

# 1 **Diagnosing spatial biases and uncertainties in global fire emissions** 2 **inventories: Indonesia as regional case study**

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## 16 **Abstract**

17 Models of atmospheric composition rely on fire emissions inventories to reconstruct and  
18 project impacts of biomass burning on air quality, public health, climate, ecosystem dynamics,  
19 and land-atmosphere exchanges. Many such global inventories use satellite measurements of  
20 active fires and/or burned area from the Moderate Resolution Imaging Spectroradiometer  
21 (MODIS). However, differences across inventories in the interpretation of satellite imagery, the  
22 emissions factors assumed for different components of smoke, and the adjustments made for  
23 small and obscured fires can result in large regional differences in fire emissions estimates across  
24 inventories. Using Google Earth Engine, we leverage 15 years (2003-2017) of MODIS  
25 observations and 6 years (2012-2017) of observations from the higher spatial resolution Visible  
26 Imaging Infrared Radiometer Suite (VIIRS) sensor to develop metrics to quantify five major  
27 sources of spatial bias or uncertainty in the inventories: (1) primary reliance on active fires  
28 versus burned area, (2) cloud/haze burden on the ability of satellites to “see” fires, (3)  
29 fragmentation of burned area, (4) roughness in topography, and (5) small fires, which are  
30 challenging to detect. Based on all these uncertainties, we devise comprehensive “relative fire  
31 confidence scores,” mapped globally at 0.25° x 0.25° spatial resolution over 2003-2017.

32 We then focus on fire activity in Indonesia as a case study to analyze how the choice of a  
33 fire emissions inventory affects model estimates of smoke-induced health impacts across  
34 Equatorial Asia. We use the adjoint of the GEOS-Chem chemical transport model and apply  
35 emissions of particulate organic carbon and black carbon (OC+BC smoke) from five global  
36 inventories: Global Fire Emissions Database (GFEDv4s), Fire Inventory from NCAR  
37 (FINNv1.5), Global Fire Assimilation System (GFASv1.2), Quick Fire Emissions Dataset  
38 (QFEDv2.5r1), and Fire Energetics and Emissions Research (FEERv1.0-G1.2). We find that

39 modeled monthly smoke  $PM_{2.5}$  in Singapore from 2003-2016 correlates with observed smoke  
40  $PM_{2.5}$ , with  $r$  ranging from 0.64-0.84 depending on the inventory. However, during the burning  
41 season (July to October) of high fire intensity years (e.g., 2006 and 2015), the magnitude of  
42 mean Jul-Oct modeled smoke  $PM_{2.5}$  can differ across inventories by more than  $20 \mu g m^{-3}$  (>  
43 500%). Using the relative fire confidence metrics, we deduce that uncertainties in this region  
44 arise primarily from the small, fragmented fire landscape and very poor satellite observing  
45 conditions due to clouds and thick haze at this time of year. Indeed, we find that modeled smoke  
46  $PM_{2.5}$  using GFASv1.2, which adjusts for fires obscured by clouds and thick haze and accounts  
47 for peatland emissions, is most consistent with observations in Singapore, as well as in Malaysia  
48 and Indonesia. Finally, we develop an online app called FIRECAM for end-users of global fire  
49 emissions inventories. The app diagnoses differences in emissions among the five inventories  
50 and gauges the relative uncertainty associated with satellite-observed fires on a regional basis.

## 51 **1. Introduction**

### 52 *1.1 Global fire emissions inventories: role in modeling studies and methodological differences*

53 Models of atmospheric composition depend on global fire emissions inventories to  
54 reconstruct and project the impacts of biomass burning on air quality (Cusworth et al., 2018),  
55 public health (Crippa et al., 2016; Koplitz et al., 2016), climate (Rogers et al., 2015; Tosca et al.,  
56 2013), ecosystem dynamics (Yi et al., 2014), and land-atmosphere exchanges (Prentice et al.,  
57 2011). Many regional and global modeling studies consider only one global fire emissions  
58 inventory as input primarily to limit computational cost (Crippa et al., 2016; Kim et al., 2015;  
59 Koplitz et al., 2016; Maasakkers et al., 2016; Marlier et al., 2019). End-users may simply choose  
60 an inventory based on spatio-temporal resolution, near-real-time availability, or keep the default  
61 inventory imposed in some chemical transport models (CTM). However, disagreements in the  
62 magnitude and temporal variability of emissions among inventories can significantly impact  
63 model estimates of variables relevant to air quality (Cusworth et al., 2018), public health  
64 (Koplitz et al., 2018b), or the budgets of atmospheric species (Heymann et al., 2017; Li et al.,  
65 2019; Shi et al., 2015; Zhang et al., 2014). Thus, it is important to understand the underlying  
66 causes for differences in both the magnitude and spatio-temporal variability of fire emissions in  
67 order to better inform fire prediction (Chen et al., 2017), land management decisions (Marlier et  
68 al., 2019), and other applications. While previous studies have identified regional discrepancies  
69 among various global fire emissions inventories (e.g., Li et al., 2019; Shi et al., 2015), here we  
70 also construct metrics to diagnose such discrepancies, and we present the online app FIRECAM  
71 to allow end-users to rapidly compare inventories across the globe and view the metrics.

72 Five global fire emissions inventories are widely used in modeling studies: (1) Global  
73 Fire Emissions Database (GFED; van der Werf et al., 2017), (2) Fire Inventory from NCAR  
74 (FINN; Wiedinmyer et al., 2011), (3) Global Fire Assimilation System (GFAS; Kaiser et al.,  
75 2012), (4) Quick Fire Emissions Dataset (QFED; Darmenov and da Silva, 2013), and (5) Fire  
76 Energetics and Emissions Research (FEER; Ichoku and Ellison, 2014) (Table 1). Estimates of  
77 fire emissions generally follow the “bottom-up” (e.g. GFED, FINN) or “top-down” approach  
78 (e.g. QFED, GFAS, FEER). In this study, we broadly define “bottom-up” as burned area-based  
79 and “top-down” as fire energy-based. The bottom-up burned area approach in GFED and FINN

80 is based on MODIS burned area (MCD64A1) and/or active fire (MOD14, MYD14) products. It  
81 is important to note that even the bottom-up approach relies on active fire data: GFED has  
82 essentially become a hybrid product that ingests active fire locations for its small fire boost  
83 (Randerson et al., 2012), and the MCD64A1 algorithm itself is coupled with active fire data  
84 (Giglio et al., 2009). Fuel loadings, combustion completeness, and emissions factors, which are  
85 dependent on region and land use and land cover (LULC), are then used to convert burned area  
86 to fire emissions. Fuel loadings are derived from biogeochemical models (Hoelzemann et al.,  
87 2004; van der Werf et al., 2010), and combustion completeness is estimated as a function of soil  
88 moisture (van der Werf et al., 2017) or tree cover (Wiedinmyer et al., 2011). Emissions factors  
89 are compiled from lab experiments and vary by LULC (Akagi et al., 2011; Andreae and Merlet,  
90 2001). The top-down approach in QFED, GFAS, and FEER uses fire energy from MODIS-  
91 derived fire radiative power (FRP), which is remotely sensed at top-of-atmosphere. Fire radiative  
92 energy (FRE), or the temporal integral of FRP, approximately linearly scales with the mass of  
93 dry matter (DM) consumed as fuel due to combustion (Wooster et al., 2005). Besides correcting  
94 for fires obscured by clouds in the top-down approach, GFAS, QFED, and FEER also use  
95 MODIS aerosol optical depth (AOD) to determine scaling factors for emissions of organic  
96 carbon (OC), black carbon (BC), and particulate matter less than 2.5  $\mu\text{m}$  in diameter ( $\text{PM}_{2.5}$ ),  
97 which includes OC and BC (Darmenov and da Silva, 2013; Ichoku and Ellison, 2014; Kaiser et  
98 al., 2012).

99 To understand the causes for differences in fire emissions estimates, we first devise five  
100 “relative fire confidence metrics” based on major methodological differences between the five  
101 global inventories and factors that can affect satellite observing conditions: (1) type of input  
102 satellite fire dataset (i.e., burned area versus active fires), (2) cloud/haze obscuration of land  
103 surface, (3) burn extent and fragmentation, (4) variance in topography, and (5) additional small  
104 fires from VIIRS. We combine the five relative fire confidence metrics to map the relative fire  
105 confidence score for bottom-up emissions inventories primarily based on burned area (e.g.  
106 GFED) or active fire area (e.g. FINN). For top-down inventories, we estimate an FRP-based  
107 score to estimate the potential FRP enhancement from small fires below the MODIS detection  
108 limit, large fires not well-captured by the MODIS active fire product, and fires obscured by  
109 clouds and thick haze.

## 110 *1.2 Regional case study: smoke exposure from fires in Indonesia*

111 We then focus on Indonesia as a regional case study, as Indonesia can contribute a  
112 substantial fraction of annual global fire emissions. By some estimates, fires in Equatorial Asia,  
113 which mostly occur in Indonesia, account for 8% of carbon emissions from global fire activity on  
114 average, but as much as over a third during high fire intensity years (van der Werf et al., 2017).  
115 From incomplete combustion, fires release greenhouse gases and aerosols, including  $\text{PM}_{2.5}$ , and  
116 such emissions can trigger haze events, impacting visibility, air quality, climate, ecosystem  
117 services, and human health (Harrison et al., 2009; Page et al., 2009). Three main factors  
118 exacerbate haze episodes over Equatorial Asia: (1) synoptic meteorology, (2) fire-driven  
119 deforestation and agricultural management, and (3) carbon-rich peatlands in Indonesia (Marlier  
120 et al., 2019). First, during years with a strong El Niño and positive Indian Ocean Dipole phase,  
121 such as 2006 and 2015, suppression of convection over Indonesia leads to drought conditions  
122 (Crippa et al., 2016; Fernandes et al., 2017; Koplitz et al., 2016). Chen et al. (2017) found that a

123 temporal cascade of pan-tropical fires, including large fires in Indonesia, is driven by the El Niño  
124 Southern Oscillation (ENSO) and changes in precipitation and terrestrial water storage. Second,  
125 smallholder farms and industrial concessions (oil palm, pulpwood, and rubber) are typically  
126 managed by fire to clear residues; forests are also cleared for agriculture and new plantations via  
127 burning (Dennis et al., 2005; Hoscilo et al., 2011; Marlier et al., 2015). Third, if the water table is  
128 low, peat fires can burrow underground and become extremely difficult to extinguish. Such fires  
129 can smolder for days to weeks, releasing substantial amounts of smoke into the atmosphere (Gras  
130 and Jensen, 1999; Hayasaka et al., 2014; Rein et al., 2008; van der Werf et al., 2008). Although  
131 fires occur every year in Indonesia (e.g., Koplitz et al., 2018a), the combination of these three  
132 natural and human-induced factors leads to especially severe haze over Equatorial Asia, such as  
133 in 1997, 2006, and 2015.

134 The high concentrations of PM<sub>2.5</sub> generated by fires in Equatorial Asia pose adverse  
135 health risks, leading to increased premature mortality. For example, Koplitz et al. (2016), Crippa  
136 et al. (2016), and Marlier et al. (2019) estimate 75,600-100,300 long-term premature adult deaths  
137 from cardiovascular and respiratory disease in Equatorial Asia due to the 2015 severe haze event.  
138 However, each of these studies differ in methodology, and specifically, in the global fire  
139 emissions inventory used: GFASv1.0 in Koplitz et al. (2016), FINNv2.0 in Crippa et al. (2016),  
140 and GFEDv4s in Marlier et al. (2019). In this study, we diagnose the impact of using different  
141 emissions inventories on estimates of population-weighted smoke exposures for Singapore,  
142 Indonesia, and Malaysia, following Koplitz et al. (2016) and Marlier et al. (2019).

### 143 *1.3 Google Earth Engine: online platform for rapid geospatial analysis*

144 In this study, we leverage Google Earth Engine (GEE; <https://earthengine.google.com>),  
145 an online platform for rapid geospatial analysis (Gorelick et al., 2017). Recently, GEE has been  
146 used in studies that require ease of access to satellite datasets and high computational power,  
147 such as for mapping crop yields (Azzari et al., 2017; Azzari and Lobell, 2017), trends in land use  
148 change (Kennedy et al., 2018), travel distance to cities (Weiss et al., 2018), and smoke exposure  
149 from fires (Marlier et al., 2019). Some of these studies also incorporate GEE's user interface  
150 capabilities, including Earth Engine Apps (<https://www.earthengine.app>) into online apps. Our  
151 use of GEE is two-fold: (1) to apply the relative fire confidence metrics at the global scale and  
152 (2) to use Earth Engine Apps to build the FIRECAM online tool.

153 The main objective of this study is to identify the methodological differences between  
154 five global fire emissions inventories and for end-users, show how these differences may lead to  
155 biases in results. To do so, we first use GEE to develop five relative fire confidence metrics to  
156 quantify some of the uncertainties. Next, we isolate the impact of using different inventories to  
157 estimate smoke exposure in Equatorial Asia from fires in Indonesia. Finally, we develop an  
158 online tool to help end-users to rapidly gauge the regional differences in emissions estimates and  
159 reduce potential biases in model results.

## 160 **2. Methods**

161 In this study, we use GEE to access and analyze satellite-derived datasets, many of which  
162 are already included in the GEE public data catalog. GEE couples a multi-petabyte-scale data

163 catalog with cloud computing to make rapid geospatial analysis possible at scale (Gorelick et al.,  
164 2017). Use of GEE is thus critical to this study in order to apply the relative fire confidence  
165 metrics at a global scale and build the FIRECAM online tool.

## 166 *2.1 Satellite fire datasets*

167 We primarily use the Collection 6 (C6) satellite fire datasets from the MODIS sensors  
168 aboard the Terra and Aqua satellites, which have daily overpasses at ~10:30 am/pm and ~1:30  
169 am/pm local time, respectively. These datasets are used in the construction of the five global fire  
170 emissions inventories considered here and publicly available from the NASA Earthdata catalog  
171 (<https://earthdata.nasa.gov/>). We analyze 15 years (2003-2017) of data from Collection 6  
172 MCD64A1 burned area at monthly, 500-m spatial resolution (Giglio et al., 2018, 2009),  
173 MOD/MYD14A1 FRP and fire mask at daily, 1-km resolution (Giglio et al., 2016, 2003), and  
174 MCD14ML active fire geolocations also at daily, 1-km resolution. We hereafter refer to the  
175 Level-3 gridded active fire products MOD14A1 (Terra) and MYD14A1 (Aqua) collectively as  
176 MxD14A1 and Level-2 swath products as MxD14. We also use Collection 1 VNP14IMGML  
177 active fire geolocations, available since 2012, from the VIIRS sensor aboard the Suomi National  
178 Polar-orbiting Partnership (S-NPP) satellite. VNP14IMGML is analogous to MCD14ML, but  
179 provides data at higher spatial resolution (375 m) and only during the Aqua overpass times  
180 (Schroeder and Giglio, 2017).

## 181 *2.2 Relative fire confidence metrics*

182 We devise five simple fire confidence metrics ( $\phi$ ) to assess the overall spatial variability  
183 and relative bias in global fire emissions inventories at  $0.25^\circ \times 0.25^\circ$  spatial resolution and  
184 aggregated across 15 years (2003-2017) from monthly timesteps, as described below. Table 2  
185 describes the satellite-derived datasets used. Then, as an example to end-users, we integrate the  
186 five metrics into more comprehensive “scores” to independently evaluate the spatial variability  
187 in uncertainty for bottom-up and top-down inventories. That is, we identify regions where each  
188 inventory may capture fire emissions either well or poorly, based on the five metrics.

189 **(1) Spatial discrepancy between burned area and active fire area ( $\phi_{area}$ ):** We classify two  
190 main types of bottom-up emissions inventories, based on the observations used to derive these  
191 inventories. For example, both GFED and FINN estimate burned area, but GFED uses the  
192 MCD64A1 burned area product, and FINN relies on MCD14ML active fire geolocations.  
193 MODIS burned area is typically classified based on the difference in the surface reflectance, or  
194 Normalized Burn Ratio (NBR), of pre-burn and post-burn images, while MODIS active fires are  
195 detected as “hotspots,” or thermal anomalies, each of which can be associated with areal extent  
196 to estimate burned area. To avoid confusion, we refer to burned area derived from MCD64A1 as  
197  $BA_{MCD64A1}$  or burned area (BA; as in GFED) and that from MxD14A1 as  $BA_{MxD14A1}$  or “active  
198 fire area” (AFA; as in FINN). In contrast to the high threshold for the MCD64A1 burned area  
199 product, which reliably classifies burn scars  $> 1.2 \text{ km}^2$  (Giglio et al., 2006), the MxD14A1 active  
200 fire product can detect cool, smoldering fires more consistently and fires as small as  $100 \text{ m}^2$   
201 under clear-sky conditions (Giglio et al., 2003). However, burned area products may better  
202 capture short-lasting fires (sub-daily) and fires obscured by thick haze or clouds, since the  
203 burned area pre-burn versus post-burn algorithm is not limited by satellite overpass times (Giglio

204 et al., 2009). The persistence of burn scars enables satellites to detect fires after clouds and haze  
 205 have dissipated. To gauge the relative areal discrepancy of  $BA_{MCD64A1}$  and  $BA_{MxD14A1}$ , we first  
 206 aggregate  $BA_{MCD64A1}$  to the 1-km spatial resolution of  $BA_{MxD14A1}$ . We then estimate total  
 207  $BA_{MCD64A1}$  outside  $BA_{MxD14A1}$  ( $BA_\beta$ ) and  $BA_{MxD14A1}$  outside  $BA_{MCD64A1}$  ( $BA_\alpha$ ), over 2003-  
 208 2017, and calculate the normalized difference index of  $BA_\beta$  and  $BA_\alpha$  at  $0.25^\circ \times 0.25^\circ$  spatial  
 209 resolution:

$$210 \quad \phi_{area} = \frac{\Sigma BA_\beta - \Sigma BA_\alpha}{\Sigma BA_\beta + \Sigma BA_\alpha} \quad (1)$$

211 where

$$212 \quad BA_\beta = BA_{MCD64A1} - (BA_{MCD64A1} \cap BA_{MxD14A1}) \quad (2)$$

$$213 \quad BA_\alpha = BA_{MxD14A1} - (BA_{MCD64A1} \cap BA_{MxD14A1}) \quad (3)$$

214 The range of the normalized difference index (-1 to +1) for the BA-AFA discrepancy indicates  
 215 whether grid cells are either dominated by burned area ( $> 0$ ) or active fire area ( $< 0$ ). If either  
 216 burned area or active fire area dominates (near -1 or +1), the datasets will not agree, and  
 217 uncertainty is high. If the index is  $\sim 0$ , the discrepancies between the datasets are minimal,  
 218 wherein  $BA_\beta \approx BA_\alpha$ ; in this case, however, the magnitude of  $BA_\beta$  and  $BA_\alpha$  can vary while  
 219 yielding similar index values.

220 **(2) Cloud/haze effect on the ability of satellites to “see” fires ( $\phi_{cloud\_haze}$ ):** Persistent cloud  
 221 coverage and thick haze limit the opportunities for satellites to detect active fires or retrieve  
 222 usable scenes for burned area classification. This metric diagnoses the fractional monthly  
 223 cloud/haze burden at 500-m spatial resolution, weighted by FRP, but does not distinguish  
 224 between smoke and cloud or varying cloud thickness and opacity. We use FRP rather than  
 225 burned area since FRP is linearly related to DM emissions and more readily captures small fires  
 226 (Wooster et al., 2005). We use the Collection 6 MODIS daily surface reflectance products  
 227 MxD09GA and follow the algorithm proposed by Xiang et al. (2013) in each pixel, with “pixel”  
 228 defined as one satellite observation in the native MODIS sinusoidal projection:

$$229 \quad p_{cloud\_haze} = \frac{\rho_1 - \rho_7}{\rho_1 + \rho_7} > 0 \quad \text{or} \quad \rho_1 > 0.3 \quad (4)$$

230 where  $p_{cloud\_haze}$  refers to pixels designated as cloudy/hazy,  $\rho_1$  indicates the MODIS surface  
 231 reflectance in the 620-670 nm band (Red) and  $\rho_7$ , the 2105-2155 nm band (SWIR-2). Cloudy and  
 232 hazy pixels tend to be saturated in the visible bands relative to SWIR bands (Xiang et al., 2013).  
 233 Pixels are classified as cloudy/hazy if either of the two criteria in Eq. 4 is met. We consider only  
 234 those pixels with one or more active fire or burned area observations over the 2003-2017  
 235 timeframe to exclude misclassification of cloud/haze in snow, ice, and desert regions. After  
 236 averaging the fraction of clouds and haze across  $0.25^\circ \times 0.25^\circ$  grid cells, we weight the monthly  
 237 fractional cloud/haze burden by FRP aggregated by month and satellite, over 2003-2017, to place  
 238 more emphasis on the observing conditions during the months and hours of the diurnal cycle  
 239 when fires are more likely to occur.

240 Like Xiang et al. (2013), MODIS also diagnoses clouds and haze but at coarser, 1-km  
241 resolution, which can result in overestimates of the cloud/haze fraction since clear pixels are  
242 mixed with cloudy or mixed cloudy pixels. However, the MODIS algorithm is better able than  
243 Xiang et al. (2013) to separate clouds or haze from bright surfaces such as snow/ice, desert, and  
244 built-up areas. We therefore use the FRP-weighted cloud/haze fraction derived from the MODIS  
245 algorithm to identify grid cells that may be misclassified as clouds due to the underlying bright  
246 surfaces. We assume that those pixels that MODIS characterizes as “cloudy” or having “mixed”  
247 clouds, cloud shadow, or high aerosol content are pixels obscured by cloud or haze. Then, for  
248 these grid cells, we check whether the FRP-weighted cloud/haze fraction derived from the Xiang  
249 et al. (2013) algorithm is positive. If yes, we use the FRP-weighted cloud/haze fraction from the  
250 MODIS algorithm for our metric.

251 **(3) Fragmentation and size of contiguous burned area ( $\phi_{fragment}$ ):** Burned area products can  
252 better capture large, contiguous fires than small, fragmented fires due to the greater difference in  
253 NBR from pre-fire to post-fire and the persistence of burn scars on the land surface. On  
254 croplands, the small drop in NBR due to small fires can be conflated with harvest or masked by  
255 timely sowing of the next crop or by regrowth (e.g. Hall et al., 2016; Liu et al., 2019). In  
256 contrast, active fire products can generally detect such small, fragmented fires more accurately,  
257 so long as they occur during the satellite overpasses and are not obscured by clouds or haze.  
258 Dense clusters of small fires within a pixel can also increase the detection probability by  
259 enhancing the thermal anomaly or the NBR difference relative to background. For this metric,  
260 we estimate the total burned area and number of burn scar fragments over 2003-2017, using the  
261 average burned area per contiguous burn scar patch as a proxy for burn scar size and  
262 fragmentation. The *connectedComponents* function in GEE allows us to estimate the number of  
263 contiguous burn patches on a monthly basis at 500-m spatial resolution (Gorelick et al., 2017).  
264 To determine the connectivity of burn scars, we apply a circle kernel with a radius of 1 pixel; this  
265 assumes a “half neighbors” scheme, in which each pixel has 4 neighbors, and only pixels that  
266 share an edge are merged. One limitation of *connectedComponents* is that the algorithm limits  
267 the maximum number of pixels per patch at 256 pixels and identifies larger patches as  
268 background. We account for this limitation by increasing the total number of burn scar fragments  
269 in a grid cell by one if the MCD64A1 burned area is larger than the size of the patch derived by  
270 *connectedComponents*. Additionally, the 0.25° x 0.25° grid used to extract the contiguous burn  
271 scars sets an upper bound on burned area per patch for those large fires extending across multiple  
272 grid cells. Values > 2 km<sup>2</sup> per burn fragment indicate large, contiguous fires, while small values  
273 represent small, fragmented fires.

274 **(4) Roughness in topography ( $\phi_{topography}$ ):** Rough terrain, or large variances in local  
275 elevation, can inhibit active fire detection or burned area classification by introducing shadows,  
276 leading to insufficient background control pixels and artificial variations in surface reflectance  
277 (Fornacca et al., 2017). We estimate the neighborhood variance of terrain elevation as an  
278 indication of rough terrain. We use the U.S. Geological Survey (USGS) Global Multi-resolution  
279 Terrain Elevation Data 2010 (GMTED2010) at 7.5 arc seconds (~250 m) spatial resolution,  
280 derived primarily from the Shuttle Radar Topography Mission (SRTM) Digital Terrain Elevation  
281 Data from the National Geospatial-Intelligence Agency (NGA). For each pixel, we estimate the  
282 neighborhood variance using a square kernel with a radius of 2 pixels. We then mask out water

283 bodies using the 250-m MODIS/Terra land/water mask (MOD44W C6) and upscale the  
284 topography variance to  $0.25^\circ \times 0.25^\circ$  spatial resolution by calculating the mean. Values close to  
285 0 indicate flat topography, while values  $> 1000 \text{ m}^2$  indicate rough, mountainous terrain. One  
286 limitation of this simple metric is that it does not account for terrain curvature, whose calculation  
287 is not yet supported by GEE.

288 **(5) Additional small fires detected by VIIRS ( $\phi_{VIIRS_{sf}}$ ):** VIIRS aboard S-NPP detects active  
289 fires at 375-m (I-bands) and 750-m (M-bands) spatial resolution in comparison to the 1-km  
290 spatial resolution of MODIS active fire detections (Schroeder and Giglio, 2017). The difference  
291 in spatial resolution suggests that VIIRS can detect smaller and cooler fires than MODIS.  
292 However, global fire emissions inventories have historically depended on MODIS since VIIRS is  
293 available only since 2012, or over a decade less than MODIS. While these additional small fires  
294 may comprise only a small portion of the global carbon budget, they can be important local point  
295 sources that contribute to regional air pollution. We approximate additional FRP observed by  
296 VIIRS at 375-m spatial resolution as the fractional FRP of VIIRS fires outside MODIS active  
297 fire and burned area pixels during the time period when the two satellite records overlap (2012-  
298 2017). Values range from 0 (no additional VIIRS FRP outside MODIS burn extent) to 1 (only  
299 VIIRS FRP).

### 300 *2.2.1 Bottom-up inventories: relative fire confidence scores (BA-score, AFA-score)*

301 Taken together, the five metrics described above capture the primary reliance on MODIS  
302 burned area (e.g., GFED) versus active fire (e.g., FINN) products as the base input satellite-  
303 derived fire dataset in a bottom-up approach and difficulty in the satellite detection of fires due to  
304 cloud/haze obscuration and limited spatial and temporal resolution. Using these five metrics, we  
305 estimate a relative fire confidence score for the two bottom-up emissions inventories, which are  
306 based on either burned area (as in GFED) or active fire area (as in FINN). For each metric and  
307 each grid cell, we assign an initial integer confidence score ranging from 0 to 10, with 10 as  
308 highest confidence score, based on the decile distribution of all grid cells. Grid cells with only  
309 MODIS active fire, only MODIS burned area, or only VIIRS active fire observations are  
310 assigned the lowest confidence score of 0. We then average the scores from the fire confidence  
311 metrics in each grid cell and adjust the scale by setting the median score for the final relative fire  
312 confidence score for that grid cell to 0. This score represents the relative degree to which we can  
313 be confident in fire emissions for these inventories. We associate low cloud/haze burden, low  
314 variance in elevation, and low fraction of additional VIIRS fires with high confidence. To assess  
315 inventories based on burned area (e.g., GFED), we calculate a “BA-score,” in which high burned  
316 area outside active fire area (metric 1) and low burn fragmentation (metric 3) denote high  
317 confidence. For inventories based on active fires (e.g., FINN), we calculate an “AFA-score,” in  
318 which we reverse the scales for metrics 1 and 3 and place more relative confidence in grid cells  
319 dominated by active fire area over burned area and fragmented burn landscapes.

### 320 *2.2.2 Top-down inventories: adjusted potential FRP adjustment (pFRP)*

321 Top-down FRP-based inventories often include statistical cloud-gap adjustment and/or  
322 smoke AOD constraints, making them difficult to directly compare against the bottom-up  
323 inventories. Cloud-gap adjustments correct for fires blocked from satellite detection due to



324 clouds or thick haze. These adjustments rely on data assimilation of previous observations and  
325 assumptions regarding fire persistence (Darmenov and da Silva, 2013; Kaiser et al., 2012). As an  
326 additional top-down constraint, fire emissions are scaled to match smoke-aerosol emissions  
327 derived from AOD observations (Ichoku and Ellison, 2014). We thus devise a separate score, the  
328 adjusted potential FRP enhancement (pFRP), or “FRP-score,” to assess the three top-down  
329 inventories (GFAS, QFED, FEER). The pFRP score diagnoses additional fire energy,  
330 unaccounted for by the MODIS active fires product but indicated by large burn scars from the  
331 MODIS burned area product or very small fires from the 375-m VIIRS active fires product. We  
332 first estimate the potential FRP enhancement as the sum of (1) fractional FRP inside MCD64A1  
333 burned area extent but outside active fire area, over 2003-2017, and (2) fractional VIIRS FRP  
334 outside the combined extent of both MODIS burned area and active fire area, or metric 5, over  
335 2012-2017. To obtain the adjusted potential FRP enhancement, we then multiply the potential  
336 FRP enhancement by the complement of the cloud/haze obscuration fraction, or metric 2. High  
337 pFRP values suggest low confidence in top-down inventories under clear-sky conditions.

### 338 *2.3 Global fire emissions inventories*

339 To convert burned area or FRP into emissions, fire emission inventories rely on estimates  
340 and assumptions regarding an array of variables as land cover type, fuel load, or emissions  
341 factors. Here we summarize these estimates and assumptions across five inventories (GFEDv4s,  
342 FINNv1.5, GFASv1.2, QFEDv2.5r1, and FEERv1.0-G1.2) over 2003-2016 and at both global  
343 and regional scale (Table 1). The versions of the inventories considered here are current as of  
344 2018. We then compare the resulting emissions of carbon dioxide (CO<sub>2</sub>), carbon monoxide (CO),  
345 methane (CH<sub>4</sub>), OC, BC, and PM<sub>2.5</sub> emissions from five global fire emissions inventories. Each  
346 inventory is described in more detail in Supplementary Section S2.

### 347 *2.4 Modeling smoke PM<sub>2.5</sub> from regional fire emissions*

348 Following Kim et al. (2015) and Koplitz et al. (2016), we use the adjoint of the GEOS-  
349 Chem CTM to estimate the influence of upwind fires on smoke exposure at population-weighted  
350 receptors. We define smoke PM<sub>2.5</sub> as the enhancement in PM<sub>2.5</sub> due to fire activity. As used here,  
351 the GEOS-Chem adjoint maps the sensitivities of smoke PM<sub>2.5</sub> at particular receptors to fire  
352 emissions in grid cells across a source region, creating a footprint of such sensitivities. These  
353 footprints depend on the transport pathways from the source to the receptor and vary with  
354 meteorology. By multiplying these sensitivities by the different fire emissions inventories, we  
355 can easily compare estimates of monthly smoke PM<sub>2.5</sub> exposure in Indonesia, Singapore, and  
356 Malaysia, from 2003-2016. We thus apply monthly adjoint sensitivities, which span a range of  
357 meteorology from 2005-2009, to the sum of OC and BC emissions, the main components of  
358 smoke PM<sub>2.5</sub>. Due to the high computational cost of the GEOS-Chem adjoint, we match existing  
359 2005-2009 sensitivities to each emissions year from 2003-2016 by determining the closest  
360 meteorological year in terms of rainfall (Kim et al., 2015; Koplitz et al., 2016). To do so, we use  
361 daily rainfall rates from Climate Hazards Group Infrared Precipitation with Station Data  
362 (CHIRPS; Funk et al., 2015), averaged temporally over the fire season and spatially over  
363 Sumatra and Kalimantan, Indonesia (Figure S3). CHIRPS is a daily, 0.05° x 0.05° dataset that  
364 integrates both observational and satellite data to provide quasi-global rainfall data since 1981.

365 As in Fernandes et al. (2017) and Marlier et al. (2019), we define the fire season in Indonesia as  
366 July to October.

367       Following Marlier et al. (2019), we further validate modeled smoke  $PM_{2.5}$  with ground  
368 observations in Singapore. We first extend the daily  $PM_{2.5}$  observations, available from 2014-  
369 2016, from the Singapore National Environment Agency (NEA) to 2010 by converting Pollution  
370 Standards Index (PSI) observations to  $PM_{2.5}$ . As used by the Singapore NEA, PSI is an air  
371 quality index that incorporates concentrations of six pollutants: CO, sulfur dioxide ( $SO_2$ ),  
372 nitrogen dioxide ( $NO_2$ ), ozone ( $O_3$ ),  $PM_{10}$ , and  $PM_{2.5}$  (<https://www.haze.gov.sg/>). To further  
373 extend the record back to 2003, we train a multi-variate regression model of monthly mean NEA  
374  $PM_{2.5}$  observations using visibility, air temperature, wind speed, and rainfall observations from  
375 the Singapore Changi airport, available from NOAA Global Summary of the Day (GSOD). The  
376 model yields an adjusted  $r^2$  with observations of 0.94 (Figure S5). We then reconstruct monthly  
377  $PM_{2.5}$  for 2003-2016 and subtract the background  $PM_{2.5}$ , or the median  $PM_{2.5}$  ( $13.77 \mu g m^{-3}$ )  
378 during non-fire season months (January to June and November to December), to obtain smoke  
379  $PM_{2.5}$  for our validation. Validation for Malaysia and Indonesia is described in Supplementary  
380 Section S3.2.

## 381 **4. Results**

### 382 *4.1 Spatial patterns in relative fire confidence metrics and scores*

383       Overall, the five relative fire confidence metrics broadly differentiate: (1) large,  
384 continuous versus small, fragmented landscapes, (2) cloudy/hazy versus clear satellite observing  
385 conditions during the fire season, and (3) flat versus mountainous or rugged terrain. First, the  
386 map of BA-AFA discrepancies (metric 1) reveals the regions where the burned area  $BA_\beta$  and  
387 active fire area extent  $BA_\alpha$  disagree. Regions dominated by high burned area outside the active  
388 fire area extent ( $BA_\beta \gg BA_\alpha$ ) include the western Australia shrublands, sub-Saharan Africa  
389 savannas, and Kazakhstan and eastern Mongolia grasslands. Regions dominated by active fire  
390 area outside burned area extent ( $BA_\beta \ll BA_\alpha$ ) are more widespread and primarily cover  
391 agricultural and/or mountainous areas (Figure 1). Additionally, this metric highlights artificial  
392 discontinuities in the MODIS burned area product, most prominently north of the Black Sea,  
393 likely due to separate data processing for each MODIS tile (Giglio et al., 2018). Second, the  
394 FRP-weighted cloud/haze fraction (metric 2) shows that tropical and boreal forest regions, as  
395 well as eastern China, are conducive to poor satellite observing conditions due to cloud or haze  
396 during the fire season, with index values greater than 0.5 (Figure 2). These areas with persistent  
397 cloud/haze burden are consistent with independent estimates of high mean cloud frequency  
398 (Wilson and Jetz, 2016) and are also co-located with high MODIS burn date uncertainty,  
399 indicating that many retrieved satellite scenes are unusable (Figure S9). Third, the pattern of burn  
400 size and fragmentation (metric 3) is similar to that of the BA-AFA discrepancy: areas with large,  
401 contiguous fires are better captured by burned area, while areas with small, fragmented fires are  
402 better represented by active fire detections (Figure 3). Our method for burn size/fragmentation  
403 yields spatial patterns consistent with fire size from the Global Fire Atlas, a catalog that  
404 characterizes over 13 million individual fires detected by MODIS (Andela et al., 2019). Fourth,  
405 topographical variance (metric 4) differentiates mountainous or rugged terrain, such as in

406 western U.S. and southeast Asia, versus flat terrain, such as in northern India and western  
407 Australia (Figure 4). Fifth, the map of VIIRS fires outside the MODIS burn extent (metric 5)  
408 reveals locations dominated by small fires that are not well-detected by a coarser resolution  
409 sensor like MODIS (Figure 5). In total, 38% of total VIIRS FRP does not overlap with the  
410 MODIS burn extent, revealing the importance of very small fires.

411 Taken together, the five metrics compose the relative fire confidence scores for bottom-  
412 up emissions inventories primarily derived from either burned area (BA-score; Figure S1a), such  
413 as GFEDv4s, or active fire area (AFA-score; Figure S1b), such as FINNv1.5. While the mapped  
414 BA-score and AFA-score mostly track the patterns of the large, contiguous fires versus small,  
415 fragmented fires, some areas exhibit low relative confidence (e.g., croplands in eastern China,  
416 tropical forests in the Democratic Republic of Congo) or high relative confidence (e.g., tropical  
417 forests in central-southern Amazon, savannas in Botswana and Namibia) for both scores due to  
418 the effects of cloud/haze cover and/or topographical variance. Some caveats apply here. While  
419 we take the BA-score to apply to GFEDv4s, this inventory also boosts burned area using active  
420 fire counts to account for small fires. Additionally, for AFA-score, we assume an active fire area  
421 of 1 km<sup>2</sup> for all fires, while FINNv1.5 uses 0.75 km<sup>2</sup> for savanna and grassland fires and further  
422 scales the active fire area for all fires by the fractional vegetation cover of a given 1-km pixel  
423 (Wiedinmyer et al., 2011). Both GFEDv4s and FINNv1.5 rely on outdated MODIS products:  
424 GFEDv4s on MCD64A1 C5.1 burned area and FINNv1.5 on MCD14DL C5 active fires;  
425 however, for all our metrics, we use updated satellite products from MODIS C6 (MCD64A1 and  
426 MxD14A1). Despite our simplified approach and use of different versions of the satellite fire  
427 products, the normalized difference between GFEDv4s burned area and FINNv1.5 active fire  
428 area is spatially well-correlated with the BA-AFA discrepancy ( $r = 0.59$ ,  $p < 0.01$ ), or metric 1.  
429 We also find that the normalized difference between GFEDv4s and FINNv1.5 emissions for all  
430 six species is also moderately correlated with the BA-AFA discrepancy ( $r = 0.53$ - $0.57$ ,  $p < 0.01$ ),  
431 confirming that the difference between GFEDv4s and FINNv1.5 emissions is related to the  
432 satellite fire input dataset used.

433 The pFRP metric assesses top-down FRP-based emissions inventories (GFAS, QFED,  
434 and FEER; Figure S2). In total, we estimate 24% and 38% potential FRP enhancement from  
435 large fires (using MODIS BA) and very small fires (using VIIRS FRP), respectively, from 2003-  
436 2017. Put another way, the FRP-based inventories may be missing nearly two-thirds of fires  
437 under clear-sky conditions. Regions with low pFRP, and thus high uncertainty, include India and  
438 sub-Saharan Africa. In these regions, the low pFRP implies that either the satellite overpasses are  
439 missing a large number of short-lived or fast-spreading fires or the fires are too small to detect at  
440 coarse resolution. For example, the satellite overpasses at 10:30 am and 1:30 pm likely  
441 underestimate fire energy in the sub-tropics, where fire activity generally peak in the late  
442 afternoon (Giglio, 2007). Regions characterized by high cloud/haze cover during the fire season,  
443 such as tropical and boreal forests, have low pFRP due to our assumption that the cloud-gap  
444 corrections in these inventories successfully capture the fires obscured by clouds/haze.

#### 445 *4.2 Comparison of global fire emissions inventories: speciation and emissions factors*

446 We find inconsistencies in the speciation of the overall emissions budget for CO<sub>2</sub>, CO,  
447 CH<sub>4</sub>, OC, BC, and PM<sub>2.5</sub> across the five global fire emissions inventories. For example,

448 QFEDv2.5r1 and FEERv1.0-G1.2 estimate ~2-3 times as much OC, BC, and PM<sub>2.5</sub> emissions  
449 than the other inventories, with QFEDv2.5r1 higher than FEERv1.0-G1.2 (Table 3). Mean  
450 annual OC + BC emissions, from 2003-2016, among inventories differ by 5-126% in coefficient  
451 of variation (CV; Figure 6). In regions with a high CV, such as temperate North America (102%)  
452 and the Middle East (126%), QFEDv2.5r1 OC+BC emissions are much higher than those from  
453 other inventories. These discrepancies shed light on the impact of the different algorithms that  
454 convert burned area or fire energy into aerosol emissions. For example, QFED and FEER apply  
455 top-down constraints on aerosol emissions to match smoke AOD, while such adjustments are  
456 absent in GFED, FINN, and GFAS. FEER uses smoke AOD to directly calculate TPM, which is  
457 then broken down into aerosol species, while QFED enhances aerosol emissions with a constant  
458 global scaling factor for each LULC (Darmenov and da Silva, 2013; Ichoku and Ellison, 2014).  
459 This global, rather than regional, AOD-based scaling in QFED may explain the large CV in the  
460 Middle East and North America. Indeed, using MODIS/Aqua AOD, Darmenov and da Silva  
461 (2013) find significant variation in these scaling factors across each LULC – e.g., from 2-3 in  
462 tropical forest, 3-5 in extratropical forests, and 1-3 in grasslands and savannas.

463 To better understand the discrepancies across inventory emissions, we examine the  
464 emissions factors used in GFEDv4s and in earlier versions of FINN, GFAS, and QFED:  
465 FINNv1.0, GFASv1.0, and QFEDv2.4. We assume that emissions factors for the current versions  
466 of these three inventories do not deviate significantly from those in previous versions (Darmenov  
467 and da Silva, 2013; Kaiser et al., 2012; Wiedinmyer et al., 2011). First, we assess the impact of  
468 LULC classification on emissions factors by deriving a globally averaged emissions factor for  
469 each emitted species in each inventory, weighted by the total DM emissions for each LULC. To  
470 isolate the differences in LULC classification among inventories, we use the GFEDv4s DM  
471 emissions partitioned by LULC for the weighting. Since FINN subdivides the GFEDv4s savanna,  
472 grasslands, and shrublands LULC into two smaller LULC, we derive weights for these LULC  
473 using FINNv1.5 emissions. We find that the coefficients of variation in emission factors across  
474 the four inventories are relatively small for CO<sub>2</sub>, CO, OC, and BC (1.75-6.67%), compared to  
475 those for CH<sub>4</sub> and PM<sub>2.5</sub> (20.3-26.7%; Table 4). On average, GFEDv4s and GFAS, which  
476 consider peatlands as a separate LULC, have about 60% higher weighted mean emissions factors  
477 for CH<sub>4</sub> than FINN and QFED. This discrepancy arises because the peat emissions factor (20.8 g  
478 CH<sub>4</sub> kg<sup>-1</sup> DM) is ~2.5-14 times as high as CH<sub>4</sub> emissions factors for other LULC (Table S1), and  
479 only GFEDv4s and GFAS consider peatlands separately. In contrast to Li et al. (2019), we do not  
480 consider that FEERv1.0-G1.2 accounts for peatlands (Table 1), since FEER only uses the  
481 “permanent wetland” classification from the MODIS land cover product, which misses much of  
482 the peatland cover in Indonesia compared to the Olson et al. (2001) dataset used by GFED (van  
483 der Werf et al., 2017) and GFAS (Heil et al., 2010; Kaiser et al., 2012). The high CH<sub>4</sub>, as well as  
484 CO, emissions factors for peat fires can be attributed to incomplete combustion from smoldering  
485 fires, which are common in boreal and tropical peatlands (Kasischke and Bruhwiler, 2002;  
486 Stockwell et al., 2016). Additionally, the PM<sub>2.5</sub> emissions factors used in FINN for woody  
487 savanna/shrubland and savanna/grassland (8.3-15.4 g PM<sub>2.5</sub> kg<sup>-1</sup> DM) are 16-214% higher than  
488 those used in GFEDv4s, GFAS, QFED (4.9-7.17 g PM<sub>2.5</sub> kg<sup>-1</sup> DM) for the broader savanna,  
489 grassland, and shrubland LULC, which may explain the high PM<sub>2.5</sub> weighted mean emissions  
490 factor for FINN (Table S1).

#### 491 4.3 Modeling monthly smoke $PM_{2.5}$ from Indonesia fires

492 We use monthly GEOS-Chem adjoint sensitivities, from 2005-2009, with the five global  
493 fire emissions inventories to model smoke  $PM_{2.5}$  in Singapore, Malaysia, and Indonesia from  
494 2003-2016, focusing on the impact of upwind Indonesian fires (Figure 7-8, S7-8). According to  
495 GFEDv4s, peat fires contributed almost half of total OC+BC emissions in Indonesia from 1997-  
496 2016. Modeled monthly mean smoke  $PM_{2.5}$  is moderately to strongly correlated with  
497 observations ( $r = 0.64$  to  $0.84$ ,  $p < 0.01$ ), with GFASv1.2 smoke  $PM_{2.5}$  most closely matching the  
498 temporal variability of observed  $PM_{2.5}$  enhancement from smoke (Figure 8a). We find similarly  
499 strong correlations for population-weighted smoke  $PM_{10}$  in Malaysia ( $r = 0.54$  to  $0.89$ ,  $p < 0.01$ )  
500 and satellite AOD in Indonesia ( $r = 0.63$  to  $0.93$ ,  $p < 0.01$ ; Figures S7-S8). While the correlation  
501 of modeled and observed smoke  $PM_{2.5}$  in Singapore is consistent across inventories, the  
502 magnitude of modeled smoke  $PM_{2.5}$  can differ by more than  $20 \mu\text{g m}^{-3}$  for the Jul-Oct average  
503 during extreme smoke episodes, such as in 2006 and 2015 (Figure 8b). For example, the models  
504 yield mean Jul-Oct smoke  $PM_{2.5}$  concentrations in 2006 that differ from observed smoke by -  
505 64% to +70%. For the 2006, 2009, and 2015 high fire intensity years, modeled Jul-Oct smoke  
506  $PM_{2.5}$  using GFASv1.2 yields the smallest mean absolute error relative to the observations  
507 (16%), compared to such errors from the other four inventories (39-66%).

##### 508 4.3.1. 2006 and 2015 severe haze events

509 Koplitz et al. (2016) used GFASv1.0 and the GEOS-Chem adjoint to investigate the  
510 public health effects of smoke from Indonesian fires in 2006 and 2015. These authors estimated  
511 over 150% higher premature mortality over Equatorial Asia in 2015 (100,300 excess deaths) than  
512 in 2006 (37,600 excess deaths). This suggests higher exposure to smoke and more prolonged fire  
513 activity, as well as drier El Niño conditions, in 2015 compared to 2006. In this study, we first  
514 compare relative changes in modeled Jul-Oct mean smoke exposure in Singapore between the  
515 2006 and 2015 fire seasons. In addition, the strong negative exponential relationship between  
516 rainfall and metrics of fire activity (e.g., active fire count, burned area) in Indonesia is well-  
517 established (Fernandes et al., 2017; van der Werf et al., 2017). However, Eck et al. (2019)  
518 suggest that thick smoke may obscure fires from satellite detection. To determine whether fire  
519 activity in Equatorial Asia is under-detected in 2015 due to haze, we first model the linear  
520 relationship between rainfall and fire activity, as well as with satellite AOD, in the log-log space  
521 for the 2003-2016 period. We use Jul-Oct rainfall rates from CHIRPS and MxD08\_M3 AOD. As  
522 measures of seasonal mean fire activity, we use the MxD14A1 active fire mask, MxD14A1 FRP,  
523 and MCD64A1 burned area, averaged over the Indonesian provinces of Sumatra and  
524 Kalimantan, where most fires are concentrated. We then predict 2015 fires in the context of the  
525 log-log linear regression of rainfall and fires, modeled excluding 2015 observations. If fires are  
526 under-detected due to haze in 2015, then active fire counts, FRP, and burned area should deviate  
527 negatively from the modeled log-log rainfall-fire relationships, compared to AOD, which should  
528 not deviate significantly.

529 Several phenomena indicate a more severe haze episode in 2015 than in 2006. The Niño  
530 3.4 index, which is a proxy for ENSO and based on anomalies in tropical Pacific sea surface  
531 temperatures, suggests a stronger El Niño in 2015 than in 2006 (Koplitz et al., 2016). In addition,  
532 lower rainfall rates (-29%) and higher AOD (+31-34%) over Sumatra and Kalimantan in 2015

533 suggest drier and hazier conditions over these fire-prone regions, relative to 2006. In contrast,  
534 minimal increases in active fire count (+6%) and FRP (+10%) in 2015 relative to the long-term  
535 MODIS record, and even decreases in burned area (-35%) suggest that increased haziness in  
536 2015 may have obscured many fires, making satellite detection of fires challenging. During the  
537 Indonesia fire season (Jul-Oct), satellite-observed smoke AOD and indicators of fire activity  
538 strongly correlate with rainfall in log-log space over 2003-2016 when 2015 is excluded ( $r = -0.87$   
539 to  $-0.98$ ,  $p < 0.01$ ; Figure 9). Given these relationships with rainfall, the 2015 fire activity  
540 appears severely underestimated, with active fire 60% less than expected, burned area 93% less,  
541 and FRP 62% less. In contrast, AOD in 2015 does not deviate significantly (-12%) from the  
542 modeled log-log relationship with rainfall.

543 The observed AOD and FRP in 2015 are within the 95% prediction interval for these  
544 variables, but both burned area and active fire counts are outside this interval. We now examine  
545 how these potential underestimates in 2015 fire activity may have affected the fire emissions  
546 inventories. We find that GFEDv4s, which includes a small fires boost, and FINNv1.5, which  
547 uses active fires to estimate burned area, less severely underestimate (63-76%) burned area in  
548 2015 than the MODIS burned area product (Figure S4). Inventories that make cloud-gap  
549 adjustments for obscured fires are better able to discern the more severe haze event in 2015 and  
550 match the observed enhancement of 183% in smoke  $PM_{2.5}$  in Singapore: GFASv1.2 shows a  
551 155% increase in smoke  $PM_{2.5}$  relative to 2006, and QFEDv2.5r1 and FEERv1.0-G1.2 yield  
552 increases of 96-137% (Figure 8b). In contrast, GFEDv4s and FINNv1.5 do not capture the  
553 enhanced smoke  $PM_{2.5}$  in Singapore in 2015. Overall, GFASv1.2 most accurately captures both  
554 the magnitude and temporal variability of observed smoke  $PM_{2.5}$ , while FINNv1.5 consistently  
555 underestimates smoke  $PM_{2.5}$  in high fire intensity years and most poorly captures the temporal  
556 variability of observed smoke  $PM_{2.5}$ .

## 557 **5. Discussion and Conclusion**

### 558 *5.1 Relative fire confidence metrics: spatial patterns*

559 The goal of this study has been to quantify and interpret differences across five bottom-  
560 up and top-down global fire emission inventories. While it is difficult to directly compare  
561 bottom-up and top-down inventories, end-users may use the relative confidence indicated by the  
562 BA-score, AFA-score, and FRP-score (pFRP) to select a “best” inventory if limited by  
563 computing resources. Nevertheless, these simple scores represent just one way for end-users to  
564 evaluate the metrics together; end-users, for example, may choose to assess the five relative fire  
565 confidence metrics individually. One important limitation is that the relative fire confidence  
566 metrics are time-averaged and therefore do not fully account for interannual or seasonal  
567 variability in fire activity. However, in constructing these metrics, we have placed greater weight  
568 on high fire intensity years and the dominant fire-prone months in order for end-users to  
569 diagnose the overall spatial biases among inventories. Another caveat is that we do not  
570 investigate in as much detail the spatial differences in inventory-specific LULC, which affect the  
571 fuel consumption and emissions factors imposed.

572 We first find that two fire landscapes – large and cohesive versus small and fragmented –  
573 account for broad differences in the bottom-up fire emissions inventories, GFED and FINN.

574 GFED, which relies primarily on observed burned area, better captures emissions from large,  
575 cohesive fires, while FINN, which depends on observed active fires, better captures emissions  
576 from small, fragmented fires. Second, the presence of thick cloud/haze during peak fire activity  
577 makes satellite fire detection more difficult in equatorial regions, boreal regions, and eastern  
578 China. Third, fires located in mountainous regions are also challenging to detect, especially by  
579 moderate-resolution sensors, such as MODIS (500 m or 1 km) or VIIRS (375 m or 750 m). For  
580 top-down fire emissions inventories (e.g., GFAS, QFED, and FEER), we calculate a pFRP score,  
581 which indicates potential underestimates in FRP under clear-sky conditions. We find high pFRP  
582 scores suggest that areas dominated by fast-spreading, large fires or short-lived, small fires under  
583 clear-sky conditions are not well-captured by MODIS due to limited overpasses or moderate  
584 spatial resolution.

### 585 *5.2 Regional application: validation of modeled smoke PM<sub>2.5</sub> across Equatorial Asia from* 586 *Indonesia fires*

587 Here we discuss the application of the relative fire confidence metrics for Indonesia fires.  
588 (Additional examples for the contiguous United States and northwestern India are discussed in  
589 Supplementary Section S6.) We do not explicitly consider the influence of spatial resolution in  
590 applying these fire emissions datasets. We focused on regional scale, so this influence is likely  
591 diluted. However, we acknowledge that spatial resolution may be important at local scale.

592 We can first deduce that fire-prone regions in Indonesia generally follow the small,  
593 fragmented fire landscape pattern (metrics 1, 3, and 5) and that high cloud cover and/or haze  
594 (metric 2) may impede observation during the fire season. While metric 4 shows rough terrain in  
595 parts of Indonesia (e.g., western Sumatra, Java, and northern Kalimantan), most fires occur on  
596 flat terrain. However, smoldering peat fires even on flat land may also be difficult to detect.

597 First, we find that thick haze in very high fire intensity years, such as 2015, likely leads to  
598 lower-than-expected fire activity derived from satellite observations. The AFA-score suggests  
599 high relative confidence for FINN, in contrast to the low relative confidence by BA-score for  
600 GFED; pFRP shows low potential FRP enhancement over Indonesia, primarily because of the  
601 presence of thick clouds or haze. Our results suggest that the 93% burned area underestimate in  
602 Indonesia arises primarily due to thick haze, an effect greater than the effect of such haze on  
603 active fire count (-60%) or FRP (-62%). For Singapore, as well as for Malaysia and Indonesia,  
604 we find that top-down inventories yield modeled smoke PM<sub>2.5</sub> concentrations that are more  
605 consistent with observed PM<sub>2.5</sub> than bottom-up inventories, with  $r = 0.78-0.84$  for top-down  
606 versus  $r = 0.64-0.73$  for bottom-up inventories. This result is likely due to the cloud-gap  
607 adjustments in the top-down inventories.

608 Second, only GFAS and GFED consider peatlands as a separate LULC, while in other  
609 inventories, peatlands may be classified as savanna, tropical forest, or cropland. These  
610 discrepancies have implications for emissions since the carbon-rich peatlands are associated with  
611 high fuel load (van der Werf et al., 2010). While the moderate to strong correlation of observed  
612 and modeled smoke PM<sub>2.5</sub> is consistent across inventories, the magnitude of mean Jul-Oct smoke  
613 PM<sub>2.5</sub> in the high fire intensity years of 2006 and 2015 can vary by more than 20  $\mu\text{g m}^{-3}$ , with  
614 GFEDv4s and GFASv1.2 best capturing the magnitude of observed smoke PM<sub>2.5</sub> and yielding

615 higher smoke PM<sub>2.5</sub> than the other three inventories. Additionally, estimated ratios of peat  
616 OC/BC emissions factors ratios are ~150 compared to just 3-39 for other LULC types, thereby  
617 affecting the composition of smoke PM<sub>2.5</sub>. Indeed, GFEDv4s and GFASv1.2 show 78-380%  
618 higher Jul-Oct OC/BC ratios over Sumatra and Kalimantan during 2003-2016 than the other  
619 three inventories. In summary, GFASv1.2, which adjusts for cloud gaps in satellite observations  
620 of fires and considers peatlands as a separate LULC class, performs best in terms of modeling  
621 smoke PM<sub>2.5</sub> that is consistent with observations in both temporal variability and magnitude.

### 622 *5.3 Uncertainties in global fire emissions inventories*

623 The uncertainties in global fire emissions inventories influence estimates of emissions  
624 budgets, the spatio-temporal variability of fires, and fire trends, with different inventories leading  
625 to different conclusions (Supplementary Section S7). Here we discuss the main sources of  
626 uncertainty in inventories: small fires, cloud gap adjustments, aerosol emissions enhancements,  
627 and emissions factors and LULC classification. Sole reliance on burned area from MCD64A1  
628 may capture large, contiguous fires well but not the spatial allocation of small fires in fragmented  
629 burn landscapes. This is demonstrated by the moderate spatial correlation ( $r = 0.36$ ,  $p < 0.01$ )  
630 between the BA-AFA discrepancy (metric 1) and burn size/fragmentation (metric 3). Additional  
631 VIIRS FRP detected outside the MODIS active fire extent (metric 5) also implies low confidence  
632 in areas dominated by small fires. As an example of low confidence in small fires, we find that  
633 many grid cells in GFEDv4s would not have any emissions without the small fires boost.  
634 Approximately one-fourth of grid cells with nonzero GFEDv4s fire emissions from 2003-2016  
635 persistently show 100% spatial coverage by small fires, and the small fire boost alone contributes  
636 all the emissions in 57% of GFEDv4s grid cells, on average. Zhang et al. (2018) recommended  
637 that grid cells with only small fire contribution, or no MCD64A1 burned area input, be treated  
638 with caution. For example, these authors found that GFEDv4s significantly overestimates DM  
639 fuel consumption and emissions for areas with infrequent but small fires in eastern China during  
640 summer months. Under such conditions, when no burned area is detected, the scaling parameters  
641 applied to the total active fire count are not specific to individual grid cells and instead are  
642 averaged across regions, seasons, and land cover types (van der Werf et al., 2017).

643 On the other hand, because MODIS retrieves thermal anomalies only during satellite  
644 overpass times, use of MCD14ML active fires in the bottom-up inventories, as well as MxD14  
645 FRP in the top-down inventories, may lead to underestimates of burned area and fire energy from  
646 large, contiguous fires. In addition, the FINN emissions inventory may overrepresent small fire  
647 emissions due to the assumption that at least 75% of the nominal pixel area is burned  
648 (Wiedinmyer et al., 2011). The active fire product also has coarser resolution and a lower  
649 detection threshold compared to the burned area product. Using FRP may address this  
650 overestimate since small fires are cooler and exhibit lower FRP. Nonetheless, the dependence of  
651 the top-down inventories on GFED to convert FRP to DM burned may lead to underestimates of  
652 small fire emissions, as seen in the case of agricultural fire emissions in northwestern India  
653 (Cusworth et al., 2018).

654 The cloud/haze fraction (metric 2) indicates that regions with persistent cloud cover or  
655 thick haze during the fire season, such as boreal and tropical regions, degrade the quality of  
656 satellite observations of fire activity. By adjusting for cloud gaps and scaling with observed



657 AOD, the top-down inventories – GFASv1.2, QFEDv2.5r1 and FEERv1.0-G1.2 – may be better  
658 able to match observations than the bottom-up inventories in these regions (Kopplitz et al.,  
659 2018b). However, the scaling factor of 3.4 recommended by Kaiser et al. (2012) for GFAS  
660 aerosol emissions, as well as the simple global QFED scaling by LULC, may bias regional  
661 smoke exposure estimates (e.g., Kopplitz et al., 2016) due to spatial variations in AOD scaling  
662 (Darmenov and da Silva, 2013; Ichoku and Ellison, 2014). We thus recommend comparison of  
663 aerosol emissions from QFEDv2.5r1 to FEERv1.0-G1.2, which directly estimates TPM using  
664 smoke AOD by region. Further, QFED calibrates the coefficient  $\beta$  relating FRP to DM globally,  
665 while GFAS uses LULC-specific  $\beta$  coefficients, which vary from 0.13 to 5.87 kg DM MJ<sup>-1</sup> FRP  
666 (Kaiser et al., 2012). We also show that certain species, such as CH<sub>4</sub>, are greatly affected by  
667 LULC classification within the inventories, and in particular, by the treatment of peatland  
668 emissions. In our case study of Indonesian fires, GFEDv4s and GFASv1.2, both of which  
669 account for peatlands, yield much higher smoke PM<sub>2.5</sub> more in line with observations than the  
670 other three inventories. Finally, coarse-resolution LULC maps (0.5°-1°), which are used in  
671 GFASv1.2 and FEERv1.0-G1.2, may also bias emissions due to differences in fuel loadings in  
672 regions with more heterogenous LULC, such as in Southeast Asia (Figure S10b).

#### 673 *5.4 Future directions and recommendations*

674 Integration of both burned area and active fire products into fire emission inventories  
675 may reduce underestimation of fires in small and fragmented or large and contiguous fire  
676 regions, respectively. Similar to the hybrid approach of using active fires for the small fire boost  
677 in GFEDv4s, incorporation of burned area in FINN could retroactively improve emissions  
678 estimates for large fires. For the top-down inventories of GFAS, QFED, and FEER, use of  
679 burned area as a secondary input satellite fire dataset may yield emissions more closely matched  
680 with observations compared to the current dependence on assumptions of fire persistence across  
681 cloud gaps and satellite overpasses. Standardization of emissions factors, in particular in the  
682 partitioning of LULC, could help reduce inconsistencies between inventories. In particular, the  
683 peatland maps used, if any, are incomplete and could be improved using more comprehensive  
684 global peatland datasets, such as PEATMAP (Xu et al., 2018). We also expect that the updated  
685 MODIS MCD12Q1 land cover dataset from C5 to C6 will lead to some differences between  
686 current and future emissions estimates (Sulla-Menashe et al., 2019). Further, access to high  
687 spatial resolution surface reflectance datasets from Landsat (30 m, every 16 days) and Sentinel-2  
688 (20 m, every 5 days) in the GEE data catalog makes feasible both ground truth validation and  
689 improvement of burned area estimates and LULC classifications (Casu et al., 2017). Recent  
690 studies have shown overall improvement in accuracy and small burn scar detection using  
691 Landsat and Sentinel, but low revisit times may limit this improvement in areas with high  
692 cloudiness and rapid land use change (Crowley et al., 2019; Goodwin and Collett, 2014;  
693 Hawbaker et al., 2017; Roteta et al., 2019).

694 For end-users, we recommend use of multiple bottom-up and top-down inventories, if  
695 possible. Further, end-users should be aware that outdated emissions estimates can persist in  
696 models, leading to biases and errors in model results (Supplementary Section S8). We present  
697 here an online tool, “Fire Inventories: Regional Evaluation, Comparison, and Metrics”  
698 (FIRECAM; <https://globalfires.earthengine.app/view/firecam>), that allows users to compare

699 regional monthly and yearly emissions, from 2003-2016, from the five global inventories for six  
700 species (CO, CO<sub>2</sub>, CH<sub>4</sub>, OC, BC, and PM<sub>2.5</sub>) and to interpret the regional differences between  
701 fire emissions by using the five relative fire confidence metrics (Figure S11, Supplementary  
702 Section S5). FIRECAM will be updated regularly in the foreseeable future as new versions of the  
703 inventories and underlying datasets become available. We identify three key factors that should  
704 influence the end-user's inventory selection and can also significantly affect the results of  
705 modeling studies: input satellite fire dataset, statistical adjustments, and LULC classification and  
706 emissions factors. For example, in our case study on Indonesian fires, we find that the cloud-gap  
707 adjustment and representation of peatland emissions are two important factors that distinguish  
708 different inventories in the regional validation of smoke PM<sub>2.5</sub>; both factors are included in the  
709 GFAS inventory. FIRECAM allows users to rapidly assess such differences in regional fire  
710 emissions.

## 711 **Code Availability**

712 R and Google Earth Engine code for the FIRECAM tool and relative fire confidence metrics can  
713 be accessed from <https://github.com/tianjialiu/FIRECAM>.

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## 977 List of Figure Captions

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979 methodological details and technical parameters. Broadly, we define “bottom-up” as burned  
980 area-based and “top-down” as fire energy-based inventories.

981 **Table 2.** Satellite-derived datasets used for the five relative fire confidence metrics, which are  
982 described in Section 2.2.

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985 BA outside AFA and AFA outside BA. Values are averaged over 2003-2017 and mapped at  
986  $0.25^\circ \times 0.25^\circ$  spatial resolution. High values (darker red) indicate relatively more confidence in  
987 BA than AFA, and low values (darker blue) the opposite.

988 **Figure 2. Metric 2 for relative fire confidence score ( $\phi_{cloud\_haze}$ ):** Cloud/haze fraction based  
989 on MxD09GA surface reflectance and weighted by FRP. Values are averaged 2003-2017 and  
990 mapped at  $0.25^\circ \times 0.25^\circ$  spatial resolution. High FRP-weighted cloud/haze fraction indicates  
991 fewer opportunities for satellite observation of the land surface during the fire season.

992 **Figure 3. Metric 3 for relative fire confidence score ( $\phi_{fragment}$ ):** average burned area ( $\text{km}^2$ )  
993 per “fragment,” or contiguous patch of burned area, averaged over 2003-2017 and mapped at  
994  $0.25^\circ \times 0.25^\circ$  spatial resolution. High values indicate dominance of large, contiguous fires; low  
995 values denote dominance of small, fragmented fires.

996 **Figure 4. Metric 4 for relative fire confidence score ( $\phi_{topography}$ ):** roughness in topography,  
997 expressed as variance in elevation ( $\text{m}^2$ ), averaged over 2003-2017 and mapped at  $0.25^\circ \times 0.25^\circ$   
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999 mountainous terrain, whereas low values indicate relatively flat terrain.

1000 **Figure 5. Metric 5 for relative fire confidence score ( $\phi_{VIIRS\_sf}$ ):** additional fires detected by  
1001 VIIRS. Values are the areal fraction of VIIRS FRP occurring outside MODIS burned area and  
1002 active fire pixel area, averaged over 2003-2017 and mapped at  $0.25^\circ \times 0.25^\circ$  spatial resolution. A  
1003 value of 0 indicates that all VIIRS active fires overlap MODIS active fires, and a value of 1  
1004 indicates the presence of VIIRS active fires but no MODIS burned area or active fire  
1005 observations.

1006 **Table 3.** Average annual global  $\text{CO}_2$ , CO,  $\text{CH}_4$ , organic carbon (OC), black carbon (BC) and fine  
1007 particulate matter ( $\text{PM}_{2.5}$ ) emissions ( $\text{Tg yr}^{-1}$ ,  $\pm 1\sigma$ ) by inventory, from 2003-2016. The percent  
1008 difference in emissions relative to GFEDv4s is in brackets. For each species, the inventory with  
1009 the highest emissions is denoted in bold font. The coefficient of variation (CV; %) indicates the  
1010 spread of values, normalized by the mean, across the five inventories.

1011 **Figure 6. Mean annual OC + BC emissions ( $\text{Tg yr}^{-1}$ ,  $\pm 1\sigma$ ), over 2003-2016, from five global  
1012 fire emissions inventories (GFEDv4s, FINNv1.5, GFASv1.2, QFEDv2.5r1, and FEERv1.0-  
1013 G1.2) for the 14 GFEDv4s basis regions** (Figure S12; van der Werf et al., 2017). Acronyms for  
1014 the 14 basis regions are given in Figure S12. The fraction of OC emissions is denoted by darker  
1015 shades, and that of BC emissions by lighter shades. Vertical bars show one standard deviation of

1016 the means over time. The coefficient of variation across inventories (CV, %) is shown for each  
1017 region.

1018 **Table 4.** Average emissions factors (g species kg<sup>-1</sup> dry matter) for CO<sub>2</sub>, CO, CH<sub>4</sub>, OC, BC and  
1019 PM<sub>2.5</sub>, weighted by fractional emissions over GFEDv4s land use and land cover (LULC). The  
1020 coefficient of variation (CV; %) gives the variation, normalized by the mean, across inventories  
1021 by species.

1022 **Figure 7. Indonesia fires, smoke exposure in Singapore, and AOD in Equatorial Asia**  
1023 **during July-October in 2006.** (a) Total organic carbon (OC) and black carbon (BC) emissions  
1024 from GFASv1.2. Sum of OC+BC fire emissions over Indonesia is shown inset. (b) Sensitivity of  
1025 mean July-October smoke concentrations in Singapore to the location of fire emissions,  
1026 calculated by the GEOS-Chem adjoint. (c) Contribution of smoke PM<sub>2.5</sub> in Singapore from fires  
1027 in individual grid cells over Indonesia, modeled using GFASv1.2 fire emissions. Average,  
1028 calculated smoke PM<sub>2.5</sub> exposure in Singapore, which is the sum of these contributions, is shown  
1029 inset. (d) Average MODIS Terra and Aqua aerosol optical depth (AOD) in Equatorial Asia. (e)  
1030 Distribution of peatlands in Sumatra and Kalimantan, Indonesia. The approximate total peatland  
1031 area in these regions is shown inset.

1032 **Figure 8. Smoke PM<sub>2.5</sub> exposure in Singapore, from 2003-2016.** (a) Timeseries of monthly  
1033 mean observed (black dots) and modeled (colored lines) smoke PM<sub>2.5</sub> concentrations. Observed  
1034 smoke PM<sub>2.5</sub> is reconstructed from meteorological observations from the Singapore Changi  
1035 Airport; only non-zero monthly smoke PM<sub>2.5</sub> observations are shown. Modeled values are from  
1036 the GEOS-Chem adjoint using different global fire emissions inventories: GFEDv4s, FINNv1.5,  
1037 GFASv1.2, QFEDv2.5r1, and FEERv1.0-G1.2. Correlations between observed and modeled  
1038 smoke PM<sub>2.5</sub> are shown inset for each inventory and are statistically significant ( $p < 0.01$ ). (b)  
1039 Jul-Oct mean smoke PM<sub>2.5</sub> by inventory, with observed smoke PM<sub>2.5</sub> indicated by dashed  
1040 horizontal lines.

1041 **Figure 9. Under-detection of 2015 Indonesia fires in MODIS active fire and burned area**  
1042 **products relative to the 2003-2016 period.** CHIRPS rainfall rates (mm day<sup>-1</sup>) are plotted  
1043 against MODIS (a) aerosol optical depth, (b) active fire count, (c) burned area (km<sup>2</sup>), and (d)  
1044 FRP (GW) in log-log space. All variables are averaged temporally over July-October and  
1045 spatially over Sumatra and Kalimantan, Indonesia. Colors denote different years from 2003-  
1046 2016, with later years depicted by redder shades; values for 2015 are circled. Inset shows the  
1047 correlation ( $r$ ,  $p < 0.01$ ), slope of the linear regression (gray dashed line), and slope with 2015  
1048 removed (black line) for each pair of observations. Standard errors for the slopes are shown in  
1049 parentheses. There is no statistically significant linear trend in any variable over time. Blue  
1050 arrows in (b), (c), and (d) show that observed fires are lower than expected based on prediction  
1051 from the linear regression of rainfall and fires that excludes 2015 observations. Percent  
1052 underestimate of each fire variable based on these predictions is shown in blue.

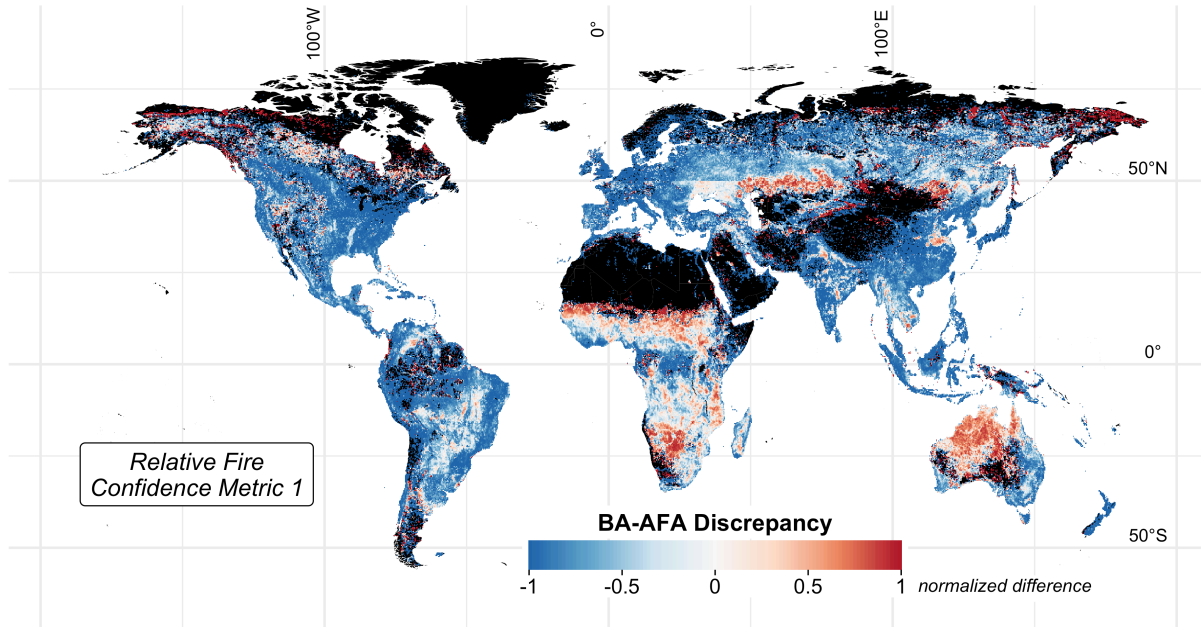
1053 **Table 1.** Comprehensive comparison of the global fire emissions inventories for various  
 1054 methodological details and technical parameters. Broadly, we define “bottom-up” as burned  
 1055 area-based and “top-down” as fire energy-based inventories.

Inventory	GFEDv4s	FINNv1.5	GFASv1.2	QFEDv2.5r1	FEERv1.0-G1.2
	“Bottom-up”		“Top-down”		
Primary satellite fire input	MCD64A1 C5.1 burned area (500 m)	MCD14DL C5 active fire area (1 km)	MOD14/MYD14 C5/C6 FRP (1 km)	MOD14/MYD14 C6 FRP (1 km)	GFASv1.2 FRP (0.1°)
Spatio-temporal resolution	0.25°, monthly (daily fraction)	1 km, daily	0.1°, daily	0.1°, daily (0.25° x 0.375°, NRT)	0.1°, daily
Temporal range	1997-2018*	2002- (NRT)	2003- (NRT)	2000- (NRT)	2003- (NRT)
Statistical boosts	Small fires boost	x	Cloud gap adjustment		
Conversion to dry matter (DM) emissions	CASA biogeochemical model (van der Werf <i>et al.</i> , 2010)	Hoelzemann <i>et al.</i> (2004)	GFAS FRP-GFEDv3 DM conversion factors by LULC	QFED FRP-GFEDv2 DM global calibration	x
Smoke AOD constraints for aerosol emissions	x	x	Recommends 3.4 global scaling	Applies global scaling constants for OC, BC, PM <sub>2.5</sub> separately	Uses FRP-smoke AOD relationships to derive regional TPM emissions
Primary land use/land cover (LULC)	MCD12Q1 (UMD), annual (500 m)	MCD12Q1 (IGBP), 2005 (500 m)	GFEDv3 dominant fire-prone LULC (0.5°)	IGBP-INPE (1 km)	MODIS IGBP dominant fire-prone LULC, 2004 (1°)
Peatland maps	Olson <i>et al.</i> (2001)	x	Same as GFED3 Heil <i>et al.</i> (2010)	x	x
Partitioning of emissions by LULC	yes	yes	x	yes	x
Emissions factors	Akagi <i>et al.</i> (2011) + updates from M.O. Andreae in 2013	Akagi <i>et al.</i> (2011), Andreae & Merlet (2001)	Andreae and Merlet (2001) + updates from literature	Andreae and Merlet (2001)	Andreae and Merlet (2001) + updates from M.O. Andreae in 2014
Speciation	41 species	27 species	42 species	17 species	30 species
Ancillary products	boosted BA, diurnal cycle, NPP	x	cloud-gap adjusted FRP density, plume top/ smoke injection altitude	cloud-gap adjusted FRP density by LULC	x
References	van der Werf <i>et al.</i> (2017)	Wiedinmyer <i>et al.</i> (2011)	Kaiser <i>et al.</i> (2012)	Darmenov and da Silva (2013)	Ichoku and Ellison (2014)

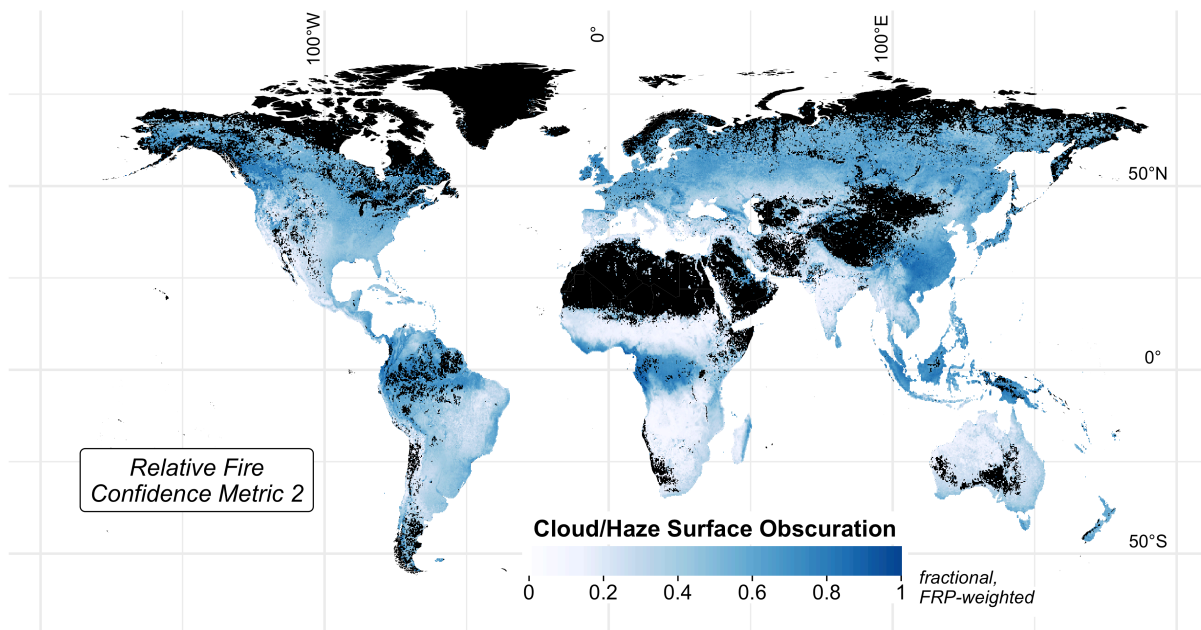
1056 NRT = near real time; CASA = Carnegie Ames Stanford Approach; UMD = University of Maryland;  
 1057 IGBP = International Biosphere-Geosphere Program; INPE = Instituto Nacional De Pesquisas Espaciais  
 1058 (Brazil’s National Space Institute); NPP = Net Primary Production; \*2017-2018 are beta version releases  
 1059 **Table 2.** Satellite-derived datasets used for the five relative fire confidence metrics, which are  
 1060 described in Section 2.2.

<b>Dataset</b>	<b>Description</b>	<b>Resolution</b>	<b>Satellite</b>	<b>Sensor</b>	<b>GEE ID</b>
MCD64A1	Burned Area	Monthly, 500 m	Terra/Aqua	MODIS	MODIS/006/MCD64A1
MOD14A1	Active Fires	Daily, 1 km	Terra		MODIS/006/MOD14A1
MYD14A1			Aqua		MODIS/006/MYD14A1
MOD09GA	Surface Reflectance	Daily, 500 m	Terra		MODIS/006/MOD09GA
MYD09GA			Aqua		MODIS/006/MYD09GA
MCD12Q1	Land Cover	Yearly, 500 m	Terra/Aqua		MODIS/006/MCD12Q1
MCD14ML	Active Fire Geolocations	Daily, 1 km	Terra/Aqua		projects/GlobalFires/MCD14ML
VNP14IMGML		Daily, 375 m	S-NPP	VIIRS	projects/GlobalFires/VNP14IMGML
GMTED2010	Terrain Elevation	2010 only, 7.5 arc sec	NGA’s SRTM Digital Terrain Elevation Data		USGS/GMTED2010

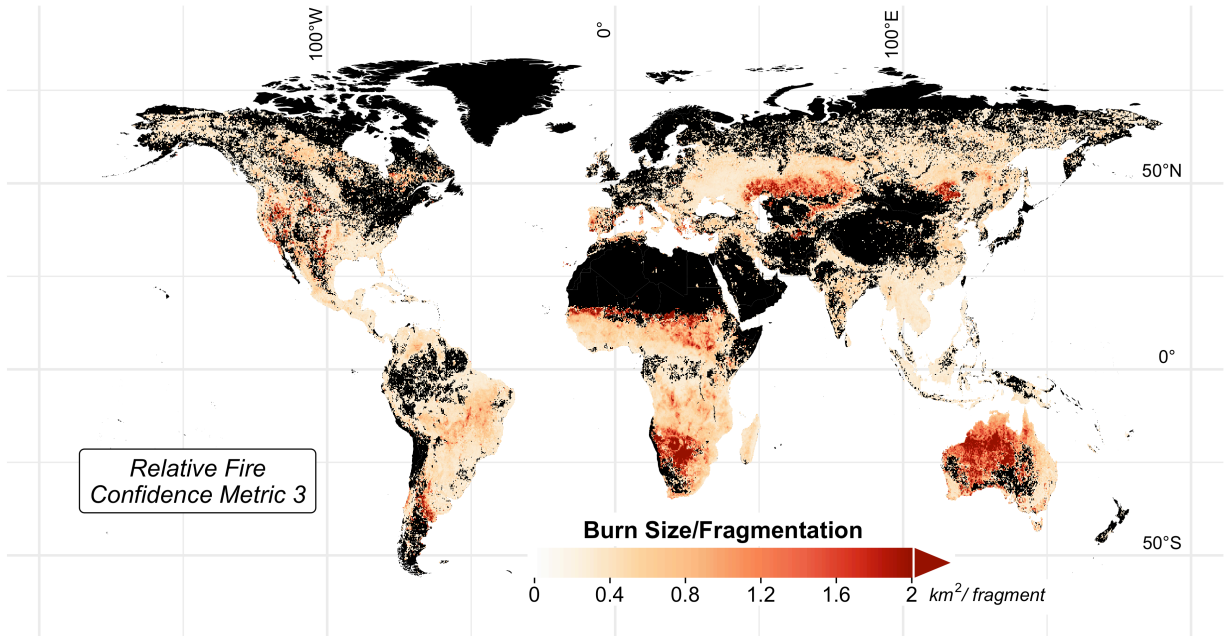
1061 NGA = National Geospatial-Intelligence Agency



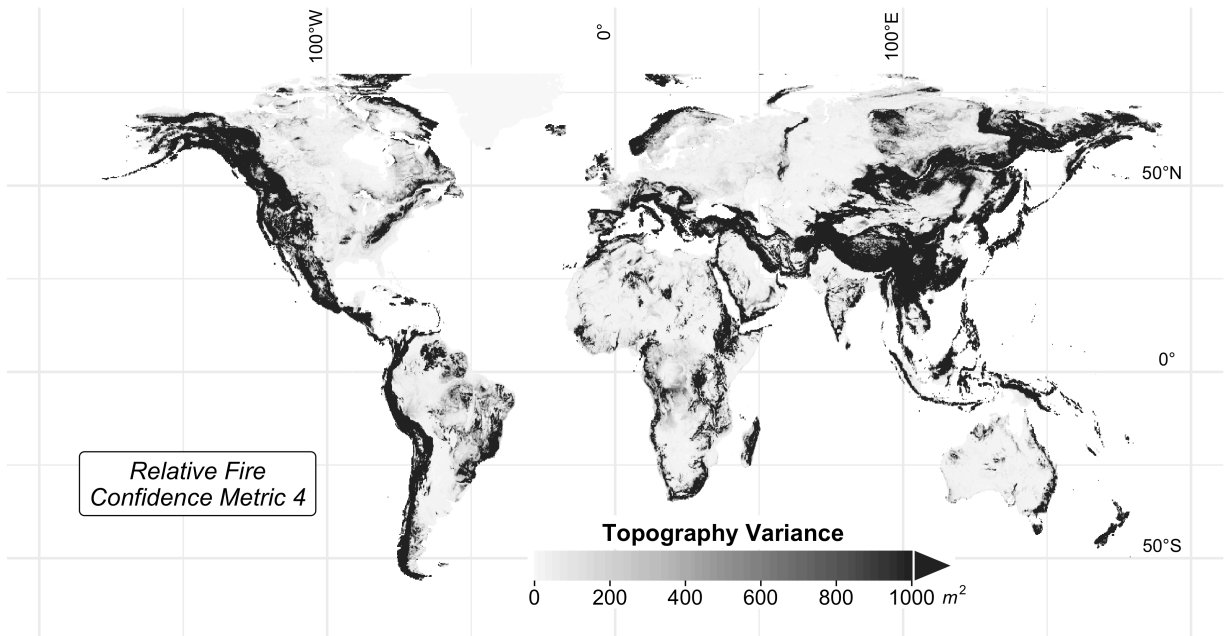
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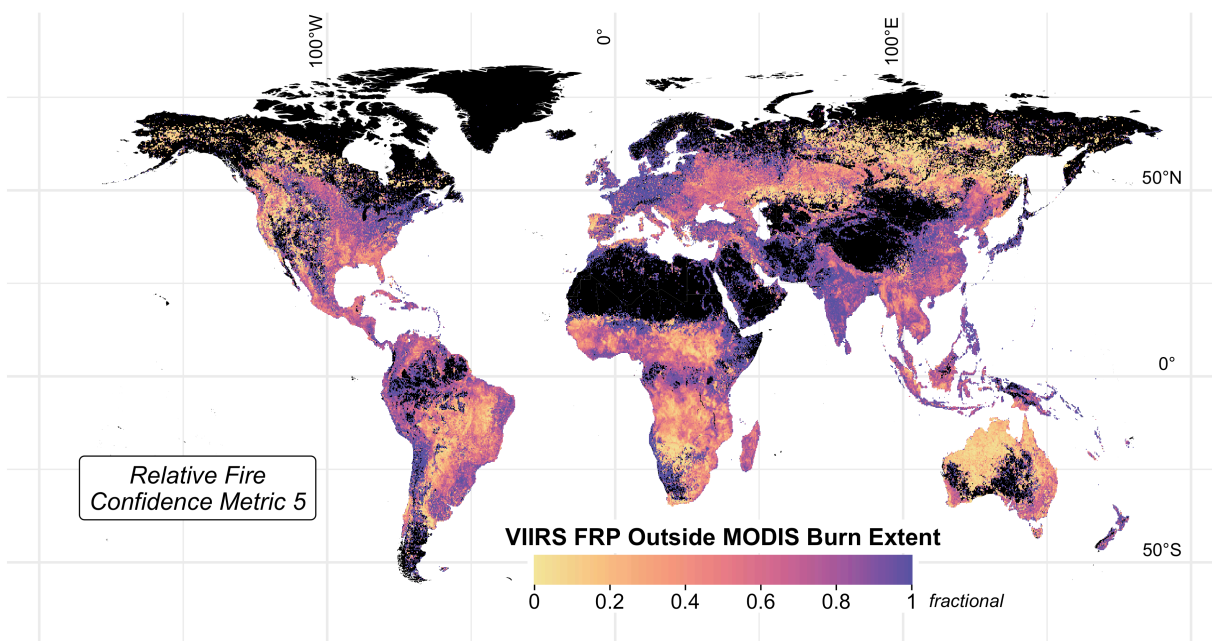
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1072 fewer opportunities for satellite observation of the land surface during the fire season.



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1074 **Figure 3. Metric 3 for relative fire confidence score ( $\phi_{fragment}$ ):** average burned area (km<sup>2</sup>)  
1075 per “fragment,” or contiguous patch of burned area, averaged over 2003-2017 and mapped at  
1076 0.25° x 0.25° spatial resolution. High values indicate dominance of large, contiguous fires; low  
1077 values denote dominance of small, fragmented fires.



1078  
1079 **Figure 4. Metric 4 for relative fire confidence score ( $\phi_{topography}$ ):** roughness in topography,  
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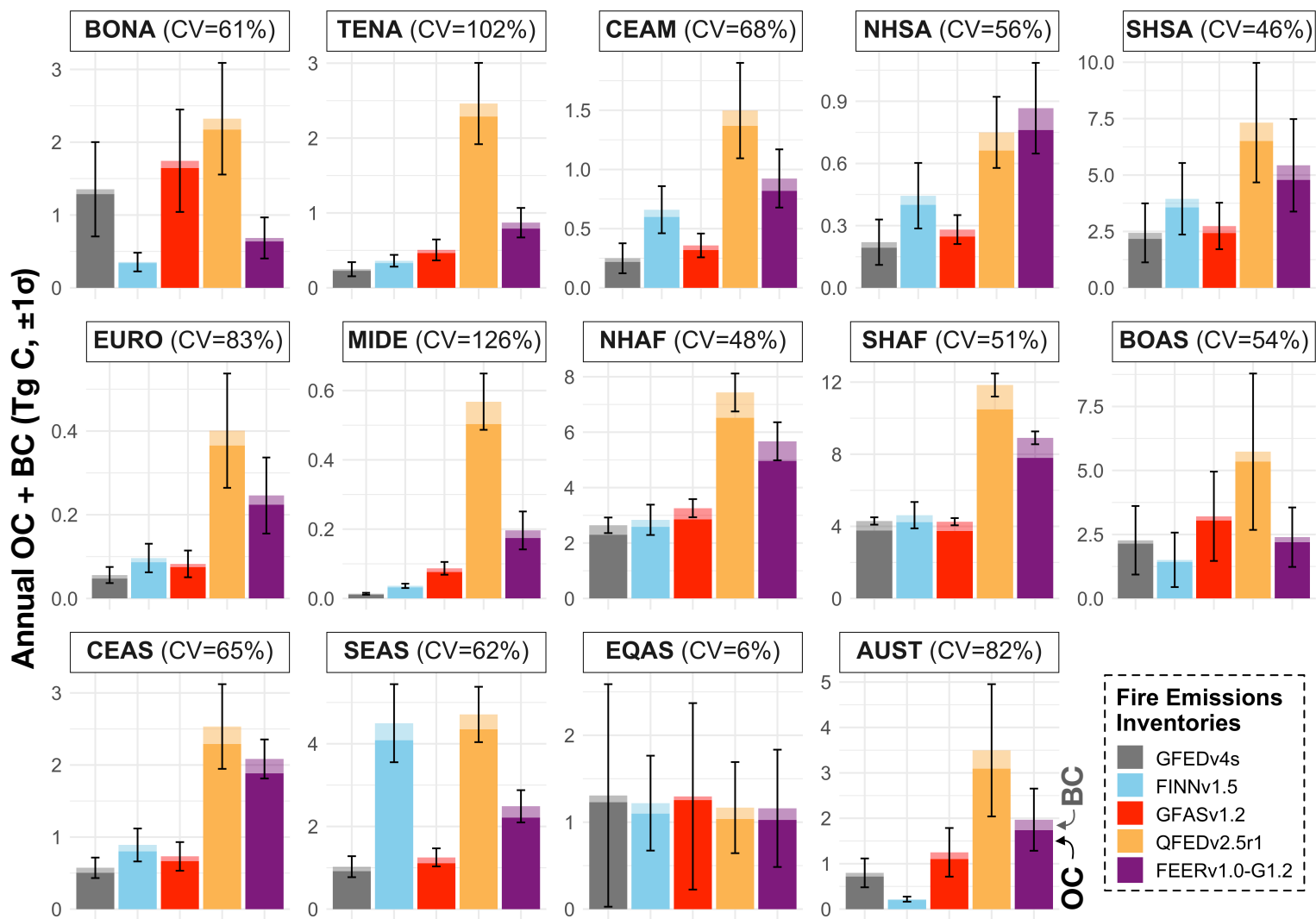
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 1092 difference in emissions relative to GFEDv4s is in brackets. For each species, the inventory with  
 1093 the highest emissions is denoted in bold font. The coefficient of variation (CV; %) indicates the  
 1094 spread of values, normalized by the mean, across the five inventories.

Species	Mean Annual Global Emissions (Tg)					CV (%)
	<i>GFEDv4s</i>	<i>FINNv1.5</i>	<i>GFASv1.2</i>	<i>QFEDv2.5r1</i>	<i>FEERv1.0-G1.2</i>	
CO <sub>2</sub>	6986 (595) --	6362 (1025) [-9%]	7083 (604) [+1%]	7449 (665) [+7%]	<b>13205 (1044)</b> [+89%]	34
CO	336 (39) --	334 (54) [-1%]	366 (43) [+9%]	348 (31) [+4%]	<b>609 (52)</b> [+81%]	30
CH <sub>4</sub>	15 (3) --	16 (3) [+8%]	20 (3) [+35%]	15 (1) [+2%]	<b>30 (3)</b> [+103%]	33
OC	16 (2) --	20 (3) [+26%]	19 (2) [+21%]	<b>47 (5)</b> [+199%]	30 (3) [+91%]	48
BC	1.8 (0.2) --	1.9 (0.3) [+8%]	2.1 (0.2) [+15%]	<b>5.3 (0.5)</b> [+196%]	3.9 (0.3) [+119%]	52
PM <sub>2.5</sub>	35 (3) --	35 (6) [+2%]	31 (3) [-11%]	<b>74 (7)</b> [+112%]	51 (4) [+47%]	39

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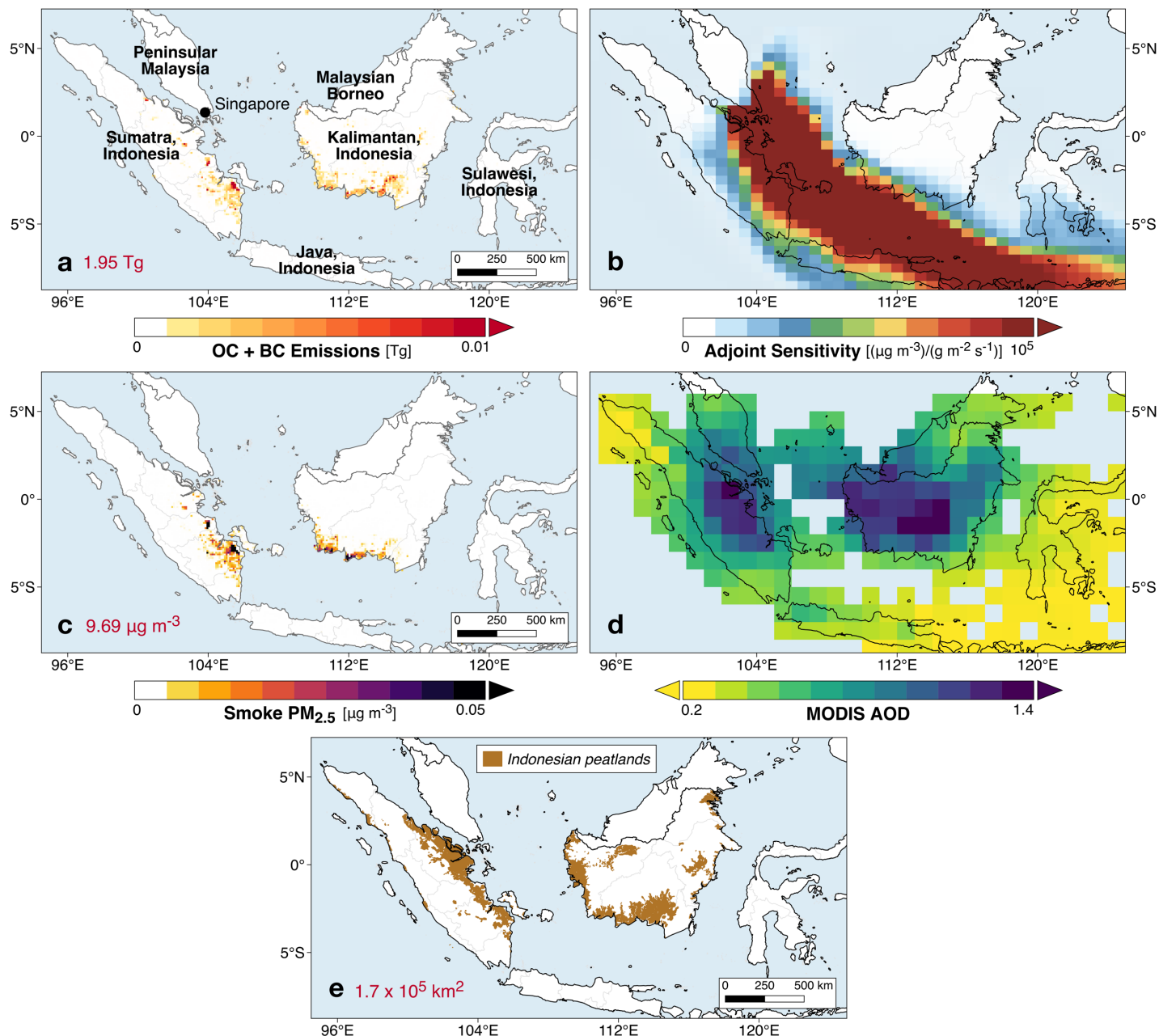




1097 **Figure 6. Mean annual OC + BC emissions (Tg yr<sup>-1</sup>, ±1σ), over 2003-2016, from five global**  
 1098 **fire emissions inventories (GFEDv4s, FINNv1.5, GFASv1.2, QFEDv2.5r1, and FEERv1.0-**  
 1099 **G1.2) for the 14 GFEDv4s basis regions (Figure S12; van der Werf et al., 2017). Acronyms for**  
 1100 **the 14 basis regions are given in Figure S12. The fraction of OC emissions is denoted by darker**  
 1101 **shades, and that of BC emissions by lighter shades. Vertical bars show one standard deviation of**  
 1102 **the means over time. The coefficient of variation across inventories (CV, %) is shown for each**  
 1103 **region.**

1104 **Table 4.** Average emissions factors (g species kg<sup>-1</sup> dry matter) for CO<sub>2</sub>, CO, CH<sub>4</sub>, OC, BC and  
 1105 PM<sub>2.5</sub>, weighted by fractional emissions over GFEDv4s land use and land cover (LULC). The  
 1106 coefficient of variation (CV; %) gives the variation, normalized by the mean, across inventories  
 1107 by species.

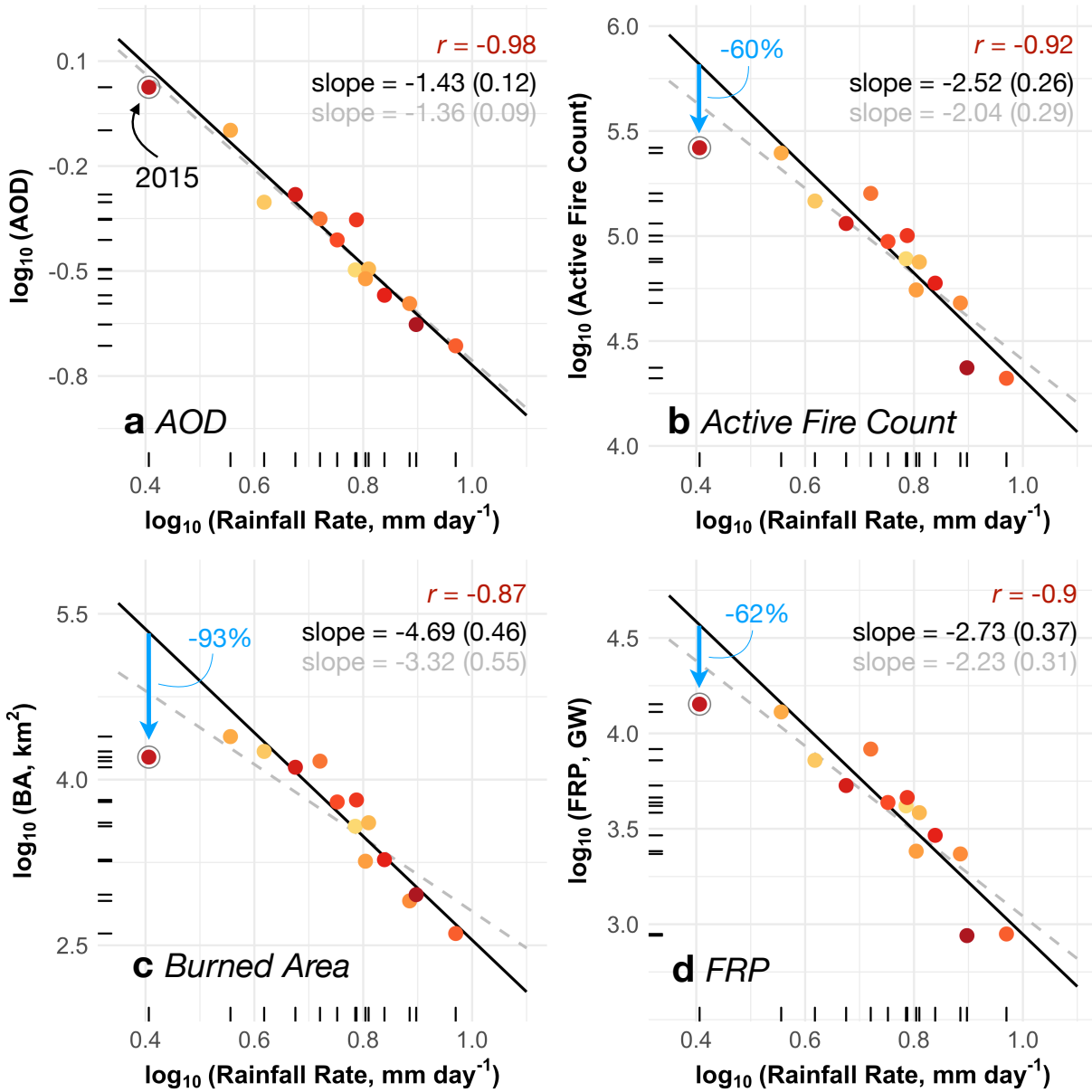
Species	Mean Emissions Factors (g species kg <sup>-1</sup> dry matter), Weighted by GFEDv4s LULC				CV (%)
	<i>GFEDv4s</i>	<i>FINNv1.0</i>	<i>GFASv1.0</i>	<i>QFEDv2.4</i>	
CO <sub>2</sub>	1648	1660	1611	1601	1.75
CO	95	87	91	84	5.45
CH <sub>4</sub>	6.67	4.43	7.1	4.2	26.7
OC	5.73	6.43	5.77	6.09	5.38
BC	0.47	0.46	0.49	0.53	6.67
PM <sub>2.5</sub>	9.65	12.46	8.29	8.29	20.3



1  
 1109 **Figure 7. Indonesia fires, smoke exposure in Singapore, and AOD in Equatorial Asia**  
 1110 **during July-October in 2006.** (a) Total organic carbon (OC) and black carbon (BC) emissions  
 1111 from GFASv1.2. Sum of OC+BC fire emissions over Indonesia is shown inset. (b) Sensitivity of  
 1112 mean July-October smoke concentrations in Singapore to the location of fire emissions,  
 1113 calculated by the GEOS-Chem adjoint. (c) Contribution of smoke PM<sub>2.5</sub> in Singapore from fires  
 1114 in individual grid cells over Indonesia, modeled using GFASv1.2 fire emissions. Average,  
 1115 calculated smoke PM<sub>2.5</sub> exposure in Singapore, which is the sum of these contributions, is shown  
 1116 inset. (d) Average MODIS Terra and Aqua aerosol optical depth (AOD) in Equatorial Asia. (e)  
 1117 Distribution of peatlands in Sumatra and Kalimantan, Indonesia. The approximate total peatland  
 1118 area in these regions is shown inset.



1119  
 1120 **Figure 8. Smoke PM<sub>2.5</sub> exposure in Singapore, from 2003-2016.** (a) Timeseries of monthly  
 1121 mean observed (black dots) and modeled (colored lines) smoke PM<sub>2.5</sub> concentrations. Observed  
 1122 smoke PM<sub>2.5</sub> is reconstructed from meteorological observations from the Singapore Changi  
 1123 Airport; only non-zero monthly smoke PM<sub>2.5</sub> observations are shown. Modeled values are from  
 1124 the GEOS-Chem adjoint using different global fire emissions inventories: GFEDv4s, FINNv1.5,  
 1125 GFASv1.2, QFEDv2.5r1, and FEERv1.0-G1.2. Correlations between observed and modeled  
 1126 smoke PM<sub>2.5</sub> are shown inset for each inventory and are statistically significant ( $p < 0.01$ ). (b)  
 1127 Jul-Oct mean smoke PM<sub>2.5</sub> by inventory, with observed smoke PM<sub>2.5</sub> indicated by dashed  
 1128 horizontal lines.



1129

1130 **Figure 9. Under-detection of 2015 Indonesia fires in MODIS active fire and burned area**  
 1131 **products relative to the 2003-2016 period.** CHIRPS rainfall rates ( $\text{mm day}^{-1}$ ) are plotted  
 1132 against MODIS (a) aerosol optical depth, (b) active fire count, (c) burned area ( $\text{km}^2$ ), and (d)  
 1133 FRP (GW) in log-log space. All variables are averaged temporally over July-October and  
 1134 spatially over Sumatra and Kalimantan, Indonesia. Colors denote different years from 2003-  
 1135 2016, with later years depicted by redder shades; values for 2015 are circled. Inset shows the  
 1136 correlation ( $r$ ,  $p < 0.01$ ), slope of the linear regression (gray dashed line), and slope with 2015  
 1137 removed (black line) for each pair of observations. Standard errors for the slopes are shown in  
 1138 parentheses. There is no statistically significant linear trend in any variable over time. Blue  
 1139 arrows in (b), (c), and (d) show that observed fires are lower than expected based on prediction  
 1140 from the linear regression of rainfall and fires that excludes 2015 observations. Percent  
 1141 underestimate of each fire variable based on these predictions is shown in blue.