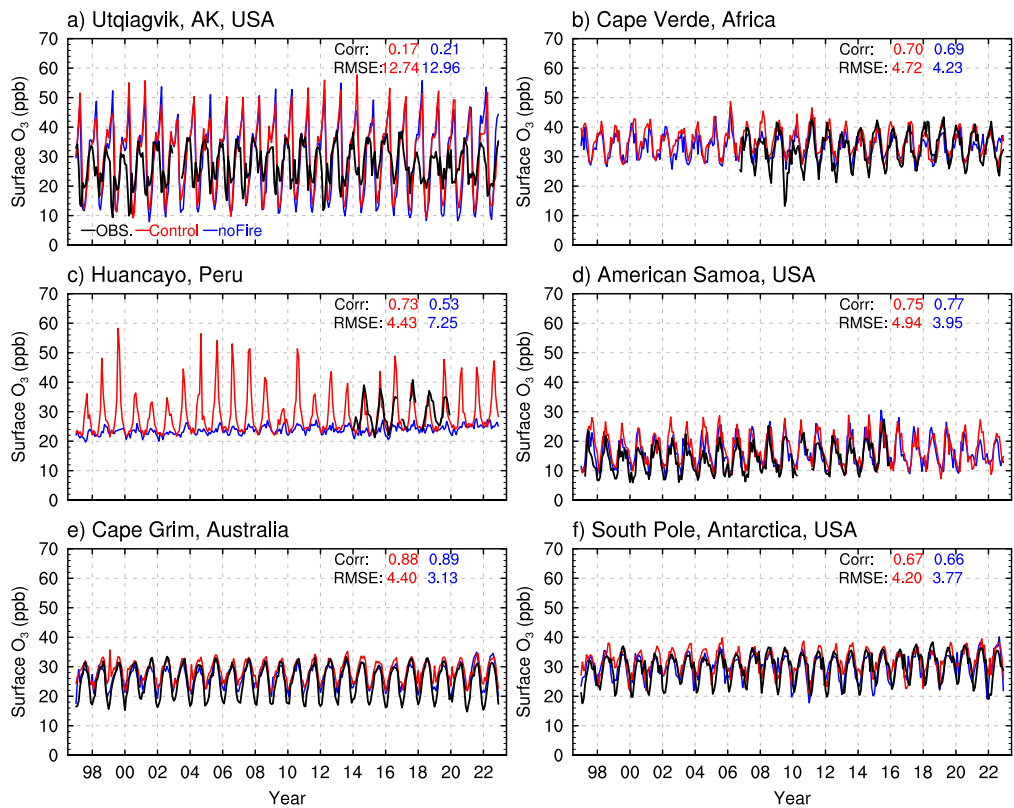


Figure 9: Time series of surface O_3 mole fractions (ppb) from in-situ observations (black line), the control (red line) and no-fire simulations (blue line) during 1997-2022 in a) Utqiagvik, AK, USA (formerly Point Barrow), b) Cape Verde, Africa, c) Huancayo, Peru, d) American Samoa, USA, e) Cape Grim, Australia, f) South Pole, Antarctica, USA. The Pearson correlation and root mean square error (i.e., RMSE) between the modeled and observed values are given in each panel. The red and blue texts represent the computed values for the control and no-fire simulations, respectively.



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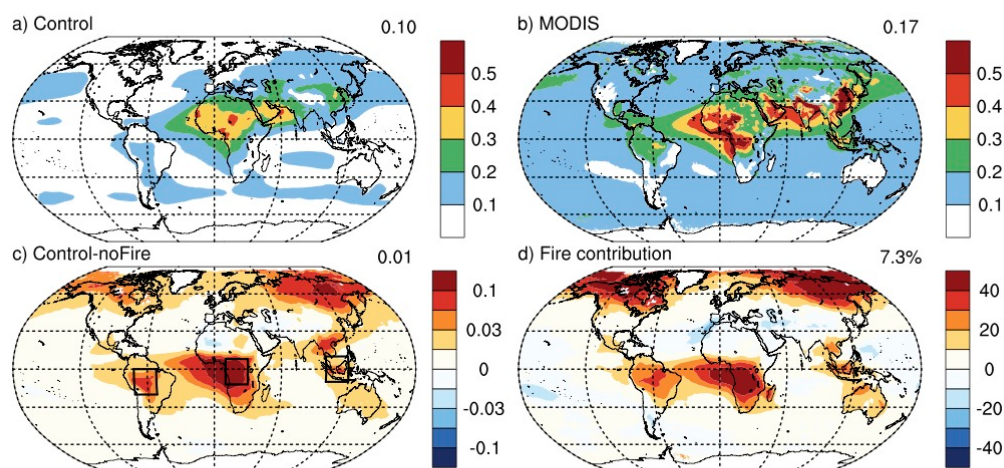


Figure 10: Annual mean aerosol optical depth (AOD) at 550 nm during February 2000–December 2022 for a) the control run, b) the MODIS satellite data, c) the absolute difference between the control and no-fire run, d) fire contribution in terms of the relative percentage difference (%) between the control and no-fire runs. The selected $20^{\circ} \times 20^{\circ}$ three tropical regions in the southern Amazon, central Africa and tropical Asia are marked with black squares. The global area-weighted mean values are shown in the upper right corner of each panel.



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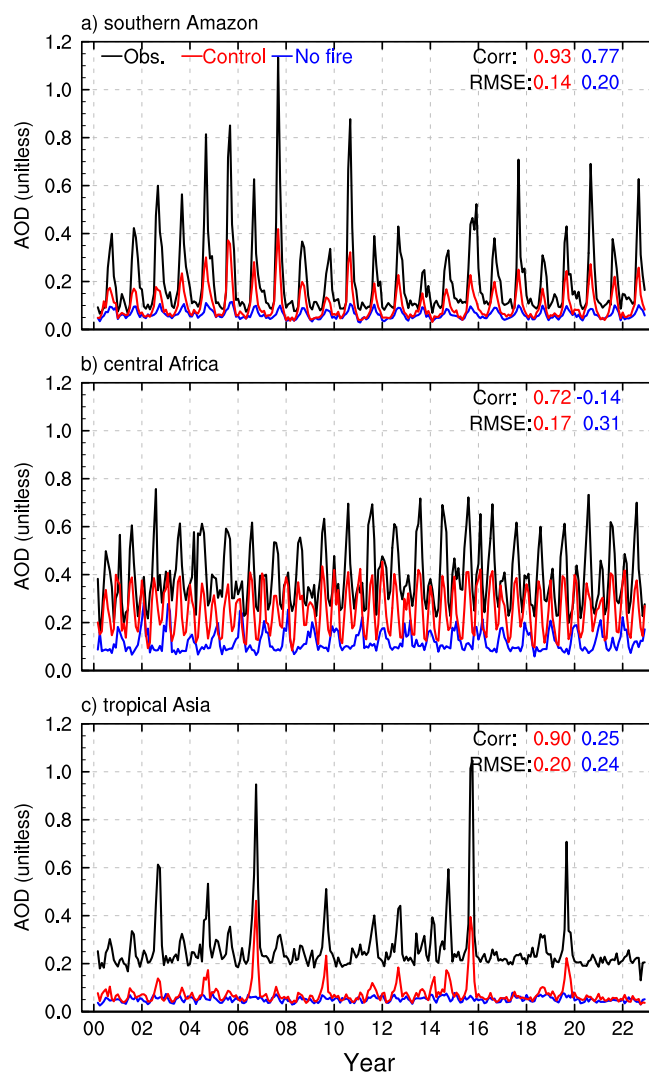


Figure 11: Time series of the MODIS observed and modeled aerosol optical depth (unitless) from the control (red line) and no-fire (blue line) simulations during February 2000–December 2022 in a) Southern Amazon, b) Central Africa, and c) Tropical Asia. The correlation and root mean square error (i.e., RMSE) between the modeled and observed values are given in each panel. The red and blue texts represent the computed values for the control and no-fire simulations, respectively.

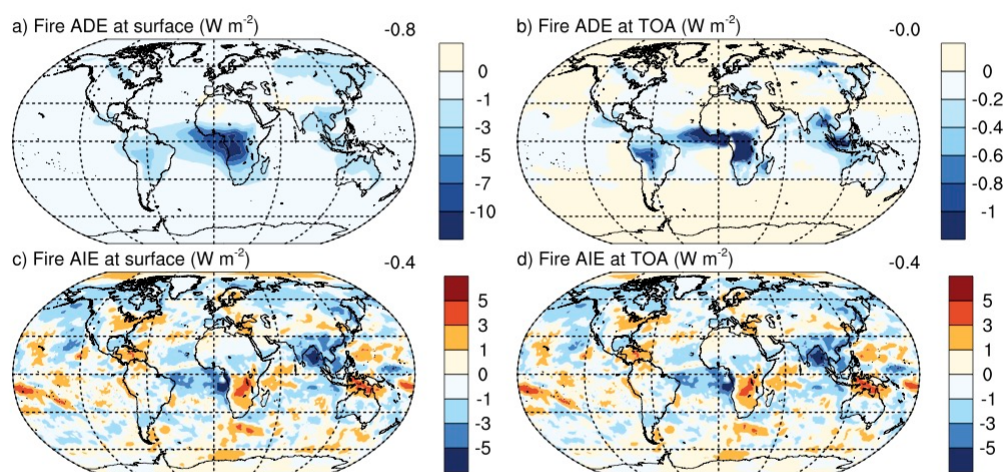


Figure 12: Annual average simulated a) fire aerosol direct effect (ADE) at surface (W m^{-2}), b) fire aerosol direct effect at the top of atmosphere (TOA) (W m^{-2}), c) fire aerosol indirect effect (AIE) at surface (W m^{-2}), d) fire aerosol indirect effect at the top of atmosphere (TOA) (W m^{-2}) during 1997-2022. The global area-weighted mean values are shown in upper right corner of each panel.



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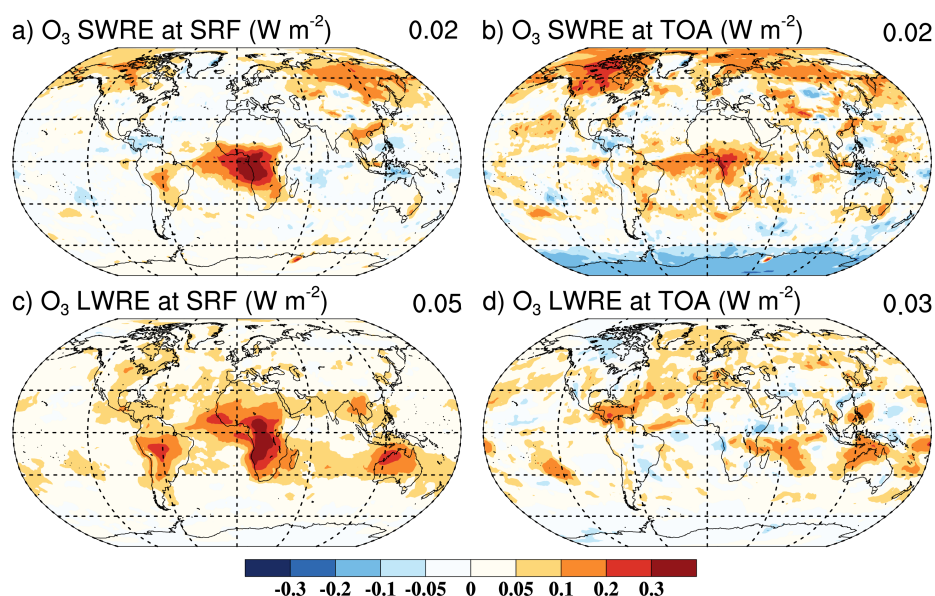


Figure 13: Annual average simulated fire-induced a) O₃ shortwave radiative effect (SWRE) at surface (W m⁻²), b) O₃ shortwave radiative effect at the top of atmosphere (TOA) (W m⁻²), c) O₃ longwave radiative effect (LWRE) at surface (W m⁻²), d) O₃ longwave radiative effect at the top of atmosphere (W m⁻²) during 1997-2022. The fire-induced radiative effects were calculated as the difference in radiative flux of O₃ between the control and no-fire simulations. The global area-weighted mean values are shown in upper right corner of each panel.



1229 Table 1: Numerical experiments used in this study.

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Experiment	Description
Control	Include all direct emissions for trace gases and aerosols
No fire	Exclude fire emissions for trace gases and aerosols

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1233 Table 2: Annual mean fire emissions of trace gases and aerosols from 1997-2022 used in this study
 1234 and their relative contribution to total emissions from all sources. Standard deviations are derived
 1235 from year-to-year variability in emissions and do not capture the full range of uncertainty
 1236 stemming from biomass emissions and emission factor estimates.

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Species ^a	Fire Emissions (Tg species y ⁻¹)	Fire relative contribution (%)
CO	529.7±74.2	46.5±3.1
C ₂ H ₄	7.4±0.7	16.7±1.4
C ₂ H ₆	5.4±0.7	48.3±3.6
C ₃ H ₈	1.9±0.9	25.2±7.7
CH ₂ O	9.9±0.9	59.8±2.2
CH ₃ CHO	11.9±1.0	37.0±2.0
CH ₃ COCH ₃	3.5±0.4	8.3±0.8
Isoprene	1.0±0.2	0.2±0.0
Monoterpene	4.6±1.0	4.6±0.8
NO	24.3±1.8	22.1±1.5
SO ₂	5.9±0.6	4.6±0.7
SOAG0	57.0±7.7	68.0±3.2
BC	2.5±0.2	37.1±2.0
POM	38.0±5.1	72.7±2.6

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1239 ^aAnnual CH₄ emissions from GFED5 are estimated to be 18.7 ± 3.4 Tg CH₄ y⁻¹. These
 1240 emissions were not included in this work because CH₄ tracer is not implemented as a
 1241 fully interactive tracer in the current model version.

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Table 3: Correlations between E3SM simulations and observations for the annual mean spatial pattern, a monthly climatological annual cycle, monthly anomalies (IAV only) and the full time series. For CO, the model was compared with MOPITT column observations, for O₃ the model was compared with OMI/MLS column observations, and for aerosol optical depth (AOD), the model was compared with MODIS observations.

Species	Simulations	Annual mean (180°×360°)	Annual cycle (12m×180°×360°)	IAV only (276m×180°×360°) ^a	Full time series (276m×180°×360°) ^a
CO	Control	0.88	0.85	0.45	0.80
	No fire	0.75	0.61	-0.24	0.52
O ₃	Control	0.69	0.70	0.26	0.62
	No fire	0.75	0.72	0.19	0.63
AOD	Control	0.75	0.70	0.19	0.60
	No fire	0.65	0.60	0.07	0.49

^aThe total time dimension for the CO and AOD modeled data and measurements during 2000-2022 is 276 months (i.e., 23 years) while that for O₃ data during 2005-2020 is 192 months (i.e., 16 years).

Table 4: Pearson correlation (r) and root mean square error (RMSE) for the time series of the regional average modeled CO column and MOPITT CO column shown in Figure 5, the regional modeled tropospheric O₃ column and OMI/MLS O₃ column shown in Figure 8, and the regional modeled aerosol optical depth (AOD) and MODIS data shown in Figure 11 in Southern Amazon, Central Africa and Tropical Asia. The modeled CO column, O₃ column and AOD from both control and no fire simulations are reported.

Variable	Simulations	Regions					
		Southern Amazon		Central Africa		Tropical Asia	
		r	RMSE	r	RMSE	r	RMSE
CO	Control	0.93	2.53	0.83	3.15	0.84	2.09
	No fire	0.46	5.27	-0.07	8.13	-0.02	5.26
O ₃	Control	0.85	6.82	0.41	10.56	0.56	8.28
	No Fire	0.31	5.16	0.39	2.40	0.37	6.30
AOD	Control	0.93	0.14	0.72	0.17	0.90	0.20
	No fire	0.77	0.20	-0.14	0.31	0.25	0.24